Continuous monitoring of environmental disturbances by cumulative sums of dense SAR satellite timeseries

Javier Ruiz Ramos DipHE, M.Sc

Thesis
submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

The Open University

March, 2022
Abstract

Climate change together with growing socio-economic pressures are leading to a significant increase in alterations to natural ecosystems. The alteration of natural cycles and dynamics through the direct destruction or continuous degradation, are threatening the conservation of these natural spaces on a global scale. Satellite remote sensing is a suitable solution for large-scale monitoring and evaluation of natural landscapes under threat, as it provides a consistent source of information for both historical and updated environmental studies. However, most current remote sensing-based environmental monitoring tools still present certain limitations which hinder access to continuous and real-time information. The design and development of new methods and approaches to environmental remote sensing is required to mitigate the current environmental degradation trends.

This thesis analyses the current challenges associated with environmental monitoring to focus on the development of new change detection methods applied to the study of environmental disturbances in highly dynamic natural ecosystems. By exploiting the frequent monitoring capabilities of Synthetic Aperture Radar (SAR) dense timeseries, this research introduces new approaches based on Cumulative Sum (CuSum) strategies for continuous and near-real-time investigation. These approaches have been applied to monitor permanent and cyclical disturbances in highly threatened forest and wetland ecosystems.

The main scientific contribution of this thesis is the introduction of three novel SAR-based change detection approaches capable of exploiting dense satellite imagery time series for continuous and near-real-time monitoring. The outcome of this research provides environmental managers with a fully operational alternative tool capable of rapid and continuous monitoring of environmental dynamics.
Acknowledgements

This thesis would not have been possible without the support of a vast group of people. This adventure has been long and difficult, but equally beautiful and full of valuable learning experiences. In the same way that this work aims to expand the frontiers of scientific knowledge a little further, it is safe to say that this thesis has also brought a life-changing personal growth.

I wish to express my sincere appreciation to all the people who have supported and contributed, to a greater or lesser extent, to the completion of this thesis. Nonetheless, I would like to make a special mention to the following people.

To my project supervision team, for their unconditional professional and personal support, encouragement and patience, giving me the opportunity to freely explore and develop my own ideas. Armando Marino, none of this would have been possible without you. I must admit that the distance has only made the entire journey a little more difficult; Thanks for the countless technical talks, the support and push in moments of doubt, and especially, for the beers in Scotland. Sincerely, it is difficult to find individuals so kind and committed to teaching in the world of academia, and for this reason I am proud to have you as a mentor.

I would like to express my sincere gratitude to Carl Boardman, for guiding me along this path. Many challenges have been overcome, and you have always been there supporting, providing unquestionable support and a catalog full of brilliant ideas. Many thanks for the countless hours of proofreading and advice, always knowing how to direct me to the right paths. It has been a real pleasure sharing this exciting journey with you.

Andrea Berardi, thank you for your creativity and passion, I am extremely grateful to have been a part of so many exciting projects. All of our thoughtful conversations, plans, and ideas have helped me better understand the power of science and its capability not only to solve problems but to improve people's lives. Your experience and way of living have helped me to understand that knowledge has always been and always must be in the hands of the people, and therefore, whenever we can, we must fight to protect it. For many more ideas, projects and friendships with you and the Cobra Collective.

To Juan Suarez, for trusting my ideas right away and giving us the opportunity to develop our research, being a key player in launching this project. Extending my thanks to Forest Research, thank you for letting us 'play' in your forests and for always providing us access to any data and materials required. To John Hair, James Kyle of Forestry and Land Scotland, and Jakob Iglhaut and Ruben Manso, thanks for your invaluable help and fun field trips.
To Cristian Silva, my colleague and accomplice in the vicissitudes of this journey. It has been a pleasure to have such a partner during our studies and side projects. After so many conversations imagining this moment, we have achieved it.

To Alessandra Marino, Deirdre Jafferaly, the rest of colleagues from DETECT and SMART projects, and, in particular, to the North Rupununi researchers. Thank you for helping me grow professionally and for all the valuable lessons on the importance of social and ethical values in science.

To Ricardo Diaz-Delgado, Matthew Simpson, and Andy Hardy, thank you for your invaluable advice and dedication to this project, offering a wealth of ideas and insights on ecology and remote sensing.

To the entire Nightjaring team, for nurturing my love for nature and environmental conservation, making me learn about science in an entertaining, fun and very nocturnal way.

To all my climbing family, thanks for all the outdoor trips, dips in the cold ocean and lots of laughs. I will be always grateful for having you there, belaying me in what, to date, has been my ‘9c’ Project.

To my friends, ‘los niños’. Juanjo, Jesús, José, Selu and Guille, thank you for always being there. Thanks for all the support and for putting up with me, always being there with a cold beer and a good joke when I needed it most. Years, situations, places and lives will pass but you will always have me there.

Lastly, to my family. To my parents, Jose Javier and Mª Carmen. Thank you for everything, for raising me with love, truth, honesty and care. A whole life pushing me to be better, in all aspects, allowing me to develop as I have always wanted, letting me explore my own frontiers. For letting me choose, fail and learn and at the same time be there whenever I've needed it. To my sisters, Mar and Alba, and the flowers that grew from them, thank you for your unconditional support. Another experience for the team. To all of you, thank you for teaching me to look at nature, moments like these evoke the smell of pine, lakes and snacks.

Julia, half of all this belongs to you, only you know all the effort and what this means to me. We arrived practically barefoot, with more desire than resources, with more love than goals and, look at us now, I could not be prouder of what we build together every day. Thank you for the patience, the unconditional smile, for dancing together in the beautiful moments and for battling side by side against the storms. A brave, strong and determined woman... the best decision of my life, my friend, my companion in adventures, my most precious stroke of luck.

Thank you all!
Aunque suene a tópico, esta tesis no habría visto la luz si no hubiese contado con el apoyo de un enorme grupo de personas. Esta aventura ha sido larga y difícil, pero igualmente bonita y llena de aprendizaje. Al igual que este trabajo pretende contribuir a empujar las fronteras del conocimiento y la ciencia un poco más allá, no es arriesgado decir que esta tesis también ha supuesto un importante crecimiento a nivel personal, el cual me llevo para toda la vida.

Agradeciendo a todas aquellas personas que hayan ayudado, ya bien en mayor o menor medida, a la consecución de esta tesis, querría hacer una mención especial a las siguientes personas.

A mi equipo de supervisión, por su apoyo incondicional a nivel profesional y personal, ofreciéndome la posibilidad de explorar y desarrollar mis ideas con total libertad.

Armando Marino, nada de esto hubiese sido posible sin ti. He de reconocer que la distancia solo ha hecho todo el camino un poco más difícil, gracias por las innumerables charlas técnicas, el apoyo y empuje en los momentos de dudas y sobre todo por las cervezas en Escocia. Sinceramente, es difícil encontrar personas tan amables y comprometidas con la enseñanza dentro del mundo de la academia, y por ello estoy orgulloso de tenerte como mentor.

Carl Boardman, gracias por guiarme durante este camino. Han sido muchos los retos superados, y tú siempre has estado ahí apoyando, con un apoyo incuestionable y aportando un sinfín de ideas brillantes. Mil gracias por las innumerables horas de proofreading y consejos, sabiendo siempre dirigirme hacia los caminos correctos. Ha sido un verdadero placer compartir este excitante viaje contigo.

Andrea Berardi, gracias por confiar cuando incluso yo mismo dudaba. Todos proyectos en los que hemos trabajado juntos durante estos me han servido para comprender mejor el poder de la ciencia y su capacidad no solo de resolver problemas, sino de ayudar a mejorar la vida de las personas. Contigo he aprendido que el conocimiento siempre ha estado y siempre ha de estar en las manos del pueblo, y por ello, siempre que podamos, nos debemos a esto. Por muchos más ideas, proyectos y amistades contigo y con el Cobra Collective.

A Juan Suarez, por confiar en mis ideas a las primeras de cambio y brindarnos la posibilidad de desarrollar nuestra investigación, siendo una pieza clave para que este proyecto alzara el vuelo. Extendiendo este agradecimiento a la Scottish Forest Research, gracias por dejarnos ‘jugar’ en vuestros bosques y por poner siempre a nuestro servicio ideas, datos y materiales. A John Hair, James Kyle, de Forestry and Land Scotland, y a Jakob Iglhaut y Ruben Manso, gracias por vuestra ayuda inestimable y las divertidas campanas de campo.
A Cristian Silva, compañero desde el inicio y cómplice de las vicisitudes de este camino. Ha sido un placer tener un compañero como durante nuestros estudios y los proyectos paralelos. Tras muchas conversaciones imaginando este momento, lo hemos conseguido.

A Alessandra Marino, Deirdre Jafferally, resto de compañeros de DETECT y SMART, y en especial, a los investigadores del North Rupununi. Gracias por ayudarme a crecer profesionalmente y guiarme en el aprendizaje de los valores sociales y éticos de la ciencia.

A Ricardo Díaz-Delgado, Matthew Simpson y Andy Hardy, gracias por vuestros invalorables consejos y a vuestra dedicación a este proyecto, ofreciendo un arsenal de ideas y conocimientos sobre ecología y teledetección.

A todo el equipo de Nightjaring, por alimentar mi amor por la naturaleza y la conservación ambiental, haciéndome aprender sobre ciencia de una manera amena, divertida y muy nocturna.

A todos mis amigos escaladores, gracias por todos esos viajes a la roca, los baños helados en el Atlántico y las noches de camping y risas. Siempre os estaré agradecido por haber estado ahí, asegurándome en lo que, hasta la fecha, ha sido mi proyecto de 9c.

A los niños. Juanjo, Jesús, José, Selu y Guille, gracias por estar siempre ahí. Son ya unos cuantos de años los que llevo fuera, pero aún así, nada cambia. Gracias por aguantar mis charlas y estar siempre ahí con una cerveza fresquita y una buena broma o carga cuando más lo necesitaba. Pasan y pasaran los años, situaciones, lugares y vidas, pero siempre me tendréis ahí, listo para lo que venga.

Por último, a mi familia. A mis padres, Jose Javier y Ma Carmen, gracias por todo, por criarme en el amor, la verdad, la honestidad y el cuidado. Toda una vida empujándome a ser mejor, en todos los aspectos, permitiéndome desarrollarme como siempre he querido, dejándome explorar mis propias fronteras. Por dejarme elegir, fallar y aprender y a la vez estar ahí siempre que lo he necesitado. A mis hermanas, Mar y Alba, y las flores que crecieron de ellas, gracias por el apoyo incondicional. Otra experiencia más para el equipo. A todos vosotros, gracias por enseñarme a mirar a la naturaleza, momentos como estos me evocan olor a pino, lagos y bocadillos.

Julia, la mitad de todo esto te pertenece, sólo tú conoces todo el esfuerzo y lo que esto significa para mí. Llegamos prácticamente descalzos, con más ganas que recursos, con más amor que objetivos y, miranos ahora, no puedo estar más orgulloso de lo que cada día construimos y cuidamos. Gracias por la paciencia, la sonrisa incondicional, por bailar juntos en los momentos bonitos y por luchar codo a codo contra las tempestades. Mujer valiente, fuerte y decidida… la mejor decisión de mi vida, mi amiga, mi compañera de aventuras, mi más preciado golpe de suerte.

Gracias a todos!
# Table of contents

Chapter 1 - Introduction ............................................................................................................. 1

1.1 Introduction ....................................................................................................................... 2
  1.1.1 Background - Land use and land cover change (LULCC) .................................................. 2
  1.1.1.1 Deforestation and forest degradation ................................................................. 3
  1.1.2 Remote sensing for environmental monitoring ........................................................... 5
     1.1.2.1 Optical remote sensing .................................................................................. 6
     1.1.2.2 Radar remote sensing ................................................................................... 8

1.2 Remote sensing approaches for environmental monitoring ............................................. 12
  1.2.1 Forest monitoring ....................................................................................................... 12
  1.2.2 Wetland monitoring .................................................................................................. 14

1.3 Research needs and research questions .......................................................................... 15

1.4 Thesis structure ............................................................................................................... 17

Chapter 2 - Continuous forest monitoring using cumulative sums of Sentinel-1 timeseries... 19

2.1 Introduction ....................................................................................................................... 21

2.2 Study Area ....................................................................................................................... 22

2.3 Materials .......................................................................................................................... 23
  2.3.1 SAR Data .................................................................................................................. 23
  2.3.2 SAR Data Pre-Processing ....................................................................................... 24
  2.3.3 Validation data: Forest mask and Logging activities reference data ........................ 24

2.4 Methodologies .................................................................................................................. 25
  2.4.1 Cumulative Sum Change Detection Analysis ............................................................ 25
  2.4.2 CUSU-SMC ............................................................................................................. 26
  2.4.3 CUSUMs Implementation ....................................................................................... 27
  2.4.4 Z Score Calculation ................................................................................................. 28
  2.4.5 Logging Area Detection Accuracy Assessment ....................................................... 29
  2.4.6 Post-Processing and Sieve Filtering ......................................................................... 30
  2.4.7 CUSUMs Framework .............................................................................................. 30

2.5 Results .............................................................................................................................. 32
  2.5.1 Trends and Biases of CUSUMs ............................................................................... 32
  2.5.2 Testing the Assumptions .......................................................................................... 34
  2.5.3 CUSUM Logging activities detection ....................................................................... 34
     2.5.3.1 Comparison with Pairwise Analysis ............................................................... 37
     2.5.3.2 ROC Curves .................................................................................................... 38
     2.5.3.3 Final Detection Mask ..................................................................................... 39
  2.5.4 Post-Processing Sieve Filter .................................................................................... 40
  2.5.5 Forest Logging Detection Maps with Sieve Filter ..................................................... 41

2.6 Discussion .......................................................................................................................... 42
  2.6.1 Near Real Time ......................................................................................................... 43
  2.6.2 Adaptability to Other Sensors and Applications (Synergies) .................................... 43

2.7 Conclusions ....................................................................................................................... 44
Chapter 3 - Modifying the original CUSUM to work with cyclical disturbances integrating ancillary data: A natural wetland study case

3.1 Introduction ................................................................................................................................. 47
  3.1.1 Research context ...................................................................................................................... 48
  3.1.1.1 The DETECT project .......................................................................................................... 49

3.2 Data ............................................................................................................................................. 52
  3.2.1 Sentinel-1 dense timeseries ..................................................................................................... 52
  3.2.1.1 SAR data pre-processing ...................................................................................................... 52
  3.2.2 Open water edges ground truth data ........................................................................................ 54

3.3 Area of study ................................................................................................................................. 54
  3.3.1 The North Rupununi wetlands ............................................................................................... 54

3.4 Methods ....................................................................................................................................... 55
  3.4.1 Land Use and Land Cover classification map ......................................................................... 56
  3.4.2 Adaptation of CUSUM for flood detection ............................................................................. 57
    3.4.2.1 Selection of the reference period for the CUSUMs ............................................................... 57
    3.4.2.2 Assessing CUSUM-SAR monitoring capabilities for highly dynamic environments .......... 59
    3.4.2.3 The KerCuSum change detection approach ...................................................................... 60
  3.4.3 Post-processing: Result refinement from ancillary datasets ................................................... 63
  3.4.4 Validation ................................................................................................................................. 64
    3.4.4.1 Accuracy Assessment .......................................................................................................... 64
    3.4.4.2 Proximity analysis to water bodies edges ......................................................................... 65

3.5 Results .......................................................................................................................................... 66
  3.5.1 Seasonal floods change detection .......................................................................................... 66
  3.5.2 Validation results ..................................................................................................................... 69
  3.5.3 Proximity analysis .................................................................................................................. 72
  3.5.4 Ancillary data for flood mapping optimization ........................................................................ 73
  3.5.5 DETECT | CUSUM Web App .................................................................................................. 75

3.6 Conclusions .................................................................................................................................. 77

Chapter 4 - Enhancement of the Ker-CuSum for non-stationary environments: Current deforestation trends in Tropical forests of the North Rupununi

4.1 Introduction .................................................................................................................................. 81

4.2 Study Area .................................................................................................................................... 82

4.3 Data .............................................................................................................................................. 83
  4.3.1 Sentinel-1 data timeseries ....................................................................................................... 83
  4.3.1.1 SAR data pre-processing .................................................................................................... 84
  4.3.1.2 Multitemporal averaging – Monthly Composites ................................................................. 85

4.4 Methods ...................................................................................................................................... 86
  4.4.1 CFAR - Kernel Cumulative Sum (CFAR-KerCuSum) change detection ................................. 86
    4.4.1.1 Selection of the temporal forest reference ........................................................................... 87
    4.4.1.2 CFAR-KerCuSum forest change detection .......................................................................... 88
  4.4.2 Post-Processing – Sieve filtering and Occurrence confidence analysis ..................................... 90
  4.4.3 Accuracy Assessments (spatial validation) ............................................................................. 92

4.5 Results ......................................................................................................................................... 94
  4.5.1 Testing the Assumptions: Normality ....................................................................................... 94
Chapter 5 - Conclusions

5.1 Main Results

5.2 Reflection & outlook

5.3 Summary

References

Appendix A – Multi-orbit and optical data fusion: Doñana wetlands study case

Appendix B - CFAR-KerCuSum - Annual Above Ground Biomass loss estimation

List of publications

Short biography
List of Figures

Figure 1. Time line illustrating some of the most important optical remote sensing programs. Classification based on their functional period and their spatial resolution. Diagram modified from (Elliott, Walters and Wright, 2016). ................................................................. 7

Figure 2. Timeline showing radar satellite missions as well as their specific electromagnetic work spectrum (Bands); Diagram modified from (UNAVCO, 2020)........................................................................................................... 9

Figure 3. Illustration of the oscillation pattern described by both the electric (E) and magnetic (B) fields, typical of the electromagnetic signals. Diagram modified from (Gibbs, 2016). .................................................................................................................. 10

Figure 4. A visual explanation of the most recurrent geometric distortions generated when converting the radar information to a two-dimensional plane. Data sources: a), b) (Earth-ESA, no date); c) (Elachi and van Zyl, 2006, p.250). ................................................................................................................................. 11

Figure 5. (a) Surface scattering mechanism from wet soil, (b) radar signal reflection from shallow open water, (c) double bounce scattering mechanism from signal interaction with vegetation stems and water surface and (d) volume scattering due to random scattering within the dense flooded vegetation canopy. Illustration modified from (Dabboor, Iris and Singhroy, 2018).................................................................................................................. 15

Figure 6. Overview and research connections between all the data chapter of this thesis. ......................... 18

Figure 7. Reference map showing the location and areas covered by the Queen Elizabeth Forest Park....... 23

Figure 8. Forest logging activity identification. (a) Landsat 8 shortwave infrared image used for the visual identification of forest changes. Acquired: 28 June 2019; pink tone areas represent land cover transformation from forest to bare ground. (b) Colored polygons represent Forest and Land Scotland (FLS)-verified forest logging activities carried out between 1 January 2019 and 30 September 2019. ........................................................... 25

Figure 9. Graphical explanation of the reference mean calculation strategies used both for the CUSUM-SAR (left) and the CUSU-SMC (right) approaches................................................................. 28

Figure 10. Proposed methods for the cumulative sum (CUSUM) and cumulative sum-spatial mean corrected (CUSU-SMC) forest change detectors. ................................................................. 31

Figure 11. Spatial mean normalization. Ratio of backscatter variation of each class (’change’, ‘conifer’, ‘broadleaves’) for the entire timeseries, based on the cumulative sum methodologies; (a) CUSUM based on (Kucera, Barbosa and Strobl, 2007) , (b) CUSU-SM spatial forest mean variant, (c) CUSU-SMC proposed method (spatial mean constant bias correction applied). ................................................................. 33

Figure 12. Assessing if CUSUM and CUSU-SMC are normally distributed over the reference year. The data used for generating the histograms was obtained by masking out each region (“forest”, “conifer”, “broadleaves”) over a CUSU-SMC ratio image (29.07.2019). Data used for Q-Q plots correspond to temporal values of unique pixels, randomly selected, for each region. ................................................................. 34

Figure 13. This figure illustrates the sensitivity of different polarization channels to forest structural changes by comparing the annual backscatter timeseries of logging areas with undisturbed forest. Temporal differences extracted from the comparison of logging areas and undisturbed forest (bottom) showed the higher sensitivity of the VH polarization channel. ................................................................. 35

Figure 14. Synthetic aperture radar (SAR) backscatter signal comparison for mean reference values used for the CUSUM and CUSU-SMC change detection methods. The lack of significant differences in the values obtained for the forest mask for both cases tested could explain the similarity in the final results. .................. 37

Figure 15. This figure compares the performance of the pairwise approaches with the CUSUM and CUSU-SMC methods using a ROC curve representation, for both the Ratio (VH/VV) and VH channels. PW = pairwise. ROC curves were generated using the results obtained for the accuracy assessment, performed for the image acquired on 29 September 2019, using significance levels of (α=0.4, 0.3, 0.2, 0.15, 0.1, 0.05, 0.01, 0.001). ................................................................................................................................. 39
Figure 16. Logging activities change detection maps obtained for pairwise (static approach) (left) and CUSU-SMC (right) methods. The images show the probability of change (being \( P = 1 \) considered as change, and \( P = 0 \) as no change), obtained for the 29 September 2019 and ratio data cube, for the areas affected by clear-cuts “Unknown 4” (top), and “33020” (bottom). .................................................................

Figure 17. Contribution of the tested sieve filter to detection performance of the CUSUM and CUSU-SMC approaches. Accuracy test carried out using a significance level of (\( \alpha = 0.05 \)). .................................................................

Figure 18. Forest changes detected in the Queen Elizabeth Forest Park using the conservative strategy (CUSUM VH). (a) Shows the logging activities reference dataset obtained for the period of study. (b) Illustrates the changes detected (red) for the CUSUM VH detector. Subsets (c) and (d) show a closer look of the effect of the sieve filter on the final change detection maps [(c) 10 pixels; (d) 25 pixels]. .................................................................

Figure 19. Illustration of the evolution of the Malaria infection rates in Guyana over the past decade. Graph extracted from (WHO, 2020). ........................................................................................................

Figure 20. Speckle filter comparison. Comparison of the products derived from the application of the circular boxcar mean filter (top-right), Refined Lee (bottom-left), and Perona-Malik (bottom-right) for a Sentinel-1 GRD (VH-pol) acquired on 04/06/2020 on the Amoko lake region. .................................................................

Figure 21. Example of the land/water edge ground truth transects used for validation. Three Mile Bush water body, 02/10/2020 (yellow), 14/10/2020 (red), 26/10/2020 (blue), 07/11/2020 (purple), 19/11/2020 (brown) and 01/12/2020 (green); Basemap: Bing aerial.........................................................

Figure 22. Reference map of the region of study, the North Rupununi natural wetlands, Guyana..........

Figure 23. Final land cover map of the Southwestern region of the North Rupununi wetland used to develop and test the DETECT system resulting from the Random Forest (RF) classification analysis. ...........57

Figure 24. Sentinel 1 – VH polarisation channel signal backscatter timeseries. Top figure illustrates the complete timeseries (01/01/2017 – 01/04/2020); Bottom shows the 2019 timeseries (01/01/2019 – 31/12/2019). Analysis performed for entire region of study. As a reference, annual hydrology is shown by the bars below the graphs; Blue illustrates the wet periods while the dry periods are represented in green.................................................................

Figure 25. Evaluation of the behaviour of the CUSUM-SAR method to seasonal variations in the study region. Comparison of A) polarization ratio (VH / VV) of Sentinel-1 preprocessed backscatter intensity (dB) with B) CUSUM-SAR values; period (01/01/2020 - 07/31/2021). Please note the progressive decrease of the CUSUM-SAR values for the ‘wetland’ class after the first floods of 2020 (May, 2020). As a reference, annual hydrology is shown by the bars below the graphs; Blue illustrates the wet periods while the dry periods are represented in green.................................................................

Figure 26. Illustration of the operational principle of the Ker-CuSum flood detection algorithm.............

Figure 27. Overview of the Ker-CuSum flood change detection system...........................................

Figure 28. Illustration showing the water body edge ground truth data and the Ker-CuSum open water edge points used for the proximity analysis over Three Mile Bush on the 14th October 2020. The ground truth edge line (yellow) was created using the ground truth points and subsequently smoothed (PAEK – 10m) in order to reduce sharp angles between adjacent samples. ..........................................................................................

Figure 29. Comparison of the backscatter radar for the dry and wet season, showing, in black, the reduction in intensity for the open water zones. Sentinel-1 Ratio (VH / VV) (dB) pre-processed composites; A) Reference dry mean and B) Mean composite computed from 2020 peak-wet season acquisitions (07/01 - 09/15). ....

Figure 30. Timeseries of the Z-score values for the land cover classes. Top graph A) illustrates to the ratio combination (VH/VV) while bottom B) shows the values for the co-polarised VV channel. Results obtained for the period from 01/01/2020 to 06/07/2021. As a reference, annual hydrology is shown by the bars below the graphs; Blue illustrates the wet periods while the dry periods are represented in green. ........................................

Figure 31. Example of a comparison of the Zscore values on different land cover classes for dry and wet conditions. Dry condition values (left) extracted from the peak dry image acquire on 05/04/2020 while wet
condition values were obtained from the peak flood image acquired on 03/08/2020. The red lines correspond to the threshold values used to map the open water (top) and flooded vegetation (bottom). ........................................68

Figure 32. Interannual variation of the flood area for the natural wetlands of northern Rupununi. Comparison of the flooded extension during the wet season (01/05 - 30/09) for both Classes of open water (Top left) and flooded vegetation (Top right). N refers to the number of Sentinel-1 images acquired during each annual maximum flood season in the study area and considered for this analysis. .................................................................68

Figure 33. CUSUM-SAR derived flood area calculation. Timeseries extracted for The North Rupununi natural wetlands for the entire 2020 period. ....................................................................................................................69

Figure 34. Illustration of the equalised stratified random sampling points used for the validation analysis performed for the results obtained on 10/07/2020. Base map corresponds to the Planet scope high-resolution imager acquired on 09/07/2020. ..................................................................................................................70

Figure 35. Ker-CuSum derived flood map for the region of study of the North Rupununi natural wetlands for the 20th September 2020 using a Bing composite as base map. Area indicated in the map compares in detail C) the combined flood map with B) the reference high-resolution (3m) Planet image acquired on 20/09/2020. .........................................................71

Figure 36. Open water edge delineation analysis for Amoko lake open water body. Comparison of Open water flood mask (19/09/2020) and reference Planet image acquired on 20/09/2020. ........................................................................................................72

Figure 37. Comparison of the total flooded extensions derived from each of the post-processing steps. The values represented correspond to the Open water masks for the entire Sentinel-1 time series of 2020 extracted for the entire study region. The sub-figure on the right shows a close-up view of the values obtained for three flood maps generated for the peak-flood period. ....................................................................................73

Figure 38. Illustration of surface water flood masks before (left) and after (right) the application of the permanent water bodies refinement. A) Lagoa de Cheirosa, B) Ireng and Tacutu confluence. ..................................................74

Figure 39. Illustration of the effect of DEM slope refinement on the surface water flood masks. False positives driven by radar geometric distortions (left) and post-processing refined flood mask (right). ..........................75

Figure 40. Screenshot of the DETECT | CUSUM GEE web-APP user interface. .............................................76

Figure 41. Reference map of the region of study. .............................................................................................83

Figure 42. Comparison of the effect of the Angular-based radiometric slope correction. Zoom overview of the mountainous region of the Alto tatuku-Alto Esequibo located between the Wowetta and Peropo communities. Co-polarised (VV) Sentinel-1 image acquired on the 15th January 2017; (A) Original pre-processed scene, (B) Corrected scene after the radiometric slope normalisation.................85

Figure 43. Comparison of the paired sums values for time series composed of daily images (every 12 days) (Top) and monthly composites (Bottom). The study area corresponds to a forest plot (4°01’13.6”N 59°02’12.2”W) near Wowetta, which was deforested in October 2019. ..............................................................86

Figure 44. GLAD - Tree canopy cover map for year 2000 (canopy cover ≥ 90%), in green, used for mapping out all the non-forest areas of the region of study. .........................................................88

Figure 45. Illustration of the operational principle followed in the forest changed detection analysis performed with the new CFAR-KerCuSum change detector in the North Rupununi tropical forest region.................90

Figure 46. Explanatory diagram showing the temporal window filters applied to the Ker-CuSum timeseries for the occurrence confidence analysis. ..........................................................................................92

Figure 47. Illustration of the validation sites used for the validation assessment. A) Yupukari region (central), B) Katoka region (south) and C) Wowetta region (central). Reference forest change areas were obtained by visual investigation of Planet imagery acquired before and after the period of study (2018-2019). ..........93

Figure 48. Distribution analysis of CuSums over the Forest reference image. The sample data used for the Anderson-Darling normality test (right) was obtained using 20 randomly distributed polygons across the forest mask. .........................................................95

Figure 49. Comparison of the change detection performance of each polarisation channel. Combined accuracy metrics (True positives = TP; False positives = FP) extracted from the 2019 annual forest change analysis performed over Wowetta, Yupukari and Katoka.. .................95
Figure 50. Map illustrating the influence of temporal flooding events on the 2019 annual Forest change map obtained using the CFAR-KerCuSum 12-K6.5 product combination. Significant commission errors can be observed in the banks of the Turantsink creek associated with the presence of flood events during the period of study. 

Figure 51. CFAR-KerCuSum forest change detection examples and comparison with HR Planet optical imagery. (Top) extensive forest fire near Crashwater community and (Bottom) New forest opening for farming, Annai region.

Figure 52. Comparison of CFAR-KerCuSum deforestation results (orange polygons indicating deforestation as a result of fire, green polygons indicating deforestation as a result of farming), with ground-truthing (red flames indicating where the team marked deforestation areas as a result of fire, while green leaf indicating deforestation areas as a result of farming).

Figure 53. Annual forest change map - Erase tool graphical illustration. A) Forest Change map 2018, B) Initial Forest Change map 2019, C) Overlap Forest Change maps 2018 & 2019 and D) Final Forest Change map 2019: Erased | Elimination of Forest change 2018.

Figure 54. Example of the annual forest changes for the Wowetta validation sites. Please note the progressive expansion of the small agricultural farms.

Figure 55. Example of the forest transitional regions affected by the image coregistration errors. Please note that all these features only appeared in the left-side of the forest edges as result of their direct exposure to the radar (right) side-looking angle.

Figure 56. The CUSUMs approaches were the ones for conservative (°C) and tolerant (°T) strategies. TP = true positives, TN = true negatives, FP = false positives, FN = false negatives, OA = overall accuracy, PA = producer accuracy, UA = user accuracy.

Figure 57. Reference comparison of the main accuracy metrics obtained for the CFAR-KerCuSum (red), pairwise (yellow), CuSum (green), Sentinel1-based change detectors, and GLAD-based annual forest map Landsat (blue). Results extracted for the product combination K6 t2 (CFAR-KerCuSum, Pairwise) and CuSum value (THD ≤ 5) (CuSum). OA = overall accuracy, PA = producer accuracy, UA = user accuracy and F1 = F-score.

Figure 58. Detailed accuracy metrics obtained for the CFAR-KerCuSum (red), pairwise (yellow), CuSum (green), Sentinel1-based change detectors, and GLAD-based annual forest map Landsat (blue). Results extracted for the product combination K6 t2 (CFAR-KerCuSum, Pairwise) and CuSum value (THD ≤ 5) (CuSum). TP = true positives, TN = true negatives, FP = false positives, FN = false negatives, OA = overall accuracy, PA = producer accuracy, UA = user accuracy and F1 = F-score.

Figure 59. Comparison of the response behaviour of the radar timeseries to post-disturbance recovery processes, CFAR-KerCuSum (top) and CuSum (bottom). The forest disturbance investigated corresponds to a forest fire occurred at the end of the 2019 dry season (February 2019) in the vicinity of the Crashwater indigenous community (3 ° 55'19.2 "N 59 ° 03'24.0" W).

Figure 60. Comparative image illustrating the results of the GLAD and RADD alerts for changes in forests for the year 2020. Visual exploration carried out to assess the detection performances in the detection of forest disturbances that occurred in the period between September 2019 and September 2020 in northern tropical forests of the Annai region, near the Wowetta settlement. Data collected from Global Forest Watch (Global Forest Watch, 2021).

Figure 61. Evolution of the CuSum algorithm. The graph shows the three main algorithms presented in this thesis and some of their variants, outlining some of the most relevant modifications/adaptations and their application to forest or wetland monitoring.

Figure A1. Illustration showing an annual data acquisition comparison between the Sentinel-1 mission for 2020 and the Landsat data used by the EBD-LAST system for the same period. As it can be observed, the total number of Sentinel-1 acquisitions (31 using the single orbit approach and 62 using the multi-orbit approach) well exceed the 21 images used from Landsat.
Figure A2. Illustrative map of the methods agreement analysis carried out for February 2020; Sentinel-1 image acquired on (23/02/2020) and Landsat 8 acquisition (18/02/2020). Ker-CuSum combined flood map ('OW', 'FV', 'High Turbidity') (green), EBD-LAST flood map (yellow) and coincidental/agreement regions (blue).

Figure A3. Example comparison map of the Ker-CuSum derived high turbidity map (light blue, figure d) with the Landsat (EBD-LAST) derived turbidity mask (b). The analysis was performed for the Sentinel-1 image acquired on 23/02/2020, and the water turbidity mask was derived from a Landsat8 image acquired on 23/02/2020. a) Planet acquisition used for visual reference acquired on 17/02/2020.

Figure B1. AGB estimates by (a) Santoro et al. (2021) CCI_Biomass map, (b) Avitabile et al., 2016, (c) Saatchi et al., 2011, and (d) Baccini et al., 2012 for a 1°×1° area in the state of Pará, Brazil. Extracted from (Santoro et al., 2021).

Figure B2. Illustration showing the original (100 x 100m) ESA’s Biomass AGB 2018 map for the North Rupununi region and the final resampled (10 x 10m) product used for the annual AGB calculations.

Figure B3. Annual Above Ground Biomass (AGB) biomass loss estimations for the forested area of the North Rupununi region.

Figure B4. Distribution of annual forest changes for the variable Above Ground Biomass. Low AGB values (red) correspond to areas of savanna and sparse vegetation, while high AGB values (green) are characteristic of highly dense secondary old-growth forests.
List of tables

Table 1. Table showing the probability of acquiring satellite optical images according to the cloud coverage in the study regions of this thesis; the Queen Elizabeth Forest Park; (Chapter 2) and the North Rupununi region (Chapter 3 and 4). Date of exploration: 30th June 2021. .................................8

Table 2. Confusion matrix for change detection classification. H0: No change, H1: Change. .........................30

Table 3. CUSUM & CUSU-SMC accuracy assessment. Accuracy rates were calculated using 2019 logging areas as reference, the same acquisition date (29th September 2019) and a significance level of (α = 0.05). TP = True positives, TN= True negatives, FP= False positives, FN= False negatives, OA= Overall accuracy, PA= Producer accuracy, UA= User accuracy. (*C= Conservative approach, *T=Tolerant approach and *NC= results obtained without the application of the fitted ramp correction). Detectors with the best performance for the conservative and tolerant strategy are shown in green, with overall accuracy and F-Score1 highlighted in bold. .................................................................36

Table 4. Pairwise vs CUSUMs detection performance comparison. The change detection accuracy assessment was performed using a significance level of (α = 0.05) and the same image (29 September 2019) for both the CUSUMs and pairwise approaches. The CUSUMs approaches were the ones for conservative (*C) and tolerant (*T) strategies. TP = true positives, TN = true negatives, FP = false positives, FN = false negatives, OA = overall accuracy, PA = producer accuracy, UA = user accuracy. .................................................................38

Table 5. Results showing the spatial filtering effects on detection performance/accuracy. ..........................41

Table 6. Description of the main tasks and functional requirements of the Ker-CuSum flood monitoring systems for the DETECT project. ........................................................................................................51

Table 7. Acquisition dates of the Sentinel-1 B GRD timeseries used for the analysis. .................................52

Table 8. Acquisition dates of the Landsat 8- T1_TOA images used for computing the reference image composite. Image properties WRS Path (232) and WRS rows (57,57). ..................................................................................56

Table 9. Reference information of the products used for the accuracy assessment analysis. .................................64

Table 10. Summary of accuracy assessment performed for the combined flood classification map: Overall accuracy % (OA); kappa coefficient; Q: Quantity disagreement; A: Allocation disagreement; C: Overall agreement; D: Overall disagreement. ..................................................................................70

Table 11. Combined error matrix for the combined flood map (% of N = 300) where: OW = Open Water; FV = Flooded vegetation; NW = Non-Flooded. .................................................................71

Table 12. Proximity analysis results for Three Mile Bush and Diamond D water bodies. All distance units are expressed in meters. ........................................................................................................72

Table 13. Acquisition dates of Sentinel-1 imagery used for the forest change detection analyses. .................84

Table 14. Table showing the probability distribution values evaluated for the forest change detection analysis. .........................................................................................................................89

Table 15. Planet optical imagery used for the digitalisation of the 2019 forest changes of the three validation sites of the North Rupununi region. .................................................................94

Table 16. Combined Accuracy metrics extracted from the 2019 annual forest change analysis performed over Wowetta, Yupukari and Katoka using the CFAR-KerCuSum over the VV pol-channel. TP = true positives, TN = true negatives, FP = false positives, FN = false negatives, OA = overall accuracy, PA = producer accuracy, UA = user accuracy. .................................................................96

Table 17. Region specific accuracy assessment results extracted from the 2019 annual forest change analysis performed over (1) Wowetta – North region, (2) Katoka – South region and (3) Yupukari – Central region; using the CFAR-KerCuSum over the VV pol-channel. TP = true positives, TN = true negatives, FP = false positives, FN = false negatives, OA = overall accuracy, PA = producer accuracy, UA = user accuracy...........97
Table 18. Table showing the influence of the temporal occurrence analysis on the True positive (*TP) and False positive (*FP) detection rates. Results obtained from the subtraction of the values resulting from $t_2$ to those obtained for $t_1$. It can be observed that the contribution to the reduction of false positives is greater for most of the probabilities evaluated. Katoka validation area, CFAR-KerCuSum derived 2019 annual forest change map.

Table 19. Total annual forest change for the tropical forests of the North Rupununi study region for the years 2018, 2019, 2020 and 2021. Values extracted from the CFAR-KerCuSum product with probability of false alarms 0.024 ($K = 6.5$) and Occurrence = $t_2$ (2 months). Normalised percentages were calculated including forest area losses from previous years.

Table 20. Main types of contribution to satellite environmental remote sensing monitoring. Classification of the various methods and modifications presented in this thesis.
**Acronyms**

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>AGB</td>
<td>Above Ground Biomass</td>
</tr>
<tr>
<td>°C</td>
<td>Celsius/Centigrade</td>
</tr>
<tr>
<td>C</td>
<td>Carbon</td>
</tr>
<tr>
<td>CART</td>
<td>Classification and Regression Trees</td>
</tr>
<tr>
<td>CFAR</td>
<td>Constant False Alarm Rate</td>
</tr>
<tr>
<td>CFAR-KerCuSum</td>
<td>Constant False Alarm Rate – Kernel Cumulative Sum algorithm (Change detection Algorithm)</td>
</tr>
<tr>
<td>CO₂</td>
<td>Carbon dioxide</td>
</tr>
<tr>
<td>CuSum</td>
<td>Cumulative Sum</td>
</tr>
<tr>
<td>CUSUM-SAR</td>
<td>Cumulative Sum (Change detection Algorithm)</td>
</tr>
<tr>
<td>CUSU-SMC</td>
<td>Cumulative Sum – Spatial Mean Corrected (Change detection Algorithm)</td>
</tr>
<tr>
<td>DAC</td>
<td>Guyana Development Assistance Committee</td>
</tr>
<tr>
<td>dB</td>
<td>Decibel (unit)</td>
</tr>
<tr>
<td>DEM</td>
<td>Digital Elevation Model</td>
</tr>
<tr>
<td>DN</td>
<td>Digital Numbers</td>
</tr>
<tr>
<td>ECV</td>
<td>Essential Climate Variable</td>
</tr>
<tr>
<td>EO</td>
<td>Earth Observation</td>
</tr>
<tr>
<td>ESA</td>
<td>European Space Agency</td>
</tr>
<tr>
<td>GFW</td>
<td>Global Forest Watch initiative</td>
</tr>
<tr>
<td>Gg</td>
<td>Gigagram (10⁹ g)</td>
</tr>
<tr>
<td>GHG</td>
<td>Greenhouse Gases</td>
</tr>
<tr>
<td>GIS</td>
<td>Geographical Information System</td>
</tr>
<tr>
<td>GLAD</td>
<td>Global Land Analysis and Discovery laboratory</td>
</tr>
<tr>
<td>GPS</td>
<td>Global Positioning System</td>
</tr>
<tr>
<td>GRD</td>
<td>Ground Range Detected</td>
</tr>
<tr>
<td>Gt</td>
<td>Gigaton (10¹⁵ g)</td>
</tr>
<tr>
<td>HAND</td>
<td>Height Above Nearest Drainage</td>
</tr>
<tr>
<td>HR</td>
<td>High Resolution</td>
</tr>
<tr>
<td>IW</td>
<td>Interferometric Wide Swath</td>
</tr>
<tr>
<td>K</td>
<td>Kappa score</td>
</tr>
<tr>
<td>KCFMS</td>
<td>Ker-CuSum Flood Monitoring System</td>
</tr>
<tr>
<td>Ker-CuSum</td>
<td>Kernel Cumulative Sum (Change detection Algorithm)</td>
</tr>
<tr>
<td>LiDAR</td>
<td>Light Detection and Ranging</td>
</tr>
<tr>
<td>LULC</td>
<td>Land Use and Land Cover</td>
</tr>
<tr>
<td>LULCC</td>
<td>Land Use and Land Cover Change</td>
</tr>
<tr>
<td>M&amp;V</td>
<td>Monitoring and Verification</td>
</tr>
<tr>
<td>MMU</td>
<td>Minimum Mapping Unit</td>
</tr>
<tr>
<td>NFI</td>
<td>National Forest Inventory</td>
</tr>
<tr>
<td>NIR</td>
<td>Near Infrared</td>
</tr>
<tr>
<td>NRDDDB</td>
<td>North Rupununi District Development Board</td>
</tr>
<tr>
<td>NTU</td>
<td>Nephelometric Turbidity Unit values</td>
</tr>
<tr>
<td>NW</td>
<td>No-water/ Non-flooded</td>
</tr>
<tr>
<td>OA</td>
<td>Overall Accuracy</td>
</tr>
<tr>
<td>OW</td>
<td>Open water</td>
</tr>
<tr>
<td>PA</td>
<td>Producer Accuracy</td>
</tr>
<tr>
<td>RF</td>
<td>Random Forest</td>
</tr>
<tr>
<td>ROC</td>
<td>Receiver Operator Characteristic curve</td>
</tr>
<tr>
<td>ROI</td>
<td>Region of Interest</td>
</tr>
<tr>
<td>RS</td>
<td>Remote Sensing</td>
</tr>
<tr>
<td>S1</td>
<td>Sentinel 1</td>
</tr>
<tr>
<td>SAR</td>
<td>Synthetic Aperture Rada</td>
</tr>
</tbody>
</table>
SFM – Spatial Forest Mean
SOC – Soil Organic Carbon
SRTM - Shuttle Radar Topography Mission
SVM – Support Vector Machine
SWIR – Short-wave infrared
TN – True Negative
TP – True Positive
UA – User Accuracy
UAV – Unmanned Aerial Vehicle
UK – United Kingdom
US – United States
UTM - Universal Transverse Mercator coordinate system
VH – Cross-polarisation channel (SAR)
VHR – Very High-Resolution
VV – Co-polarisation channel (SAR)
WGS84 - World Geodetic System 1984
WHO – World Health Organisation
1 Chapter

Introduction
“It is surely our responsibility to do everything within our power to create a planet that provides a home not just for us, but for all life on Earth. “
- David Attenborough, 2016

1.1 Introduction

This introduction will present an overview of current issues associated with land use and land cover change. It focuses on the contribution and current challenges of remote sensing of forests and wetlands, and it unravel the research needs and questions that will be addressed in this thesis.

1.1.1 Background - Land use and land cover change (LULCC)

Land use and land cover change (LULCC) has emerged as one of the topics that has received more attention over the past few decades (Lambin, 1997; Hassan et al., 2016; Pongratz et al., 2021). (Mölders, 2011, p.36). At present, land degradation, together with soil deterioration and climate change, has become one of the most alarming ecological issues globally (Bajocco et al., 2012). Until the advent of the remote sensing (RS) era, these alterations were known on a small scale, however, when satellite imagery became available, they evidenced the human footprint in global landscapes on a larger scale. The integration of RS systems into environmental monitoring programmes constituted a substantial advance in the study of natural ecosystems, allowing the investigation of these LULCC dynamics and their associated impacts at wider scales.

The implications of these land use and land cover changes on the global biochemical cycles are major, representing one of the primary sources of greenhouse gas emissions (Pongratz et al., 2021). In addition to the direct impact to the carbon cycle derived from land cover disturbances (e.g. deforestation, mining, flooding, drought), anthropogenic land use conversion such as urban sprawl, industrialization, natural forest conversion to agricultural croplands and pastures, also represent relevant contributions to the regional and global climate cycles, accounting for an annual GHG flux of approximately 11% (4.3–5.5 GtCO₂eq/yr) of the total global annual anthropogenic emissions (49 ± 4.5 GtCO₂-eq/yr) (IPCC, 2014; Dong et al., 2019). Another important factor to consider is the long-term impact of these landscape transformations. Land degradation processes lead to a significant reduction of carbon uptake rates. For instance, it is estimated that cropland soils have lost 20–60% of their organic carbon content prior to cultivation (IPCC, 2019).
Over the past century, the rise of greenhouse gas emissions associated with these changes in ecosystems has resulted in an increase in the combined land and ocean temperature at an average rate of 0.08°C per decade, with this rate increasing significantly to 0.18°C per decade since 1981 (NOAA, 2022). Furthermore, predictions based on current environmental models forecast a rise in global mean temperature of up to +1.8°C in the next 20 years and +5.8 °C by the end of the century for those scenarios without major reductions in emissions (IPCC, 2007; Wuebbles et al., 2017). This is particularly important as human-induced global warming will further exacerbate ongoing land degradation processes through increasing both frequency and severity of climate extreme events such as floods, wildfires, droughts or intensified cyclones (IPCC, 2019, 2021). Future global climate scenarios show a significant decrease in the extent of natural landscapes, threatening biodiversity and having a significant impact on climate cycles (Page and Baird, 2016; IPCC, 2019; Johnson, 2021; WMO, 2021). Both current LULCC trends and short-medium term predictions highlight the importance of developing new monitoring strategies that allow a precise quantification and better understanding of the spatio-temporal dynamics of natural ecosystems, thus contributing to tackling and reverting the global climate crisis (Winkler et al., 2021).

Natural forest and wetlands are among the most threatened natural ecosystems globally. Since they represent the main study area of this thesis, the next section summarizes the main land transformation processes that threaten these landscapes and their impacts on the conservation of these ecosystems.

1.1.1.1 Deforestation and forest degradation

Forest landscapes are one of the major contributors to climate change mitigation; however, changes in natural dynamics together with high pressures exerted by current socio-economic forces are threatening the conservation of world forests (FAO, 2004). Forests cover 31 percent of the global land area (4.06 billion hectares), contributing to the economic and social development of 1.3 billion individuals worldwide (about one-fifth of the global population) by providing enormous range of beneficial services such as food and fuel supply, water and air purification, recreational or traditional use while helping to maintain natural ecological balances (Kremen, 2005; The World Bank, 2016; FAO, 2020). The world’s forests absorb 2.4 billion tonnes of carbon dioxide (CO₂) per year, one-third of the annual CO₂ released from burning fossil fuels (IUCN, 2017). In addition, apart from the carbon storage role and the most apparent tangible benefits such as timber industry or recreation and leisure, forests are valuable in many other ways (e.g. climate regulation, watershed and soil protection or non-timber forest products including food and fibre and biodiversity) (Defries, 2013). Moreover, these ecosystems keep a wide range of resources necessary for life, a fact which has attracted human civilizations since ancient times. This human-forest interrelationship has remained relatively balanced until recent centuries, where the rapid world population growth and increasing
socioeconomic pressures have led to an overexploitation of these natural landscapes in recent times (Defries et al., 2010).

The conservation of the world's forest ecosystems is a major global concern. The high pressures exerted by human activities over natural ecosystems have been responsible for the dramatic reduction of global forested regions, a process also known as deforestation (Kissinger, Herold and De Sy, 2012; Defries, 2013; UN-REDD, 2016). The most important causes of deforestation are recognized to be the high pressure exerted by the expansion of industrial agriculture together with the demographic explosion during the last century (Apan and Peterson, 1998; Mazoyer and Roudart, 2006; Defries, 2013). Changes in consumption patterns have resulted in a greater demand for agricultural products, and consequently in the destruction of millions of hectares of forest at expenses of extensive agricultural activities. Similarly, deforestation emerges as the main driver of biodiversity loss as a result of the direct destruction, degradation and fragmentation of wildlife habitats. Current trends point to a mass extinction event over the next two centuries directly caused by these forest degradation processes (Giam, 2017; Heimpel, 2021). Furthermore, among the substantial number of environmental issues derived from deforestation processes, the removal of Above Ground Biomass (AGB) from forest landscapes is recognised as one of the major issues to be tackled in a global environmental context. The important role that forest vegetation plays in maintaining the terrestrial carbon cycle means that any change produced in these ecosystems affects climate through the disruption of a multitude of biogeophysical and biogeochemical processes such as albedo or evapotranspiration (Pongratz et al., 2010; N. Joshi et al., 2015). Deforestation and forest degradation are responsible for 12–20% of the global anthropogenic greenhouse gas (GHG) emissions in the 1990s and early 2000s (Dixon et al., 1994; Schrope, 2009; van der Werf et al., 2009; Saatchi et al., 2011). Global deforestation rates have increased over the past two decades, especially in tropical forests, where gross carbon loss from tropical forests worldwide has doubled from 0.97±0.16 Pg C yr\(^{-1}\) in 2001–2005 to 1.99 ± 0.13 Pg C yr\(^{-1}\) in 2015-2019 (Feng et al., 2022).

At present there are numerous institutions and programs that seek to reverse the current deforestation trends through the elaboration of international ecological agreements. These environmental programs focus their efforts on mapping AGB loss by capturing regrowth, deforestation and degradation processes which occur all around the world (N. P. Joshi et al., 2015). Programmes such as the United Nations’ Reducing Emissions from Deforestation and Degradation-plus (UN-REDD+)(UN-REDD, 2016), is recognised as the main international policy aiming to reduce CO\(_2\) emissions from deforestation in tropical countries, incentivising developing countries to contribute to climate change mitigation. The REDD + program also seeks to assess the current state of conservation of worldwide forests by developing a joint global inventory which contains information about these landscapes at different scales (e.g. regional, national, continental). Other examples include: UK Space-Agency’s Forest2020 program (Ecometrica, no date); European Space Agency’s Climate Change Initiative (ESA-CCI) (ESA-CCI, no date); and Norway’s International Climate and Forest Initiative
(NICFI) (NICFI, 2020). These initiatives focus on the protection of forest ecosystems by the generation of updated and accurate datasets about the current conservation status of world’s forests. Detecting deforestation activities using traditional methods, such as human patrol surveillance can be very expensive and ineffective, especially in highly dense tropical forest areas. Therefore, current Monitoring and Verification (M&V) schemes of these conservation programmes mostly rely on the use of remote sensing (RS) technologies, as they enable the development of large-scale wall-to-wall forest inventories in a rapid and more cost- and time-effective way.

1.1.1.2 Wetlands degradation

Wetlands are among the most productive natural ecosystems in the world, generally being important biodiversity hotspots. These complex landscapes perform important eco-hydrological functions providing a wide range of ecosystem services that contribute to human well-being such as food supply, climate change mitigation, water store and purification, recreational opportunities, or tourism (Costanza et al., 1997; Finlayson et al., 2005b, 2018; Green et al., 2017). Freshwater wetland landscapes are highly efficient at accumulating soil organic matter accounting for almost 30% of global C stocks while only covering around 5–8% of the land surface area (IPCC, 2014; Köchy, Hiederer and Freibauer, 2015; Valach et al., 2021). Soil carbon stocks are significantly high in wetland ecosystems because water reduces oxygen availability thus greatly reducing decomposition processes (Freeman, Ostle and Kang, 2001). However, despite the importance of these ecosystems for humanity as well as for natural ecological cycles, the complex nature of these landscapes together with the fragile and dynamic relationships among the organisms inhabiting these regions, make wetland ecosystems especially vulnerable to environmental disturbance, such as climate change.

Recent studies recognize wetlands to be one of the most rapidly degrading land cover types on a global scale. The Millennium Ecosystem Assessment (2005) estimated that approximately 50% of global wetland ecosystems were lost during the 20th century (Finlayson et al., 2005b). Similarly, more recent studies indicated a loss of 87% of the world’s wetlands since 1700, in places where data exists, with accelerated loss occurring between 1970 and 2015 of 35%, three times the rate of forest loss (Davidson, 2014; Ballanti et al., 2017; Finlayson et al., 2018; Dinesen et al., 2019). In addition to the socio-economic pressures exerted by large-scale mining and agricultural corporations to transform natural wetlands, projected trends expect global climate change to exacerbate the loss and degradation of these natural ecosystems, reducing the capacity of wetlands to mitigate impacts and resulting in further reduction in human well-being (Finlayson et al., 2005b; Ballanti et al., 2017; McInnes et al., 2020). The environmental impact of these land cover changes and land degradation processes in wetland ecosystems are of great importance. The alteration of the anaerobic conditions of these landscapes either by natural drought events or human-driven drainage processes can lead to the release of a significant global carbon pool into the atmosphere, with potentially serious implications for future global warming when this occurs on a large scale (Freeman, Ostle and Kang, 2001; Köchy, Hiederer and Freibauer, 2015; Salimi, Almuktar and Scholz, 2021). Similarly, these
land degradation processes largely determine not only the amount of water extracted from these hydrological systems but the type and incidence of contaminants entering streams, lakes or underground pathways (Gergel et al., 2002).

These facts demonstrate the need to develop new tools and methods that, through continuous monitoring and evaluation of the state of conservation, inform management and policy-making organisations. Historically, most wetland conservation programmes have relied on the interpretation of quantitative and qualitative environmental data collected by ground monitoring sensors (e.g. water depth, water quality, water turbidity, climatic parameters). However, the use of ground sensor networks presents certain limitations when investigating major hydrological processes. Ground monitoring sensors provide accurate information on a site-specific basis, but present limitations when investigating spatio-temporal dynamics and ecosystem changes for large areas, especially when these have complex drainage patterns. Likewise, the harsh environmental conditions present in these ecosystems tend to affect the performance and operation of these sensors, requiring time-consuming and cost-intensive continuous care and maintenance, which is usually compromised by difficult access and security issues (e.g. vandalism, theft, etc). These limitations promote the use of remote sensing technologies, as they allow investigating large areas in comparatively short time periods and map physically unreachable areas at reduced costs (Mwita et al., 2012).

1.1.2 Remote sensing for environmental monitoring

Since the appearance of the first Earth Observation science missions in the 1960s, remote sensing (RS) science has become an integral part of environmental research projects. The significant development of this discipline during the past decades has brought an immense variety of systems and techniques that allows an effective monitoring of Earth’s landscapes (Chuvieco, 2016). The next section will provide an overview of the most used remote sensing systems for environmental monitoring, paying special attention to radar satellites due to its particular relevance for this thesis.

1.1.2.1 Optical remote sensing

The use of optical systems for terrestrial observation goes back more than 40 years. Optical satellite imagery laid the foundations of remote sensing science and have historically dominated Earth Observation (EO) research due to numerous space programmes (Figure 1). These satellite missions have produced continuous, consistent and easy-access data, including Landsat since 1972, the Landsat Thematic Mapper (TM) since 1983, Satellite Pour l’Observation de la Terre (SPOT) since 1986, the Moderate Resolution Imaging Spectroradiometer (MODIS) since 1999 and the Sentinel program since 2014 (Joshi et al., 2016). Among the many satellite optical missions, Landsat programme provides the longest (50 year data span) record of medium spatial resolution satellite imagery (Roy et al., 2014).
Figure 1. Time line illustrating some of the most important optical remote sensing programs. Classification based on their functional period and their spatial resolution. Diagram modified from (Elliott, Walters and Wright, 2016).

Like all passive sensors, optical systems measure the energy reflected or emitted by an object after this is irradiated from an external source, mostly the Sun (Chuvieco, 2016). Clouds are recognised as a major obstacle to optical remote sensing (Asner, 2010), since they impede the radiation to go through (Table 1). This significantly limits the use of optical satellite data for near real time monitoring purposes as result of frequent data gaps in the timeseries (Hostert et al., 2015; Joshi et al., 2016). This issue can be overcome in applications that require low temporal resolution (e.g. half-yearly, annual) where dense time series of images can be acquiring hoping for enough cloud free images in the collection. Nonetheless, low availabilities of cloud-free imagery may remain problematic in regions with frequent cloud cover (e.g. Tropical rainy seasons, Scotland) (Table 1). Table 1 serves to illustrate this problem by showing the probabilities of acquiring cloud-free optical satellite images in two of the study regions investigated in this thesis.
Table 1. Table showing the probability of acquiring satellite optical images according to the cloud coverage in the study regions of this thesis; the Queen Elizabeth Forest Park; (Chapter 2) and the North Rupununi region (Chapter 3 and 4). Date of exploration: 30th June 2021.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Cloud Coverage %</th>
<th>Aberfoyle (Scotland)</th>
<th>North Rupununi (Guyana)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>№ Acquisition</td>
<td>Acquisition Probability (%)</td>
<td>№ Acquisition</td>
</tr>
<tr>
<td>Sentinel 2 – L2A</td>
<td>≤ 100%</td>
<td>927</td>
<td>732</td>
</tr>
<tr>
<td>[Since 23/06/2015]</td>
<td>≤ 25%</td>
<td>161</td>
<td>142</td>
</tr>
<tr>
<td>Rev time: 5 days</td>
<td>≤ 10%</td>
<td>81</td>
<td>37</td>
</tr>
<tr>
<td>Landsat 8 – OLI</td>
<td>≤ 100%</td>
<td>374</td>
<td>483</td>
</tr>
<tr>
<td>[Since 11/02/2013]</td>
<td>≤ 25%</td>
<td>40</td>
<td>32</td>
</tr>
<tr>
<td>Rev time: 16 days</td>
<td>≤ 10%</td>
<td>16</td>
<td>7</td>
</tr>
<tr>
<td>Landsat 7 ETM+</td>
<td>≤ 100%</td>
<td>471</td>
<td>860</td>
</tr>
<tr>
<td>[Since 15/04/1999]</td>
<td>≤ 25%</td>
<td>56</td>
<td>60</td>
</tr>
<tr>
<td>Rev time: 16 days</td>
<td>≤ 10%</td>
<td>26</td>
<td>13</td>
</tr>
</tbody>
</table>

A limitation of all remote sensing systems, which is accentuated in those systems less sensitive to structural properties of the targets, for example optical sensors, arises when the spectral reflectance is homogeneous in some landscapes. The similar spectral behaviour makes these objects hardly distinguishable, for example, different forest masses (coniferous and deciduous during the growing season) or different agricultural crops with similar phenology characteristics. Finally, another disadvantage of optical remote sensing of vegetation is the absent penetration of the optical radiation under the canopy cover. (i.e. it is not possible to see under the canopy). This constrains the range of use of optical technology for forest and wetland monitoring purposes, since any disturbance which takes place under the forest-canopy or under vegetation cannot be detected by these systems.

1.1.2.2  Radar remote sensing

The use of microwaves RS for environmental studies has grown significantly over the past three decades. This responds to the development and launch of numerous Synthetic Aperture Radar (SAR), particularly over the last decade (2010’s) (e.g. Terra-SAR X, ALOS-2 and Sentinel-1) (Figure 2). SAR systems are side-looking radars which utilizes the flight path of the platform to simulate an extremely large antenna, which generates high-resolution imagery (ESA, 2017; Wolff, 2018). The resolution of a radar system depends on the length of the antenna, since a larger antenna produces a sharper beam which result in a smaller area covered. The range resolution instead is augmented by using a linear frequency modulation signal called Chirp. These allow SAR to have resolution on the order of fraction of a meter to tens of meters from space. The active nature (independent of an external source of light) of SAR allows it to acquire data consistently as it can perform almost under any type of weather condition (e.g. dense cloud cover, rainfall). Since the appearance of the first satellite SAR system, SEASAT, in 1978, until the current fleet of satellite radars (e.g. Sentinel-1, TerraSAR-X 2, COSMO-SkyMed 2, Radarsat 2) (Döngi, F., 2011); many satellite radar programmes (e.g. JERS-1, 8
SIR-C/SIR-X, ERS-1 and ERS-2, ALOS) have contributed to the generation of a long dataset for environmental monitoring (Figure 2).

Figure 2. Timeline showing radar satellite missions as well as their specific electromagnetic work spectrum (Bands); Diagram modified from (UNAVCO, 2020).

The imaging principle of SAR sensors relies on the interaction of the electromagnetic pulse sent by the radar sensor with targets on the ground. Depending on the intensity with which the energy is redirected back to the radar antenna (i.e. backscattering), it is possible to gather information about the object or surface impinged. To interpret the interaction of microwave pulses with targets, canonical targets, of which the backscattering behaviour is well known, can be used. These are often called scattering mechanisms. In the context of forests and wetlands four major scattering mechanisms are generally used: specular, surface, double bounce and volume scattering (Kwoun and Lu, 2009; Zhang et al., 2020). The investigation of the variations in these backscattering signals allows to obtain information on changes in certain parameters of the objects or surfaces observed. In the context of forests and wetlands, radar backscattering is highly influenced by three main parameters which are inherent of any object: the geometry, roughness and moisture content. Hence, any change in these parameters will result in noticeable variation in the intensity of backscattering (Earth-ESA, no date). In addition to its capacity to see through clouds and rain and during day or night, the high sensitivity of SAR sensors to these variations in the physical properties of objects on
the Earth's surface enhances the potential of this technology for environmental monitoring applications.

A defining characteristic associated with active systems as SAR is the ability to control the characteristics of the electromagnetic radiation sent to the target. In addition to the possibility of setting transmitting signal's parameters such as the frequency or wavelength, polarization also plays an important role when configuring the microwave signal. Electromagnetic waves are composed of two energy fields, an electric and a magnetic one (Figure 3). The shape that the tip of the electromagnetic field draws on the plane perpendicular to the direction of propagation is defined as the polarisation of the wave. Different targets in the scene interact differently with transmitter polarisation, therefore the transmitter polarisation can be used to discriminate between targets in the scene.

Figure 3. Illustration of the oscillation pattern described by both the electric (E) and magnetic (B) fields, typical of the electromagnetic signals. Diagram modified from (Gibbs, 2016).

Radar polarimetry is the science of acquiring, processing and analysing the polarisation state of an electromagnetic field (Lavalle, 2008). More specifically, SAR polarimetry studies the information contained in the electromagnetic waves backscattered from a given medium, including the magnitude and relative phase, with the aim of identifying and characterising the environmental conditions of this medium or some processes associated with it (Pottier, 2017). One SAR image is not too dissimilar to a black and white optical image; however, they have some notable differences when compared to optical images: a) Speckle is inherent in all SAR acquisitions and imposes a problem when interpreting images. Speckle is an image effect showing grey level variations occurring between adjacent resolution cells (ESA, 2020). It is caused by differences in the locations of the small scatterers within the same pixel and result in images looking noisy. It requires the use of specific speckle filters (Maghsoudi, Collins and Leckie, 2011; Joshi et al., 2016). b) Geometric distortions can occur when imaging areas with tall objects or surfaces with a considerable topography (e.g. mountainous areas). The presence of distorting effects such as layover, foreshortening or radar
shadows are commonly observed in radar images and they are consequences of the SAR side-looking geometry and the fact that radar record images based on distances more than perspective (Figure 4).

Figure 4. A visual explanation of the most recurrent geometric distortions generated when converting the radar information to a two-dimensional plane. Data sources: a), b) (Earth-ESA, no date); c) (Elachi and van Zyl, 2006, p.250).

Finally, another historical disadvantage associated with the use of SAR sensors was the limited spatial coverage compared to optical systems. Long-running optical satellite missions such as the Landsat program provided global coverage with relatively high temporal resolutions. However, the launch of the European Space Agency’s (ESA) Sentinel-1 satellite constellation in 2014, revolutionized the use of SAR technology for environmental monitoring. The Sentinel-1 mission rapidly stood out as a valuable resource for effective monitoring of environmental dynamics due to its high level of performance in terms of data acquisition consistency, temporal frequency (6- or 12-day revisit period), global spatial coverage, dual-polarization, open access policies and long operational lifespan (Hardy et al., 2019; Tanase et al., 2019).

A review on satellite-based monitoring strategies for both forest and wetland ecosystems, including optical-based and SAR-based approaches is provided in the next section. A special focus is set on the use of Sentinel-1 based change detection approaches due to its relevance to this thesis. Based on this review, Section 3 elaborates on the research gaps in this field and describes the research questions.
that will be addressed in this thesis. Section 4 provides an outline of the thesis structure, with a short summary of the work carried out in each of the chapters.

1.2 Remote sensing approaches for environmental monitoring

1.2.1 Forest monitoring

Forest inventories are recognised as the standard tool for quantifying and monitoring forest characteristics (Mitchard, 2016). However, the highly dynamic nature of forests normally renders inventories inefficient tools for monitoring the continuous transformation processes that occur in these ecosystems as they are mostly generated through infrequent, sometimes one-off, ground surveys. Remote sensing techniques have emerged as valuable alternatives for overcoming this challenge, thanks to the advances that aerospace technology and geographical information systems (GIS) have accomplished over the last decades (Chuvieco, 2016).

Historically, the use of RS for forestry purposes has focused on optical systems, however this approach is hindered in areas with recurrent cloud coverage (e.g., tropical regions) or limited solar illumination (e.g. polar latitudes) (Verbyla, Kasischke and Hoy, 2008; Rüetschi et al., 2019; Tanase et al., 2019). Although this depends on canopy gap cover and density of the forest, another disadvantage of satellite optical systems stems from their limited penetration capabilities, a fact that may hinder the extraction of information from strata underneath the top canopy layer. This limits the use of optical methods for real-time monitoring in dense forests (e.g. tropical forests), since under-canopy disturbances may be unnoticed, or clouds may lead to a long wait time before the disturbance is picked up. Unmanned Aerial Vehicles (UAV) are being considered by an ever-increasing number of researchers and environmental engineers as they help to overcome some of the limitations associated with optical satellite systems. The great development of UAV technology during the past decade has led to the consideration of drones for a wide range of forest monitoring applications. Both UAV-loaded LiDARs and UAV-loaded optical digital cameras have been utilised by researchers for forest three-dimensional modelling, Above Ground Biomass estimations, map diseases or species classification applications (Mohan et al., 2017; Ota et al., 2017; Sankey et al., 2017; Lin et al., 2018; Stovall et al., 2018; Navarro et al., 2020; Michalowska et al., 2021; Neuville, Bates and Jonard, 2021). Although UAV imaging technology allows a significant improvement in spatial and spectral resolution, the use of these technologies for continuous monitoring at medium-large scales is greatly hindered by its technical limitations (e.g. limited coverage, short flight duration specific weather conditions) and its significantly higher costs for broad areas monitoring when compared to satellite imaging sensors (Lin et al., 2018). By considering all these aspects, satellite high-resolution radar sensors stand out as a great alternative to overcome these limitations/challenges.

The integration of EO datasets into forest monitoring systems has generated a significant impact in forest management and policy making. Products such as the JICA-JAXA Forest Early Warning
System in the Tropics (JJ-FAST) (JJ-FAST, no date) or the UMD-GLAD (University of Maryland Global Land Analysis and Discovery) Global Forest change map (Hansen et al., 2013); the global forest/non-forest maps from ALOS-PALSAR data (Shimada et al., 2014), or the TanDEM-X forest/non-forest global map (Martone et al., 2018) are widely used by international policymakers for reviewing the annual conservation status of the world's forests. However, the use of these products presents diverse limitations. Technical and environmental aspects such as the coarse spatial resolution (i.e., 100–1000m) or low temporal resolution, due to persistent cloud coverage, hinder the detection of small forest degradation events as well as the generation of sub-annual or rapid response alerts (Joshi et al., 2016; Mitchard, 2016; Reiche et al., 2021).

Previous studies have shown the capabilities of SAR systems for forest change monitoring at lower scales (Tanase et al., 2010, 2019, 2020; N. Joshi et al., 2015; N. P. Joshi et al., 2015; Tanase, Kennedy and Aponte, 2015; Antropov et al., 2016; Bouvet et al., 2018; Rüetschi et al., 2019; Reiche et al., 2021). Most of these studies were based on pairwise image comparison for detecting the changes between two specific dates. Others investigated the use of time series for developing near real-time change detectors by using multitemporal averages (e.g., monthly average). A major limitation to these pairwise approaches is that when comparing images acquired over a relative small time gap, possible changes occurring during this time gap may go undetected (Reiche, et al., 2018; Belenguer-Plomer, et al., 2019). For instance, direct pairwise comparison between closely acquired images could lead to misclassification errors, with divergences in environmental conditions being wrongly identified as forest structural changes. This means that minor variation in some land surface or plant parameters (i.e., soil moisture, canopy moisture, plant phenology) existing between the reference and comparison image, may result in a radar signal disparity that can be misinterpreted as forest degradation when comparing the two images. Another limitation is that often there is a time lag between the change happening and the SAR images showing the change. Several studies (Reiche et al., 2017; Ruiz-Ramos, Marino and Boardman, 2018; Watanabe et al., 2018; Belenguer-Plomer et al., 2019) have reported significant delays in the forest change detection that range from weeks to months after the disturbance. This phenomenon was also observed by Watanabe et al. (2018), where the reduced sensitivity to change was related to the persistence of branches left on the ground after the felling activities. Consequently, there are inherent difficulties in selecting the right time gap for performing pairwise difference analyses. Pairs with, for example, between 6- or 12-days difference may not be able to detect changes, whereas using larger time gaps can lead to the identification of changes due to seasonality. Lastly, pairwise change detection methods do not allow to take advantage of the information of long-time series, which facilitates the search for specific trends over the time domain. These aspects highlight the need to design and develop new approaches to monitoring forest disturbances. The exploration of new monitoring methods based on the combination and accumulation of dense SAR timeseries appears as a potential strategy that may help overcome these challenges, providing a higher level of confidence when addressing the monitoring processes.
1.2.2 Wetland monitoring

Optical remote sensing has been commonly used for general land cover classification, including wetland mapping and characterisation (Ozesmi and Bauer, 2002; Bourgeau-Chavez et al., 2009; Díaz-Delgado et al., 2016; Guo et al., 2017; Kordelas et al., 2018, 2019). However, the limitations of optical satellite imagery, requiring daylight and unable to penetrate clouds and vegetation, hinder its use for continuously monitoring flooding regimes, specially within tropical regions, where the extensive/quasi-permanent cloud cover often coincides with flood events (Huang et al., 2018). Similarly, studies have reported the limited performance of optical sensors when detecting and mapping flooded areas with vegetation or emergent vegetation (Ozesmi and Bauer, 2002; Bourgeau-Chavez et al., 2009; Díaz-Delgado et al., 2016; Kordelas et al., 2018).

Synthetic Aperture Radar (SAR) sensor emerges as valuable alternative for exploring wetland hydrological dynamics. Moisture content and presence of water greatly influences this target-signal interaction; Therefore, flood events are usually accompanied by an alteration in some properties of the SAR signal, such as amplitude and phase, which may even modify the dominant backscatter mechanism. Depending on the magnitude of the backscatter variation, it is possible to identify diverse physical properties of the target (Schmitt, Hughes and Zhu, 2018). As shown in Figure 5, a change from wet soil to open water (5a to 5b) tends to generate a significant decrease in the signal intensity as result of a change in the backscatter mechanism from surface to specular reflection (White et al., 2015; Dabboor and Brisco, 2019). The change in backscattering allows performing binary classification to differentiate between open-water-flooded and non-flooded areas. Additionally, the increase of water content in areas with low or emergent vegetation (e.g., grassland) commonly result in a rise in the backscatter intensity, associated with the dominance of the double bounce scattering mechanism (5c). This sensitivity of SAR sensors both to flooding in open water and under vegetation, makes it particularly suitable for investigating the spatio-temporal dynamics of surface water within wetland ecosystems.
Several wetland mapping studies (Ozesmi and Bauer, 2002; Bourgeau-Chavez et al., 2009; Chatziantoniou, Psomiadis and Petropoulos, 2017; Whyte, Ferentinos and Petropoulos, 2018; Kaplan and Avdan, 2018a, 2018b; DeVries et al., 2020; Hardy, Oakes and Ettritch, 2020; Huang and Jin, 2020; Muro et al., 2020; Slagter et al., 2020) use the integration of Sentinel-1 images with optical satellite imagery (generally acquired by the Sentinel-2 and Landsat missions), revealing the great potential of data fusion for single-date wetland characterization (Chatziantoniou, Psomiadis and Petropoulos, 2017; Kaplan and Avdan, 2018a; Whyte, Ferentinos and Petropoulos, 2018). Several attempts have applied a multi-temporal approach, exploiting the high-temporal resolution of Sentinel-1 data (Cazals et al., 2016; Mroz, Mleczko and Fitrzyk, 2016; Muro et al., 2016; Twiele et al., 2016; Huang et al., 2018; Martinis, Plank and Ćwik, 2018; Mleczko and Mróz, 2018; Tsyganskaya et al., 2018b; Xing et al., 2018). These approaches focus especially on the characterization of surface water dynamics in specific types of wetlands (Slagter et al., 2020). Besides, some of these Sentinel-1 multitemporal-based studies have already demonstrated the moderate potential of Sentinel-1 for monitoring vegetated water bodies or emergent flooded vegetation areas (Cazals et al., 2016; Mroz, Mleczko and Fitrzyk, 2016; Mleczko and Mróz, 2018; Tsyganskaya et al., 2018b). While the potential capabilities of C-band SAR dense timeseries for wetland mapping have already been proven, there is still a need for new continuous wetland monitoring systems which can be globally adapted to the various specific wetland types.

1.3 Research needs and research questions

Based on the review of the current optical and SAR based remote sensing environmental monitoring systems (previous section), the following points required a thorough evaluation and thus they were discussed in this thesis. First, most of the current remote sensing-based environmental
monitoring approaches are based on optical imaging, hindering the acquisition of near-real-time and continuous information on the state of natural ecosystems due to frequent cloud cover present in many regions of the globe. Especially in tropical regions, the dense and almost permanent cloud cover represents a great handicap for monitoring environmental disturbances with optical systems, significantly affecting the performance and accuracy of these tools, causing low temporal resolutions, inconsistency in the results (e.g. data gaps in time series) and misclassification errors. Second, Synthetic Aperture Radar (SAR) methods have demonstrated their capabilities for monitoring environmental disturbances over many types of natural ecosystems, climatic conditions and time of day/night. Nonetheless, most of these SAR-based approaches present certain limitations. Sparse data frequency, single date investigation or high computational requirements restrict the use of these approaches for disturbance monitoring. In addition, at present, there is still a low availability of continuous monitoring methods that fully exploit the potential monitoring capabilities of dense timeseries (Hostert et al., 2015). The current expansion of satellite remote sensing together with upcoming SAR missions point towards a notable improvement in the temporal resolution in the coming years, playing in favour of the use of methodologies based on dense time series. Finally, there is a lack of EO environmental monitoring tools which, through a single methodology, provide temporally and spatially consistent information on the land cover dynamics of different ecosystems.

Motivated by the research needs specified in the introduction, the main objective of this thesis is to develop novel SAR timeseries-based change detection methods that provide continuous and rapid information on permanent and seasonal disturbances occurring in global natural ecosystems, paying special attention to the usability of these tools, aiming for low computational requirements and simple / smooth adaptability to various EO applications. The research questions discussed in this thesis are the following:

1. How can we exploit the advantages of multi-temporal SAR dense time series and cumulative sum strategies for detecting historical forest structural disturbances?
2. How can we expand/adapt the use capabilities of the CuSum detector to other (highly dynamic) environmental monitoring scenarios?
3. How can we development a new user-friendly and fully operational SAR-based environmental tool?
4. How can we modify the CuSum algorithm for fully-unsupervised tropical forest monitoring and above ground biomass loss estimations?
1.4 Thesis structure

The core of this thesis is a series of four chapters, in which all the research questions are addressed. Figure 6 provides an overview of these core chapters.

In Chapter 2, research question 1 is addressed by the development of a novel SAR-based change detection algorithm based on the Cumulative Sum statistical test. The novel CUSUM-SAR approach is applied to dense time-series of radar Sentinel-1 data for monitoring permanent forest structural changes that occurred in mixed temperate forest masses. The outcomes of this chapter demonstrate the capabilities of the proposed methodology for environmental monitoring, thus laying the foundations for further development and testing of the approach in the following chapters.

In Chapter 3, research questions 2 and 3 are addressed by the optimization of the original CUSUM-SAR algorithm to seasonal/temporary disturbance monitoring. The new Ker-CuSum approach is adapted to monitor the hydrological dynamics of the North Rupununi wetlands, Guyana, in a continuous and near-real time manner. The implementation of the proposed methodology in Google Earth Engine platform allowed an assessment of the impact of online geo-mapping platforms and ancillary datasets on the change detection capabilities. A fully-operational online flood mapping web application is developed, emerging as the first SAR-based near-real time wetland monitoring tool for the North Rupununi wetlands. A presents an adaptation of the methods proposed in chapter 3 based on multi-orbit and data fusion approaches applied to monitor the hydrological dynamics of the Doñana natural wetlands, Spain.

In Chapter 4, research question 4 is addressed by the optimization of the Ker-CuSum method to an automatic and fully-unsupervised change detection approach for monitoring natural and human forest disturbances in tropical forest contexts. A thorough assessment was performed to evaluate the impact of advanced features such as the radiometric terrain normalisation, multi-temporal filtering and occurrence analysis on the final detector accuracies. The new CFAR-KerCuSum version was applied to dense timeseries of Sentinel-1 data to monitor forest degradation processes and above ground biomass losses between 2018 and 2021 within highly-dynamic tropical forests areas in Guyana. Appendix B elaborates on the annual Above Ground Biomass loss assessments, demonstrating the capabilities of the CFAR-KerCuSum detector for monitoring additional environmental variables through the integration of the forest change detection with ancillary data.

In Chapter 5, the final conclusions are outlined. The research questions are reviewed, discussing the main results, novel research contributions emerging from each of the chapters of this thesis, and their limitations. An overall reflection is provided, assessing the continuous process of design and development of the proposed methodologies and their contribution to environmental remote sensing. A final summary outlines the overall outcomes of this thesis while providing suggestions for future research efforts.
Figure 6. Overview and research connections between all the data chapter of this thesis.
Chapter 2

Continuous Forest Monitoring Using Cumulative Sums of Sentinel-1 Timeseries
This chapter focuses on the development of a novel approach for mapping forest structural changes in a continuous and near-real-time manner using dense Sentinel-1 image time-series. Based on the Cumulative sum statistical analysis, the proposed CUSUM-SAR change detector uses dense satellite radar image timeseries to investigate the continuous variation in radar signals derived from forest changes. In this Chapter, the CUSUM-SAR approach is tested for monitoring permanent forest changes (e.g. controlled logging activities) in mixed temperate forests of the Queen Elizabeth Forest Park, Scotland. Additionally, this study pays special attention to the influence that seasonality and vegetation phenology has on SAR signal, developing a novel strategy for the removal of forest type-derived seasonal bias from the radar timeseries. Finally, to further validate the detection performance of the method, the CUSUM change detector was tested against commonly used pairwise change detection approaches for the same period. This chapter lays the foundations of this thesis demonstrating the high capabilities of the CUSUM method for detecting forest changes and opening the door to its use for environmental monitoring applications.

The outcomes of this study have resulted in the development of a new forest monitoring method for detecting forest disturbances from the analysis of dense SAR time series. The CUSUM method stands out as a valuable monitoring tool for foresters/forest managers because it reduces the current response times, while also cuts the costs and efforts when evaluating forest damage. Overall, this research serves to emphasize the capabilities of the CUSUM approach and dense SAR time-series for environmental monitoring and provide a useful tool for optimizing national forest inventories.
2.1 Introduction

Forests are one of the major contributors to climate change mitigation, playing an integral role in the global carbon cycle by removing 2.1 Gt CO$_2$ from the atmosphere every year (Federici et al., 2015; Nunes et al., 2020). However, accelerating changes in global climate dynamics, together with high pressures exerted by current socio-economic forces, are leading to a dramatic reduction of global forested regions, which is threatening the conservation of world forest ecosystems (FAO, 2004; Kissinger, Herold and De Sy, 2012; Defries, 2013; UN-REDD, 2015; IUCN, 2017). Among the many land use and land cover changes (LULCC) that threaten global ecosystems, deforestation and forest degradation have been recognised as the most important human-induced land transformation during the last half century (Rudel, 2009). Natural disturbances such as forest fires, windstorms, droughts, floods or natural plagues pose an important threat to forest conservation, directly affecting biodiversity, natural resources and biogeochemical cycles of these ecosystems. For European temperate forests, most forest degradation events are primarily driven by windstorms and wildfires (Seidl et al., 2014). Wind storms were responsible for 53% of the damage caused by natural disturbances during the last half of the 20th century (Schelhaas, Nabuurs and Schuck, 2003; Seidl et al., 2014); having an economic impact of approximately 15 million euros for the countries of the European Union (Forest Research, 2018). In particular, the United Kingdom is one of the most affected countries by wind disturbances due to its high exposure to recurrent Atlantic windstorms, recognising small-scale windthrow events as a long-term environmental issue and a major threat to the economic and natural management of British forests (Quine and Bell, 1998; Forest Research, 2018). In addition, prediction models based on the current global environmental trends, identify climate change as an amplifier of hydro-climatic hazards, forecasting an increased frequency of natural disasters that may lead to a global canopy cover reduction of 223 million hectares by 2050 (Saxe et al., 2001; Apps, 2003; Seidl et al., 2014, 2017; Bastin et al., 2019; Chaplin-Kramer et al., 2019). These facts highlight the need to develop accurate forest monitoring systems which contribute to an optimal management and conservation of the world’s forests.

In the last decades, remote sensing technologies have played a fundamental role in forest monitoring, providing a consistent and reliable data source that has served to overcome the inadequacies and challenges associated with traditional forest inventory methods. Current operational forest cover change products are commonly based on optical satellite imagery (Hansen et al., 2013). However, clouds significantly restrict the use of these products for the continuous study of forest dynamics. Alternatively, forest cover change can be mapped using cloud penetrating Synthetic Aperture Radar (SAR) data (Cremer et al., 2020). The high sensitivity of SAR signals to variations in the geometrical or dielectric parameters of the targets, make SAR sensors particularly suitable for forest disturbance detection studies. Among all SAR frequencies, L-band data is generally preferred for forest change
monitoring as its longer wavelength allows to penetrate deeper into the forest structure (Shimada et al., 2014; Rosenqvist and Killough, 2018). Nonetheless, the use of L-band data for long-term or continuous forest monitoring is hindered by the current lack of a freely available global SAR L-Band time series dataset. The launch of the European Space Agency’s (ESA) C-band Sentinel-1 satellite constellation in 2014, opened the door to new opportunities for SAR environmental monitoring based on timeseries. With freely available data and improved sensor characteristics (eg, dual polarization 6- or 12-day revisit period), Sentinel-1 rapidly stood out as a valuable resource for effective monitoring of highly dynamic forest ecosystems (Hardy et al., 2019; Tanase et al., 2019).

Current approaches that use Sentinel-1 dense timeseries have demonstrated the high capabilities of C-band for monitoring small-forest disturbances, evidencing the effectiveness of this data for distinguishing between the forest cover and the bare soil. Nonetheless, there is still a low availability of continuous monitoring methods as these approaches mostly focus on the study of single events, relying on the use of single epoque image comparisons to detect forest changes occurring between two specific dates (Hostert et al., 2015). This work addresses these issues, focusing on the design and development of new continuous monitoring methods that provide an effective solution to the current limitations associated with national forest inventories.

This chapter aims to develop a novel approach for monitoring forest structural changes in a continuous manner using Sentinel 1 image time-series data. Based on cumulative sum statistical analysis, this method was developed for exploiting the continuous variation in radar signals derived from forest changes (e.g., logging activities). This approach was validated in the Queen Elizabeth Forest Park (Scotland) in collaboration with Forest Research (FR) and Forest and Land Scotland (FLS). However, the new forest monitoring tool is designed to be applicable to any UK National Forests.

To summarize, the main objectives of this chapter are:

- The design of statistical tests for cumulative sums using SAR data.
- Design and develop novel SAR-based change detection algorithms for continuous forest monitoring (CUSUM-SAR; CUSUM-SMC).
- Perform a quantitative evaluation of the change detection performance of the statistical tests for forest structural disturbances.

### 2.2 Study Area

The study area was located within the boundaries of the Queen Elizabeth Forest Park (19,665 ha), near Aberfoyle village, Scotland (Figure 7). This area is part of the Loch Lomond and Trossachs National Park and has been widely used as a research forest by FR. The area is characterized by large natural forests and forest plantations. Main forest types, according to the most recent (2016) National Forest Inventory (NFI), are ‘conifer woodlands’ (9,001.34 ha) and ‘broadleaved and mixed woodlands’ (1,547.76 ha).
There is a clear predominance of plantations of Sitka spruce (*Picea sitchensis*) (5,351 ha) with smaller areas of *Pinus contorta* (468 ha) and *Quercus petreae* and *robur* (612 ha).

![Reference map showing the location and areas covered by the Queen Elizabeth Forest Park.](image)

According to historical data (1981–2010) obtained from the closest Met Office climate station at Arrochymore (56.096, -4.548), 30 m above sea level, the bioclimate of this region is considered as ‘Cfb’- ‘oceanic or highland climate’ (Köppen–Geiger classification). The mean annual temperature for the area is 12.6 °C and annual rainfall (1735 mm) is distributed evenly throughout the year. July is the hottest month with an average temperature of 19.2 °C, while January shows the lowest temperatures with an average of 6.9 °C. The soils are drifts derived from acid metamorphic rocks and Lower Old Red Sandstone sediments, classified as “brown soils” (Soil Survey of Scotland Staff, 1981). To ensure the absence of any significant geometric distortion that may compromise the use of radar images, a detailed analysis of the main topographic variables (e.g. elevation, aspect, hill shade, orientation) was carried out. Results showed a predominance of lowland and foothills with generally gentle slopes, although some hills do present a significant slope, which did not condition the utilization of radar in the area of study.

### 2.3 Materials

#### 2.3.1 SAR Data

Dual polarization (VV, VH) Sentinel-1 Level-1 ground range detected (GRD) images, were retrieved from the ESA data archive using the Sentinel Data Access Service (SEDAS) platform. S1-IW_GRD_HR products were acquired in interferometric wide swath (IW) high resolution (HR). The
center frequency was 5.405 GHz (which leads to a 5.3 cm wavelength) and with around 20 x 22 meters resolution (Torres et al., 2012; Filipponi, 2019). GRD products were focused SAR data that had already been converted into intensities, multi-looked, and projected to ground range using the Earth ellipsoid model WGS84 (ESA, no date). In total, the radar time-series was composed of 84 scenes, downloaded for the period between 01 January 2018 and 30 September 2019. All images were acquired in ascending mode and using a unique orbit (i.e., relative orbit 30), aiming to maintain the identical radar geometry in all acquisitions.

2.3.2 SAR Data Pre-Processing

All images were pre-processed using ESA-SNAP 7.0 and ESA-NEST 4.1 software and following a four-step procedure: 1. subset, 2. radiometric calibration, 3. coregistration, and 4. geometric terrain correction. First, the subset process was carried out to eliminate those areas located out of the boundaries of the region of interest. Second, radiometric calibration was applied using the Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) at a resolution of 1 arc-second (∼30 m). This process provided images in which pixel values can be directly related to radar backscatter from the scene, converting the backscatter values to sigma-naught coefficient (σ0). It should be noted that in cases where the analysis considers multiple orbits, the use of sigma-naught as calibration will not be effective. A calibration process able to remove geometrical distortions associated to steep slopes will be required (e.g., gamma0). The use of a multi-orbit approach was beyond the scope of the work presented here, however; the benefits of this approach will be explored in the future. Third, data coregistration was performed, using the first acquisition of the timeseries (01st January 2018 - VV channel) as the master image, to precisely stack together all images into a single multi-layer (composite) product. Fourth, terrain correction allowed the geolocation of all pixels, using the 30 m STRM-DEM and subsequently projected to the (WGS84, UTM 30N) coordinates system. The final output resulted in a data stack formed by 168 images (84 co-polarization, 84 cross-polarization).

2.3.3 Validation data: Forest mask and Logging activities reference data

The forest mask was obtained from the 2018 United Kingdom National Forest Inventory (Forest Research, 2019). The forest definition used for the forest mask includes both conifer and broadleaves areas, regardless of their pure or mixed typology. The mixed nature of the forest investigated hindered the discrimination between forest species or forest mass typologies at the pixel level. The developed algorithms were tested for detecting clear-cut activities carried out in the Queen Elizabeth forest park between 1 January and 30 September 2019 (Figure 8b). The harvesting forest office of the FLS collaborated providing information about the logging events, including the starting and ending dates of each logging activity analysed.
To obtain the initial draft of the change map, a visual investigation of cloud-free optical images imagery (cloud coverage <10%) acquired over this period was performed. A pair of Landsat 8 (OLI) shortwave infrared images acquired on 25 June 2018 and 28 June 2019 (a year later) provided the best characteristics for the required period (Figure 8a). Shortwave infrared is a band combination highly recommended for studying vegetation health and stress, change detection, and disturbed soils (Earth Observing System, no date). It combines the Short-wave Infrared (SWIR), Near infrared (NIR), and red bands to generate images where vegetation can be clearly differentiated from bare soils.

Figure 8. Forest logging activity identification. (a) Landsat 8 shortwave infrared image used for the visual identification of forest changes. Acquired: 28 June 2019; pink tone areas represent land cover transformation from forest to bare ground. (b) Colored polygons represent Forest and Land Scotland (FLS)-verified forest logging activities carried out between 1 January 2019 and 30 September 2019.

Using a visual interpretation process, forest areas which had experienced significant transformation during the period of study were manually digitized. Finally, once all the three land classes (‘change-forest’, ‘stable-forest’ and ‘non-forest’) were mapped as vector polygons, the pixel’s boundaries of each disturbed forest area were extracted by overlapping these polygons over a terrain corrected Sentinel 1 image, extracted from the data cube. This process generated a total of 30 areas, 10 for each land class, of various sizes (from 2.5 to 50 ha). All these areas were used for the signal behavior analysis, as shown in the following section.

2.4 Methodologies

2.4.1 Cumulative Sum Change Detection Analysis

This study focuses on the adaptation of the Cumulative Sum (CuSum) statistical methods for monitoring forest disturbances over dense time series. CuSum has been widely used by the financial sector, being recognized as an excellent big data analytic tool for detecting changes in the market
Continuous forest monitoring using cumulative sums of Sentinel 1 timeseries (Manogaran and Lopez, 2017). This method however has not been extensively used in scientific and environmental applications. Recent research (Kucera, Barbosa and Strobl, 2007; Manogaran and Lopez, 2017; Kellndorfer, 2019; Eric L Bullock, Woodcock and Holden, 2020) showed the potential capabilities of this methodology for monitoring environmental variations. Manogaran et al. (Manogaran and Lopez, 2017), proposed a novel climate change detection algorithm to monitor changes in the seasonal climate. The preliminary results showed a high robustness of the method when detecting variations in climate. Kellndorfer (Kellndorfer, 2019) explores the use of CuSum for monitoring deforestation and forest degradation processes, however no quantitative validation of the method is performed. In this chapter, a novel change detection methodology, based on the concepts of the CuSum is developed, the CUSUM.

CUSUM is used to monitor the deviation of a variable from its mean based on measurements acquired over a given time frame. It stands as a powerful statistical method for analysing multitemporal processes, since it allows the detection of both slow and abrupt variations in the mean value of a quantity of interest (Kucera, Barbosa and Strobl, 2007; Manogaran and Lopez, 2017). In most cases, these changes in the mean are associated with temporal or permanent changes in the variable analysed (NCSS, 2019), a fact which makes this method especially suitable for environmental monitoring purposes. Contrary to what the name may suggest, the cumulative sum is not the cumulative sum of the values, but the cumulative sum of the differences between the values and the mean. This is:

\[
\Sigma_d = \sum_{i=0}^{N} I_i - E[I]
\]

where \(N\) is the total number of temporal samples, \(I_i\) represents a sample take at time \(i\) and \(E[I]\) is the expected value of the samples over a training time frame. The expected value \(E[I]\) is approximated by using the sampling average and assuming a large enough sample size.

2.4.2 CUSU-SMC

This section presents a modification of the CUSUM algorithm, developed to make it more suitable for working with SAR data and integrating seasonal trends. This adaptation was called CUSU-SMC (Cumulative Sum-Spatial Mean Corrected).

As the main goal of this research focuses on detecting the forest changes that occurred from the beginning of 2019 onwards, it was decided to use the information compiled in all 2018 images as control samples. As is shown later, the selection of the mean plays an important role. This research works with spatio-temporal datasets, where data are stored in cubes with spatial dimensions (range and azimuth) and a temporal dimension. Accordingly, the reference mean value \(E[I]\) can then be calculated either in the spatial domain or the temporal domain.
1. Temporal mean: previous approaches, followed by (Manogaran and Lopez, 2017; Kellndorfer, 2019), calculate the average backscatter value for each pixel, using all the images acquired over the reference time, in this case, the year 2018.

\[
E[I] = \bar{I}_t = \frac{1}{N_t} \sum_{i=0}^{N_t} I_i
\]

(2)

where \(N_t\) is the number of images in the reference time.

This will generate a single mean value \(\bar{I}_t\) for each specific pixel.

This approach presents certain theoretical disadvantages for dense time series over vegetation. A unique mean value for each pixel does not take into account any temporal variation that might be associated with the seasonal change in vegetation (e.g. phenology variations) or meteorological events (e.g., precipitation or temperature). Seasonal variations (due for instance to phenology) can represent genuine changes to some properties of the tree canopies. For example, particular drought or rain events that alter the physical or morphological properties of vegetation may be misinterpreted as structural changes.

2. Spatial mean: To minimise the possible influence that seasonal variation may have on the detection of forest structural changes, a spatial mean (instead of a temporal one), which follows the seasonal variation of forest ecosystems, was used. This approach uses the mean estimated over the forest areas at each specific date in the timeseries.

\[
E[I] = \bar{I}_s = \frac{1}{N_s} \sum_{i=0}^{N_s} I_i
\]

(3)

where \(N_s\) is the number of pixels included in forest areas and \(I_i\) are the pixels in forested areas.

In other words, each time step has a characteristic \(\bar{I}_s\).

To do this, we needed to use a forest inventory or produce a rough forest classification mask using SAR or optical images.

### 2.4.3 CUSUMs Implementation

The implementation was done in Python, downloading data using the SEDAS Sentinel Data Service Access Hub.

Data cubes were first created using the Sentinel-1 images. Three data cubes were created, using the polarization channels VV, VH, and their ratio VH/VV. The cubes were then overlaid with forest inventories masks. The forest mask was previously extracted from the 2018 Scottish National Forest Inventory (Forest Research, 2019). Forest can be classified differently based on different precision ranges. In this case, it was decided that forest must contain indistinct conifer and broadleaf masses, no matter if they are pure or mixed stands. Once the forest cube is calculated, it is possible to get
Continuous forest monitoring using cumulative sums of Sentinel 1 timeseries

both the temporal forest mean and the spatial forest mean (SFM) for each specific date and implement it into the CuSum analysis (Figure 9).

In terms of numerical implementation, the CuSum is calculated with the following iteration:

1) Temporal mean | CUSUM

\[
cusum_i = cusum_{i-1} + (I_i - \bar{I}_s) \text{ for } i = 1, 2, ..., N_t
\]  

(4)

2) Spatial mean | CUSU-SMC

\[
cusum_i = cusum_{i-1} + (I_i - \bar{I}_{s,forest}) \text{ for } i = 1, 2, ..., N_t
\]  

(5)

where \( cusum_0 = 0 \) and \( i \) is an iteration over the temporal axis of the cube. \( N_t \) is the total number of acquisitions used in the training dataset. \( \bar{I}_{s,forest} \) is the reference forest spatial mean. The image I can be the VV, VH polarization channels or their ratio. The comparison of results using the three observables is provided in the following.

![Graphical explanation of the reference mean calculation strategies used both for the CUSUM-SAR (left) and the CUSU-SMC (right) approaches.](image)

2.4.4 Z Score Calculation

The result of the CUSUMs (refers to both CUSUM and CUSU-SMC approaches) is either a cumulate intensity or ratio. In order to produce a detector, a threshold value was needed for both CUSUM algorithms. In this work, a rigorous statistical framework is proposed to set thresholds for both CUSUM algorithms. The first step was to understand which type of distribution the CUSUMs have. In section 2.5.2, it will be shown that after all the processing the CUSUM in the training dataset was distributed as a

28
Gaussian zero mean with standard deviation \(\sigma\). This allowed using a Z test for setting thresholds in a statistically rigorous way, with some significance value attached to the results. The first step was to calculate the standard score, which will provide information about the probability of a point having a set Z score. The Z score needs knowledge of the population mean \(\bar{C}\) and standard deviation \(\sigma_C\):

\[
\sigma_C - Z = \frac{\text{cusum}_i}{\sigma_i}
\]  

(6)

where, \(\sigma_C\) is calculated using all the images acquired during the reference year (2018, with 54 images in our case). \(\text{cusum}_i\) is the cumulative sum at time \(i\) and \(\sigma_i\) is the standard deviation of \(\text{cusum}_i\) at the time \(i\).

The null hypothesis is that "no change" occurred. This is the hypothesis where the \(\text{cusum}_i\), under test belongs to the same population as the training dataset. The alternative hypothesis is that a change happened, or more formally the \(\text{cusum}_i\) under test does not belong to the same population as the training dataset:

\[
H_0 = \text{No change}
\]

\[
H_1 = \text{Change}
\]

In the test, the p-value is the probability that the CUSUM sample belongs to the null hypothesis (H0). This means that a small p-value will suggest that the H0 is rather unlikely and therefore we can reject H0 and argue that there is high confidence in the acceptance of H1 as true.

### 2.4.5 Logging Area Detection Accuracy Assessment

The accuracy of the algorithm was assessed through an error matrix (or confusion matrix). This approach allowed testing the quality of the classifier, based on the correspondence between the classification results and a reference image (Table 2). From the confusion matrix, overall accuracy (OA, Equation (7)), producer accuracy (PA, Equation (8)), user accuracy (UA, Equation (9)) and F-measure (F-score, Equation (10)) were individually calculated for each data cube. Additional accuracy metrics, such as the F-measure were also considered. F-measure is one of the best measures for evaluating the detector performance since it summarizes the balance between (PA) and (OA), prioritizing the identification of real detections over the detection of true negatives (Sasaki, 2007; Ghoneim, 2019).
Table 2. Confusion matrix for change detection classification. H0: No change, H1: Change.

<table>
<thead>
<tr>
<th>Reference</th>
<th>$H_0$</th>
<th>$H_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H_0$</td>
<td>True Negative (TN)</td>
<td>False Positive (FP)</td>
</tr>
<tr>
<td>$H_1$</td>
<td>False Negative (FN)</td>
<td>True Positive (TP)</td>
</tr>
</tbody>
</table>

\[
\text{Overall accuracy (OA)} = \frac{TP + TN}{(TP + TN + FP + FN)} \tag{7}
\]

\[
\text{Producer accuracy (Recall)} = \frac{TP}{(TP + FN)} \tag{8}
\]

\[
\text{User accuracy (Precision)} = \frac{TP}{(TP + FP)} \tag{9}
\]

\[
F - \text{measure} = \frac{2 \times \text{Recall} \times \text{Precision}}{(\text{Recall} + \text{Precision})} \tag{10}
\]

### 2.4.6 Post-Processing and Sieve Filtering

The high sensitivity of electromagnetic signals to variations occurring in some target parameters (e.g., geometry, moisture contents, or surface roughness) makes SAR technology a valuable tool for detecting changes. However, this sensitivity also leads to significant misclassifications and estimation errors when performing change detection analyses. Tackling high false alarm rates is a common issue when working with satellite imagery. A methodology that can be used at the expense of spatial resolution is post-processing with morphological filters, such as the sieve filter (GDAL, 2019). The sieve filter removes all polygons smaller than a given size and merges them with their largest neighbors (Ose, 2018; GDAL, 2019). Beside the threshold on the number of connected pixels, a sieve filter differentiates among two types of pixel connectivity. A type 4 connectivity is established for adjacent pixels that share a side, while a pixel with a connectivity of 8 shares any side or a vertex with its adjacent (Ose, 2018).

The filtering impact on classification accuracy was evaluated using three different thresholds of 10, 15, and 25 pixels; with a connectivity of type 8, as this is less restrictive in terms of shape. The analysis was performed using the geospatial tools of ArcMap 10.5 (Int, Region group), and QGIS software (Gdal-Sieve filter). The final accuracy assessment was carried out in the Python environment, making use of the open source Geospatial Data Abstraction Library (GDAL).

### 2.4.7 CUSUMs Framework

All Sentinel-1 GRD images acquired for the period of study considered the VV and VH polarization channels. Channels were calibrated as normalised radar cross sections, using them to compute the ratio of VH over VV. The timeseries was stored in 3 data cubes, one for VV, one for VH, and one for ratio. In the following step, image noise was reduced by applying a boxcar filter (3 x 3 window size). The filtering significantly contributed to reduce speckle variation. Subsequently,
unitless backscatter values were converted to dB using a logarithmic transformation. This preprocessing was identical for CUSUM and CUSU-SMC.

\[
\sigma_{dB} = 10 \log_{10} DN
\]  

(11)

where \( DN \) is digital number.

The following step marks the separation between the CUSUM and CUSU-SMC approaches. CUSUM uses a unique mean value for each pixel calculated over the reference timeseries (year 2018). CUSU-SMC uses a single mean for each acquisition, this mean being updated for each acquisition. Similarly, a constant bias correction will be applied to the CUSU-SMC cumulative sums. Z-score calculation allowed evaluating the probability of change, rejecting or accepting the considered hypothesis under different levels of significance. Change detection maps were subject to a first accuracy assessment, making use of reference logging activity masks, provided by the FLS as the validation dataset. Finally, a sieve morphological filter, with multiple windows sizes, was applied to reduce the number of random flagged pixels, and the accuracy was assessed again to evaluate the effects of the morphological filter on the final result (Figure 10).

Figure 10. Proposed methods for the cumulative sum (CUSUM) and cumulative sum-spatial mean corrected (CUSU-SMC) forest change detectors.
2.5 Results

2.5.1 Trends and Biases of CUSUMs

This section focuses on the validation and comparison of both the CUSUM-SAR and CUSU-SMC strategies. As explained, the main difference between these methods relies in the use of a spatial mean instead of a temporal one. To illustrate the methods comparison, Figure 11 shows the timeseries behavior of both the CUSUM and CUSU-SMC approaches for the ratio combination. The other polarization channels showed a similar trend to the ratio. Figure 11a presents the CUSUM over three plots for three classes, “change”, “conifer”, and “broadleaves”. In this test the training was done using the 2018 data (54 dates). As can be seen in Figure 11a, all the lines seem to converge to zero after exactly one year and then diverge afterwards. This is due to a mathematical constraint that forces a value of zero when the CUSUM is calculated for exactly 54 dates. The equation used to calculate the CUSUM is linear and we get zero when the added part equals the mean:

\[
CUSUM_{54} = \sum_{i=1}^{N} \left[ I_i - \frac{1}{M} \sum_{j=1}^{M} I_j \right] = 0, \text{ for } N = M = 54
\]  

As a comparison, Figure 11b presents the proposed CUSU-SMC over the same regions for the three classes, “change”, “conifer”, and “broadleaves”. This figure shows that CUSU-SMC seems to slowly, but constantly, diverge for each of the classes. This observation can be made for almost all the pixels in the image. This is because some pixels will naturally have a backscattering which is higher (or lower) than the mean \( \bar{I}_s \) due to different forest structures. The constant change will act as a bias and accumulate over time forming a ramp. Since most of the pixels present different forest structures they will all show a ramp.
Figure 11. Spatial mean normalization. Ratio of backscatter variation of each class (‘change’, ‘conifer’, ‘broadleaves’) for the entire timeseries, based on the cumulative sum methodologies; (a) CUSUM based on (Kucera, Barbosa and Strobl, 2007), (b) CUSU-SM spatial forest mean variant, (c) CUSU-SMC proposed method (spatial mean constant bias correction applied).

Since the differences act as a constant bias the trend is approximately linear (i.e., this is the function with a constant gradient). Therefore, the line of best fit for the temporal trend during the training dataset can be easily estimated and subsequently removed for the rest of the time series. After removal, the CUSU-SM pixels will be fluctuating around 0, unless there is a change. Figure 11c shows the result of CUSU-SMC (after correction), where the ramp did not remove the change because it is estimated over the training dataset where no changes occurred. Moreover, it should be noted that the corrected trends are not constrained to be zero at the end of the training interval. The change that they show is what was actually accumulated compared to the rest of the forest.

One rationale for using the spatial mean is that in theory this will help remove anomalies due to meteorological conditions or forest phenology. Since the weather and phenology will affect all the surrounding forest in a roughly equal way, this will modify the spatial mean that we calculate and therefore the weather signal would be removed. This procedure may be seen as an attempt to calibrate the data based on the weather condition. Of course, there will still remain some random fluctuation, due to the fact that some forest species may not change backscattering in the same way compared to other forest stands. However, this should be a second order error, that could be eventually corrected.
Continuous forest monitoring using cumulative sums of Sentinel 1 timeseries

if we have, either an accurate forest inventory or a good model to predict more accurately the change of the forest behavior due to weather conditions.

2.5.2 Testing the Assumptions

To test the assumption that the CuSums obey a Gaussian zero mean distribution, a normality test was performed by investigating graphically the output of data histograms and quantile–quantile plots. The results obtained for each of the three classes “forest”, ”conifer”, and “broadleaves” provided enough evidences to ensure the data is normally distributed. As can be seen in Figure 12, histograms highlighted a close approximation of the data to the theoretical bell curve distribution; while in the Q–Q plots data points appeared closely distributed along the diagonal line.

Figure 12. Assessing if CUSUM and CUSU-SMC are normally distributed over the reference year. The data used for generating the histograms was obtained by masking out each region (“forest”, “conifer”, “broadleaves”) over a CUSU-SMC ratio image (29.07.2019). Data used for Q–Q plots correspond to temporal values of unique pixels, randomly selected, for each region.

2.5.3 CUSUM Logging activities detection

The results obtained from the accuracy assessment showed an optimal change detection performance, for both the CUSUM and the CUSU-SMC. The accuracy assessment was carried out by using multiple significance levels in order to test the performance of the methods. Despite different results being obtained for each level of significance, it was decided to set alpha =0.05 as the most appropriate value for comparing the tested products. Based on the results, shown in Table 3, the following can be concluded:

1) Best polarization channel:

Assessing the best polarimetric channel to monitor logging for temperate forest is crucial since previous studies have shown some discrepancy regarding this. Previous work (Green, 1998; Eriksson
et al., 2012; Rüetschi et al., 2019) suggested that co-polarized backscatter (HH, VV) was more sensitive to forest gaps; with other work (Tanase et al., 2018; Kellndorfer, 2019) demonstrating higher sensitivity of cross-polarized (VH, HV) for forest structural changes, as a result of the disruption of the high backscatter values associated with the complex geometries of tree canopies. The temporal trend for VV, VH, and the ratio are showed in Figure 13. Data were filtered with a 3 x 3 boxcar filter. The last row of Figure 13 shows the backscatter differences between the stable forest areas and the logging areas for the VV, VH and its ratio.

Figure 13. This figure illustrates the sensitivity of different polarization channels to forest structural changes by comparing the annual backscatter timeseries of logging areas with undisturbed forest. Temporal differences extracted from the comparison of logging areas and undisturbed forest (bottom) showed the higher sensitivity of the VH polarization channel.

The CUSUM method (Kucera, Barbosa and Strobl, 2007), showed the best results for the VH polarization channel (OA = 73.6%; F = 69.5%), providing a medium to high performance in the detection of true positives (TP = 60.2%) and a significantly high performance in the rejection of false positives (FP = 13.0%). Similarly, the proposed CUSU-SMC also showed its higher performance with the VH polarization channel (OA = 65.7% and F = 68.0%), offering a high performance in detecting true positives (TP = 72.4%), but a relatively high false alarm rate (FP = 40.6%). The ratio (VH/VV) combination provided a good performance for both CUSUM (F = 68.7%) and CUSU-SMC (F = 67.4%) methods. Finally, the impact of ground on the co-polarized channel (VV) provided the lowest separation between forest and deforested areas.
2) Detection strategies:

Despite the similar overall performance observed for both CUSUM and CUSU-SMC, a notable difference in terms of true positives and false alarms was identified. Specifically, the CUSU-SMC showed a much higher power of the statistical test, which means it is much more capable of detecting true positives, but it also had an increase of true negatives. Given that the total OA is similar, we can identify two main detection strategies as:

a) Conservative strategy (*C): This leads to low false positive rate, but also lower true positive.

b) Tolerant strategy (*T): This leads to higher true detection rates at the expense of having more false alarms.

In Table 3, it can be seen the algorithm and polarization channel that would lead to the best results for one of the two strategies.

Table 3. CUSUM & CUSU-SMC accuracy assessment. Accuracy rates were calculated using 2019 logging areas as reference, the same acquisition date (29th September 2019) and a significance level of (α = 0.05). TP= True positives, TN= True negatives, FP= False positives, FN= False negatives, OA= Overall accuracy, PA= Producer accuracy, UA= User accuracy. (*C= Conservative approach, *T=Tolerant approach and *NC= results obtained without the application of the fitted ramp correction). Detectors with the best performance for the conservative and tolerant strategy are shown in green, with overall accuracy and F-Score highlighted in bold.

<table>
<thead>
<tr>
<th></th>
<th>VV</th>
<th>VH *C</th>
<th>Ratio (VH/VV)</th>
<th>CUSU-SMC</th>
<th>VH *T</th>
<th>Ratio (VH/VV)</th>
<th>Ratio (VH/VV) *NC</th>
</tr>
</thead>
<tbody>
<tr>
<td>TP</td>
<td>0.324</td>
<td>0.602</td>
<td>0.731</td>
<td>0.724</td>
<td>0.685</td>
<td>0.654</td>
<td></td>
</tr>
<tr>
<td>TN</td>
<td>0.917</td>
<td>0.870</td>
<td>0.602</td>
<td>0.594</td>
<td>0.650</td>
<td>0.583</td>
<td></td>
</tr>
<tr>
<td>FP</td>
<td>0.083</td>
<td>0.130</td>
<td>0.398</td>
<td>0.406</td>
<td>0.350</td>
<td>0.417</td>
<td></td>
</tr>
<tr>
<td>FN</td>
<td>0.676</td>
<td>0.398</td>
<td>0.269</td>
<td>0.276</td>
<td>0.315</td>
<td>0.346</td>
<td></td>
</tr>
<tr>
<td>OA</td>
<td>0.621</td>
<td><strong>0.736</strong></td>
<td>0.667</td>
<td><strong>0.659</strong></td>
<td>0.668</td>
<td>0.618</td>
<td></td>
</tr>
<tr>
<td>PA</td>
<td>0.324</td>
<td>0.602</td>
<td>0.731</td>
<td>0.724</td>
<td>0.685</td>
<td>0.654</td>
<td></td>
</tr>
<tr>
<td>UA</td>
<td>0.797</td>
<td>0.822</td>
<td>0.648</td>
<td>0.641</td>
<td>0.662</td>
<td>0.610</td>
<td></td>
</tr>
<tr>
<td>F-score</td>
<td>0.460</td>
<td><strong>0.695</strong></td>
<td>0.687</td>
<td><strong>0.680</strong></td>
<td>0.674</td>
<td>0.631</td>
<td></td>
</tr>
</tbody>
</table>

3) Improvement of correction for CUSU-SMC:

The correction for the constant bias applied in the CUSU-SMC approach, provided a significant improvement in the detection performance (OA = +5%, F= +4.3%), as a result of a considerable reduction of the false alarms rates (FP = -6.7%) (see Table 3, *NC). It is therefore important to apply this when using the CUSU-SMC.

The similar F-score obtained for CUSUM and CUSU-SMC (F-score differences of 2.1%) may suggest that correcting for seasonal trends did not result in a significant enhancement of the detection performance. This could be explained by the stable behavior of the radar backscatter signal observed for forest areas. This behavior was also observed by Quegan et al. (Quegan et al., 2000), who found
that old forest exhibits a lower seasonal variability than younger forests. Delving into this point, Figure 14 presents a comparison of the reference means, plotting the single temporal mean (CUSUM method) and the spatial forest mean (CUSU-SMC method) as time trends, where the single temporal mean was a constant in the plot. The different curves represent conifer and broadleaf forest stands. It can be seen how conifer and broadleaf plots present opposite behaviors, in terms of time trends. The spatial forest mean averaged over all the trends, and therefore these temporal trends are averaged out. If the forest inventory is large enough, calculating the spatial forest mean over different forest types may improve the final detection.

![Image of Figure 14: Synthetic aperture radar (SAR) backscatter signal comparison for mean reference values used for the CUSUM and CUSU-SMC change detection methods. The lack of significant differences in the values obtained for the forest mask for both cases tested could explain the similarity in the final results.](image)

**Figure 14.** Synthetic aperture radar (SAR) backscatter signal comparison for mean reference values used for the CUSUM and CUSU-SMC change detection methods. The lack of significant differences in the values obtained for the forest mask for both cases tested could explain the similarity in the final results.

### 2.5.3.1 Comparison with Pairwise Analysis

In order to compare the CUSUMs performance against pairwise combination, two different approaches were considered:

1. Continuous pairwise. This approach aims to generate a continuous change analysis based on the comparison of each image present in the timeseries to the image acquired three times before.

   \[ \text{Pairwise}_i = I_i - (I_{i-3}) \quad \text{for } i = 1, 2, ..., N_t \]  

   where, \( i \) is an iteration over the temporal axis of the cube, \( N_t \) is the total number of acquisitions used in the training dataset. The image \( I \) used for the analysis corresponds to a channel, or the ratio after applying a boxcar filter (window size = 3).
2. Static pairwise. This methodology follows the common direct pairwise change detection, by which two acquisitions separated in time by a specific event (clear-cut activities in our study case) are directly compared. Considering that all logging activity studied occurred between 1st December 2018 and 20th June 2019, it was decided to use the image acquired on 3rd November 2018 as the reference image (pre-event), and the last image of the timeseries acquired on 29th September 2019 as the change image (post-event).

The results obtained for both pairwise methods are shown in Table 4. Here it can be clearly observed that the pairwise method had a significantly lower performance in the detection of logging activities when compared to the proposed CUSUM and CUSU-SMC methods. The low detection performance may have been due to the high signal variation that SAR images may have on single dates. Minor changes to weather variables (e.g., rainfall, temperature, wind) or to vegetation phenology may have led to misclassification errors.

Table 4. Pairwise vs CUSUMs detection performance comparison. The change detection accuracy assessment was performed using a significance level of (α = 0.05) and the same image (29 September 2019) for both the CUSUMs and pairwise approaches. The CUSUMs approaches were the ones for conservative (*C) and tolerant (*T) strategies. TP = true positives, TN = true negatives, FP = false positives, FN = false negatives, OA = overall accuracy, PA = producer accuracy, UA = user accuracy.

<table>
<thead>
<tr>
<th></th>
<th>CUSUM *C (VH)</th>
<th>CUSU-SMC *T (Ratio)</th>
<th>Continuous Ratio</th>
<th>Continuous VH</th>
<th>Static Ratio</th>
<th>Static VH</th>
</tr>
</thead>
<tbody>
<tr>
<td>TP</td>
<td>0.602</td>
<td>0.685</td>
<td>0.223</td>
<td>0.594</td>
<td>0.459</td>
<td>0.389</td>
</tr>
<tr>
<td>TN</td>
<td>0.870</td>
<td>0.650</td>
<td>0.882</td>
<td>0.718</td>
<td>0.697</td>
<td>0.792</td>
</tr>
<tr>
<td>FP</td>
<td>0.130</td>
<td>0.350</td>
<td>0.118</td>
<td>0.282</td>
<td>0.303</td>
<td>0.208</td>
</tr>
<tr>
<td>FN</td>
<td>0.398</td>
<td>0.315</td>
<td>0.777</td>
<td>0.406</td>
<td>0.541</td>
<td>0.611</td>
</tr>
<tr>
<td>OA</td>
<td>0.736</td>
<td>0.668</td>
<td>0.553</td>
<td>0.656</td>
<td>0.578</td>
<td>0.590</td>
</tr>
<tr>
<td>PA</td>
<td>0.602</td>
<td>0.685</td>
<td>0.223</td>
<td>0.594</td>
<td>0.459</td>
<td>0.389</td>
</tr>
<tr>
<td>UA</td>
<td>0.822</td>
<td>0.662</td>
<td>0.655</td>
<td>0.678</td>
<td>0.602</td>
<td>0.651</td>
</tr>
<tr>
<td>F-score</td>
<td>0.695</td>
<td>0.674</td>
<td>0.333</td>
<td>0.633</td>
<td>0.521</td>
<td>0.487</td>
</tr>
</tbody>
</table>

2.5.3.2 ROC Curves

Although the Gaussian model fits very well the CuSum values for the ‘no-change’ forest class, it is still important to check that it is not the statistical model adopted that is producing the different performance, but the framework to process the SAR data. Hence, the receiver operating characteristic (ROC) curves were analysed (Ulehla and Martin, 1971), thus obtaining information on the normality of the data independently from the specific threshold selection (and therefore the significance level). Figure 15 presents the ROC curves of both continuous and static pairwise approaches, CUSUM, and
CUSU-SMC using VH polarization and ratio (VV has not been shown due to its significantly lower performance). ROC curves plot the true positive rate against the false-positive rate while the threshold is varied. ROC representations have been widely used for change detection performance comparisons in multiple scientific disciplines (Zhuang et al., 2018). The closer the ROC curve is to the upper left corner, the higher the overall accuracy of the test (Zweig and Campbell, 1993). In this test, detection performance was tested over multiple significance levels (0.4, 0.3, 0.2, 0.15, 0.1, 0.05, 0.01, 0.001). A higher detection performance was obtained by both CUSUM and CUSU-SMC, which show a similar pattern. Using the ratio (VH/VV), the pairwise approaches always show lower detection accuracy, while when using the VH channel the pairwise gives similar performance when the probabilities of false alarms is very high (higher than 0.5) (Figure 15).

![ROC curves](image)

Figure 15. This figure compares the performance of the pairwise approaches with the CUSUM and CUSU-SMC methods using a ROC curve representation, for both the Ratio (VH/VV) and VH channels. PW = pairwise. ROC curves were generated using the results obtained for the accuracy assessment, performed for the image acquired on 29 September 2019, using significance levels of (α=0.4, 0.3, 0.2, 0.15, 0.1, 0.05, 0.01, 0.001).

### 2.5.3.3 Final Detection Mask

The differences between CuSums and pairwise are also clearly noticeable in the final detection maps. Since the detectors proposed in this study follow a rigorous statistical framework, it is possible to directly link probabilities to the change detection maps. This, therefore, helps evaluate how confident we are that a change is genuine.

Figure 16 compares the change detection map of the Static pairwise approach against the CUSU-SMC method for two study areas affected by clear-cuts. The change map for the CUSUM was very similar to the CUSU-SMC and therefore has not been presented here. As can be seen, CUSU-SMC offered the best performance, detecting practically the entire affected area in a homogeneous way, presenting a lower detection performance just in the most challenging areas, the forest/non-forest transitional edges. Contrary, the common pairwise analysis identified a significantly smaller area of
change, being those changed areas detected in a scattered way. Additionally, the pairwise approach showed overall lower probability values, demonstrating the lower power of the test.

![Figure 16. Logging activities change detection maps obtained for pairwise (static approach) (left) and CUSU-SMC (right) methods. The images show the probability of change (being $P = 1$ considered as change, and $P = 0$ as no change), obtained for the 29 September 2019 and ratio data cube, for the areas affected by clear-cuts “Unknown 4” (top), and “33020” (bottom).](image)

### 2.5.4 Post-Processing Sieve Filter

Results obtained for the neighbouring 'Sieve' filter indicated a significant contribution to the final detection performance, increasing the overall accuracies as a result of a reduction of the false alarm rates (see Table 5). This spatial filter added between 3.6% to 5% to the overall accuracy and 3.5% to 7% to the F-score; this improvement being greater with a smaller filter size of 10 connected pixels. Contrary to what was stated by Rüetschi et al. (Rüetschi et al., 2019), these results suggest that the use of wider windows would result in a more inefficient performance of the detector, since, considering the accuracy/resolution trade-off, the slight accuracy improvements would not compensate for the loss in spatial resolution. According to this, it can be interpreted that the best filter size must be set based on plot size and logging extent, taking into account the specific study area and the prior knowledge of the area.
Table 5. Results showing the spatial filtering effects on detection performance/accuracy.

<table>
<thead>
<tr>
<th>Method</th>
<th>OA</th>
<th>PA</th>
<th>UA</th>
<th>F - Score</th>
<th>Spatial Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>CUSU-SMC (Ratio)</td>
<td>0.668</td>
<td>0.685</td>
<td>0.662</td>
<td>0.674</td>
<td>-</td>
</tr>
<tr>
<td>Sieve (10 pixels)</td>
<td>0.717</td>
<td>0.822</td>
<td>0.679</td>
<td>0.744</td>
<td>0.4ha</td>
</tr>
<tr>
<td>Sieve (15 pixels)</td>
<td>0.711</td>
<td>0.822</td>
<td>0.672</td>
<td>0.740</td>
<td>0.6ha</td>
</tr>
<tr>
<td>Sieve (25 pixels)</td>
<td>0.708</td>
<td>0.823</td>
<td>0.669</td>
<td>0.738</td>
<td>1ha</td>
</tr>
<tr>
<td>CUSUM (VH)</td>
<td>0.736</td>
<td>0.602</td>
<td>0.822</td>
<td>0.695</td>
<td>-</td>
</tr>
<tr>
<td>Sieve (10 pixels)</td>
<td>0.772</td>
<td>0.650</td>
<td>0.859</td>
<td>0.740</td>
<td>0.4ha</td>
</tr>
<tr>
<td>Sieve (15 pixels)</td>
<td>0.778</td>
<td>0.649</td>
<td>0.875</td>
<td>0.745</td>
<td>0.6ha</td>
</tr>
<tr>
<td>Sieve (25 pixels)</td>
<td>0.786</td>
<td>0.646</td>
<td>0.898</td>
<td>0.751</td>
<td>1ha</td>
</tr>
</tbody>
</table>

The sieve filter also provided a considerable improvement in visual interpretation, since cleared areas could be distinguished more readily due to the high, and continuous, aggregation of ‘change’ pixels and the significant enhancement of the polygon edges. Finally, Figure 17 shows the influence of the sieve filter on the final change detection accuracy of both the CUSUM and CUSU-SMC methods using ROCs.

![Figure 17. Contribution of the tested sieve filter to detection performance of the CUMSUM and CUSU-SMC approaches. Accuracy test carried out using a significance level of (α = 0.05).](image)

2.5.5 Forest Logging Detection Maps with Sieve Filter

In Figure 18, the final change detection maps show the capabilities of the Cumulative Sum to detect logging activities. Despite the high presence of isolated false positives in forest areas, all clear-cut areas are distinguishable. The implementation of the pixel connectivity sieve filter significantly helped to remove those flagged pixels, which were likely caused by environmental factors (e.g., meteorological condition variation). This step contributed to the refinement of the final product by
generating a better representation of the disturbed areas, while improving the overall detection accuracy rate.

Figure 18. Forest changes detected in the Queen Elizabeth Forest Park using the conservative strategy (CUSUM VH). (a) Shows the logging activities reference dataset obtained for the period of study. (b) Illustrates the changes detected (red) for the CUSUM VH detector. Subsets (c) and (d) show a closer look of the effect of the sieve filter on the final change detection maps ([c] 10 pixels; [d] 25 pixels).

2.6 Discussion

This research demonstrates the potential capabilities of Cumulative Sum strategies for monitoring permanent forest disturbances (logging activities) in a continuous way, with similar spatial accuracy to previous forest change detectors (Schwarz et al., 2003; Bouvet et al., 2018; Tanase et al., 2018; Rüetschi et al., 2019). The analysis of SAR temporal backscatter signal showed significant differences between felled areas and intact forest areas. Despite these differences, observed in both polarizations, the cross-polarization (VH) channel showed the higher sensitivity to forest structural variations, providing the best change detection performances. From the various parameters and cumulative sum approaches tested, the combination of the CUSUM method with a 3 x 3 mean filter provided the best results, offering an OA = 73.6% and F = 69.5%. The implementation of the post-processing sieve-pixel connectivity filter (10 pixels) increased the detection accuracy values to OA = 77.2, and F = 74.0.
2.6.1 Near Real Time

The proposed method emerges as a valuable forest monitoring tool when it is compared to the existing forest change detector products. The exploitation of dense SAR timeseries for the CUSUMs allows the monitoring of forest structural disturbances in a rapid, continuous manner, which contrasts with the current monitoring methods based on optical systems. Both CUSUM and CUSU-SMC methods allow the gathering of information about changes that extends over long periods of time. This may be significantly helpful when analysing diverse patterns and trajectories associated with those disturbances which can be crucial to forecast future alterations, as in the case of illegal deforestation, agriculture expansion, or risk management. When developing a near real-time (NRT) monitoring tool, low latency is considered as the driving factor for obtaining high temporal accuracies (Hansen et al., 2016; Rüetschi et al., 2019). This stands out as the main disadvantage associated with the use of spaceborne optical sensors, since data acquisition is highly limited by cloud coverage. The CUSUM methods have been tested using a repeat-track orbit and single acquisition mode (ascending). For the 22-month study period (1 January 2019 – 30 September 2020), a total of 84 observations were used (~3.8 img/month). Despite the Sentinel-1 image acquisition plan allows a lower latency for the study area (~1 img/3 days), the irregular topography of the region hindered the use of a multi-aspect approach. The utilization of multiple acquisition modes would require an additional radiometric terrain correction (e.g. gamma flattening) in order to eliminate the potential increment of false alarm rates, caused by signal divergences between different viewing angles. Even so, the implementation of CuSums methods in flatter areas, would allow a more direct adaptation to the multi-aspect approach (ascending/descending). These points will be further explored in the following chapters of this thesis, where the contribution of processes such as radiometric terrain correction or multi-aspect approaches to the detection performance will be investigated in greater depth.

2.6.2 Adaptability to Other Sensors and Applications (Synergies)

The CUSUMs method enhance the capability of the SAR system for monitoring environmental disturbances over natural ecosystems, thus standing out as a reliable alternative to the current optical-based deforestation monitoring methods (Bouvet et al., 2018). The single requirement of having access to a continuous data acquisition program gives CUSUMs approaches the ability to be easily adaptable to other SAR missions and applications. Apart from the ensured continuity of the Sentinel-1 mission until 2030, there are other SAR missions whose image acquisition programs would allow the implementation of this method. The C-band RADARSAT Constellation Mission (RCM), operational from November 2019 and with a lifespan of 7 years, will provide additional C-band data with a revisit time of 4-days (Dabboor, Iris and Singhroy, 2018; Canadian Space Agency (CSA), 2019), a fact which will contribute to shorten the times between acquisitions (Rüetschi et al., 2019).
Moreover, the recent announcement of the future free-data policy of ALOS-2/(ScanSAR), the upcoming ALOS-4 L-band (launch date: 2021), and NASA-ISRO (NISAR) L,S-band (launch date: 2022) SAR missions might serve to enhance the performance of the CUSUMs, due to the higher sensitivity that longer wavelengths have to structural forest disturbances (Tanase et al., 2019).

With respect to adaptability to other environmental monitoring applications, this method shows high versatility. The ability of CUSUMs to detect disturbances in a continuous manner makes it potentially suitable for other applications (e.g., flood mapping, coastal erosion, land degradation) characterized by high dynamicity in the environment.

2.7 Conclusions

This study introduced a new forest monitoring method for detecting forest disturbances from the analysis of dense SAR time series. Prolonged differences in the radar backscatter signal (before and after logging activities) between stable and disturbed forest areas highlighted the sensitivity of C-band SAR systems to forest structural changes. The high spatial and temporal resolution, global coverage, and free data policy of the ESA-Sentinel 1 mission has allowed the exploitation of dense SAR time-series for environmental monitoring. The cumulative sum method makes use of dense time-series, allowing the detection of forest changes in a continuous and rapid manner. The main outcome of this study was the demonstration of the efficient detection capabilities of SAR systems over other more expensive (e.g., LiDAR, manual surveys) or weather dependent monitoring systems (e.g., optical).

The method presented was tested for logging activities in Scottish forests, providing faster detection rates (early warning/rapid response) than current optical methodologies used for the national forest inventory. With the single requirement of having access to continuous data acquisition, the proposed method can be easily implemented on other SAR sensors such as the recently launched RCM constellation or the ALOS-Palsar mission (open policy recently agreed), and on other global forests. The CuSum method stands out as a valuable monitoring tool for foresters/forest managers because it reduces the current response times, while also cuts the costs and efforts, when evaluating forest damage.
3 Chapter

Modifying the original CUSUM to work with cyclical disturbances integrating ancillary data: A natural wetlands study case
This chapter will explore the potentials of the CUSUM detector to monitor highly dynamic environmental ecosystems. Specifically, this chapter moves one step further in terms of detection complexity by covering changes that are not ‘permanent’ (e.g. deforestation), but that are temporary and/or cyclical (e.g. flooding).

In addition, a special focus is put on the examination of the impact of online geo-mapping cloud-computing platforms and ancillary datasets on the change detection capabilities. This is achieved by adapting the original CUSUM-SAR method to monitor hydrological dynamics of natural wetlands and by implementing it in the Google Earth Engine (GEE) environment. Of particular note, this chapter serves to provide evidence of the scalability and adaptivity of the CuSum algorithm over large areas and different environmental applications.

The outcomes of this research resulted in the generation of the first continuous monitoring system of the hydrological dynamics of the North Rupununi wetlands (Guyana), contributing to the study, conservation and management of these natural ecosystems.
3.1 Introduction

Wetlands are ecologically sensitive systems and provide many significant services to the human population. Despite covering an estimated 5-8% of the world's total land area, wetlands are of great ecological importance both at regional and global scales (Kingsford, Basset and Jackson, 2016; Gokce, 2018; Salehi et al., 2018). At regional and local scales, wetlands provide a wide range of critically important services to human-wellbeing including fresh water, food and fibre production, nutrient cycling or flood and drought risk reduction, amongst others (Costanza et al., 1997; Finlayson et al., 2005a; Kingsford, Basset and Jackson, 2016). Similarly, these ecosystems play an important role in maintaining the global biogeochemical cycles, as they store approximately one-third of soil organic carbon (SOC) stored globally [~500 Gt C, (Page and Baird, 2016)] and thus one-quarter of total carbon stored in terrestrial ecosystems (Ulran et al., 2021). Nonetheless, the conservation of these ecosystems is currently under threat. The socioeconomic pressures (e.g. industrial development, agricultural conversion) and the unsustainable exploitation of the valuable wetlands' natural resources (e.g. water) together with the high fragility of these complex natural systems to land cover changes are leading to the rapid degradation of wetlands on a global scale (Kingsford, Basset and Jackson, 2016; Dinesen et al., 2019; Courouble et al., 2021). With climate change accelerating wetland loss and degradation, continuous monitoring and mapping play a critical role in investigating the responses of these natural ecosystems to both human-driven and climatic disturbances (Ballanti et al., 2017; McInnes et al., 2020; Courouble et al., 2021). An effective, rapid and continuous monitoring of wetland's environmental dynamics allows a better understanding of their conservation status while it contributes to the development of improved natural resources management and conservation policies (Dabboor and Brisco, 2019).

As described in the introduction chapter (Section 2.2), previous studies have demonstrated the capabilities of C-band SAR systems for wetland monitoring. This capability was further expanded by the launch of the Sentinel-1 constellation, leading to an increase in the number of studies that focused on the exploitation of dense SAR time series for the investigation of wetland hydroperiods and surface water dynamics (White et al., 2015; Adeli et al., 2020). Currently, the fusion of SAR and optical data for single-date wetland characterization appears to be one of the most used strategies (Chatziantoniou, Psomiadis and Petropoulos, 2017; Whyte, Ferentinos and Petropoulos, 2018). However, despite the high capabilities showed by these approaches, there is still a limited availability of operational wetland monitoring products which provide near-real time and continuous information on the dynamics of these ecosystems.
The high performance offered by the Cumulative Sum (CuSum) strategies for permanent change monitoring (Chapter 2) naturally led to the exploration of the CuSum methods for the study of environmental disturbances in highly dynamic wetland environments. Similarly, the arrival of new online open-user EO platforms, such as GEE, has served to further enhance the usability of satellite imagery for global-scale applications, thus opening the door to a new era of environmental monitoring (Gorelick et al., 2017; Mullissa et al., 2021). With its multipetabyte catalog of analysis-ready geospatial data and high computing and mapping capabilities, GEE provides a powerful infrastructure that solves some of the most recurrent limiting factors (e.g. high computing power requirement, large data storages, low band-width) that commonly hinders the performance of large-scale EO analyses, especially in regions where computing resources are relatively scarcer (Gorelick et al., 2017; Hardy et al., 2019; Hardy, Oakes and Ettritch, 2020). Despite the fact that GEE has certain limitations in the use of advanced image processing tools or statistical calculations, the open user nature of this platform translates into a continuous enrichment and updating of the geospatial tool catalog with new user-defined operational functions. The aforementioned specifications and capabilities led to consider the Google Earth Engine platform as the best integrated development environment for implementing the CuSum change detection algorithm for its use in a wider range of environmental monitoring applications.

3.1.1 Research context

Guyana is a Development Assistance Committee (DAC) listed country (OECD, no date), and pressure to convert natural habitats into large-scale industrial farms or mining concessions and associated infrastructure, specially access roads, is having an increasing impact on one of the most ecologically valuable natural ecosystems of the country, the North Rupununi wetlands. The dominant geomorphology of this region, characterised by low topography and seasonal flooding, have also attracted the interest of major agricultural business, particularly for rice cultivation. These land use transformations are increasing habitat destruction risks, resulting in the loss of species in general and ecological connectivity in particular.

Increasing pressures from climate change (e.g., recurrent extreme weather events including flooding and droughts) is further threatening biodiversity and Indigenous populations in the region. A key strategy to make sure further development is sustainable is to carry out large-scale assessments, which require periodic surveys. Surveying the North Rupununi wetlands is very time demanding due to the remoteness and the logistic difficulties of reaching these vast areas during the peak floods in the wet season (April to September) when most roads become impassable. Additionally, many features are more easily identifiable from above (e.g., location and distribution of open water). Currently, there is no operational continuous flood monitoring system for the North Rupununi wetlands. Indigenous communities are highly exposed to the direct and indirect impacts of flooding (from disruption to road infrastructure to malaria outbreaks), and key decision makers from
development agencies to conservation organisations also require surface water monitoring to assess impacts on, for example, fish spawning. There is therefore a need for inexpensive, simple and rapid tools that can provide periodic surveys of the hydrological and ecological status of their surrounding landscape.

3.1.1.1 The DETECT project

In addition to the growing socioeconomic pressures for the transformation of these natural ecosystems, there are other major concerns that highlight the importance of counting on continuous flood monitoring systems. As for most tropical countries, mosquito-borne diseases are a large health issue, being one of the main causes of mortality in developing countries. In 2019, there were an estimated 229 million cases and 409,000 deaths from malaria alone (Dyer, 2020; WHO, 2020). Specifically, malaria is a major health problem in Guyana. In recent years, the number of malaria cases reported in Guyana has been continuously increasing. In 2019, the figures reached 18,826 thousand cases, an increase of 11 percent in comparison to the previous year, placing Guyana among one of the South American countries with the highest number of malaria cases (WHO, 2020) (Error! Reference source not found.).

![Number of malaria cases in Guyana from 2010 to 2019](WHO, 2020)

Figure 19. Illustration of the evolution of the Malaria infection rates in Guyana over the past decade. Graph extracted from (WHO, 2020).

The relationship in the daily activities of the communities of the North Rupununi with the wetlands makes their exposure to the malaria vector very high. There are numerous initiatives that try to reverse this situation, but they tend to work on a vertical, top-down basis. ‘Command and Control’ approaches have predominately been used for the elimination of malaria from the US, Eastern Asia,
Europe, northern Africa and parts of the South Pacific, featuring case detection and treatment strategies, preventing reinfection through the distribution of insecticide-treated bed-nets, and vector control using insecticide and wetland drainage. These early successes reduced the incentive to engage affected communities in taking ownership of the control programme. However, the failure of the vertical command-and-control strategy in completely eradicating malaria in many endemic regions resulted in increased calls for tailoring interventions to local contexts by engaging communities (Atkinson et al., 2010). Also, the spread of other mosquito-borne diseases, such as dengue, zika, and West Nile virus, has resulted in increased calls for tailoring interventions to local contexts by engaging communities. Smarter and decentralised approaches are coming to the fore as key to effective monitoring of local conditions and engaging affected communities in taking ownership of the vector control programme.

Strengthening surveillance systems for monitoring incidence of vector and epidemic disease emergence and proactively directing control interventions through the introduction of technology at appropriate levels has been recognised as an urgent need by the WHO. However, there is still a lack of near real-time geographic information on the extension and typology of mosquito breeding habitats. Focusing on Guyana, and particularly on Indigenous areas, a UK Space Agency-funded project, titled ‘Integrated Space Technology Vector Control for Enhancing Community Health and Resilience Against Escalating Climatic Disruptions’ (DETECT), was executed from August 2020 to March 2021 and developed a decentralised and community owned approach to environmental monitoring for malaria control. The DETECT system aimed to build:

“A community-based service that uses satellite, drone and ground-based environmental data to identify where mosquitoes are breeding in almost real-time and with a high spatial precision, in order to then allow communities to deploy a ‘sprayer drone’ to high-risk areas to release biocontrol agents which kill the mosquito larvae without affecting other species.”.

As one of the key elements of the DETECT project, this research focused on providing accurate and continuous information on the typology and extent of the flooded areas adjacent to the Indigenous communities of the North Rupununi – the demonstration site for the DETECT system. Developed following the specific user and functional requirements listed in Error! Reference source not found., the proposed Ker-CuSum detector provided a first assessment for the preparation of malaria risk maps.
Table 6. Description of the main tasks and functional requirements of the Ker-CuSum flood monitoring systems for the DETECT project.

<table>
<thead>
<tr>
<th>Main tasks &amp; Functional requirement:</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ker-CuSum Flood Monitoring System (KCFMS):</strong> Automatic identification and characterization of natural floods with radar satellite imagery. This system shall propose the following list of functionalities:</td>
</tr>
<tr>
<td>- Provide near-real-time (12-days) and updated information on the hydrological condition of the natural wetland.</td>
</tr>
<tr>
<td>- Map permanent and temporal water distribution for the entire North Rupununi region.</td>
</tr>
<tr>
<td>- Classification of waterbodies depending on their environmental characteristics, differentiating between Open Water and Flooded vegetation.</td>
</tr>
<tr>
<td><strong>Functional Requirement List:</strong></td>
</tr>
<tr>
<td>- Automatic ingestion of radar imagery from the European Space Agency Science data hub or Google Earth Engine platform.</td>
</tr>
<tr>
<td>- Transmit flood maps to the communities, informing environmental control officers about the extent and distribution of floods.</td>
</tr>
<tr>
<td>- Receive Environmental ground truth data from Local survey teams and sensors.</td>
</tr>
<tr>
<td>- Automatic update of flood maps in the Google earth engine web application.</td>
</tr>
</tbody>
</table>

**Scene Detail**

- Data product: Level-1 Ground Range Detected (GRDH)
- Acquisition Mode: Interferometric Wide
- Temporal resolution: 12-days
- Spatial Resolution: 20m
- Path (Relative Orbit): 164
- Flight Direction: ASCENDING
- Polarization: VV, VH

This chapter presents an adaptation of the CUSUM-SAR change detection algorithm for monitoring temporary environmental disturbances. The new Ker-CuSum emerges as the first modification of the original CUSUM-SAR detector to monitor environmental disturbances in highly dynamic scenarios. The proposed novel Sentinel-1-based flood detection monitoring system, implemented in GEE, and validated for the North Rupununi wetlands, served to highlight the capabilities of cumulative sums for mapping seasonal open water and flooded vegetation. This also provides a useful tool which could be integrated into rapid response and wetland conservation management plans.
3.2 Data

3.2.1 Sentinel-1 dense timeseries

The ESA Sentinel-1 data product was pre-processed in GEE (Gorelick et al., 2017). The timeseries was formed of dual-polarised (VV, VH) high resolution Ground Range Detected (GRD) products, acquired in interferometric wide swath (IW), with a pixel spacing of 10 x 10 meters and a spatial resolution of 20 x 22 meters (Torres et al., 2012; Filipponi, 2019; ESA (a), 2021). All images were acquired by the Sentinel-1 B sensor using the same satellite orbit path (164) and look direction (ascending). The final Sentinel-1 timeseries was composed of a total of 118 images which covered the entire period of study (1st January 2017 to 1st January 2021) using the revisit time available for this region (12-day) (see Table 7).

Table 7. Acquisition dates of the Sentinel-1 B GRD timeseries used for the analysis.

<table>
<thead>
<tr>
<th>Month</th>
<th>2017</th>
<th>2018</th>
<th>2019</th>
<th>2020</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>15th, 22nd</td>
<td>5th, 17th, 29th</td>
<td>12th, 24th</td>
<td></td>
</tr>
<tr>
<td>February</td>
<td>8th, 24th</td>
<td>10th, 22nd</td>
<td>5th, 17th, 29th</td>
<td></td>
</tr>
<tr>
<td>March</td>
<td>4th, 11th, 28th</td>
<td>6th, 18th, 30th</td>
<td>12th, 24th</td>
<td></td>
</tr>
<tr>
<td>April</td>
<td>9th, 21st</td>
<td>10th, 22nd</td>
<td>5th, 17th, 29th</td>
<td></td>
</tr>
<tr>
<td>May</td>
<td>3rd, 15th, 27th</td>
<td>5th, 17th, 29th</td>
<td>11th, 23rd</td>
<td></td>
</tr>
<tr>
<td>June</td>
<td>8th, 20th</td>
<td>10th, 22nd</td>
<td>4th, 16th, 28th</td>
<td></td>
</tr>
<tr>
<td>July</td>
<td>02nd, 14th, 26th</td>
<td>4th, 16th, 28th</td>
<td>10th, 22nd</td>
<td></td>
</tr>
<tr>
<td>August</td>
<td>7th, 19th, 31st</td>
<td>9th, 21st</td>
<td>3rd, 15th, 27th</td>
<td></td>
</tr>
<tr>
<td>September</td>
<td>12th, 24th</td>
<td>2nd, 14th, 26th</td>
<td>8th, 20th</td>
<td></td>
</tr>
<tr>
<td>October</td>
<td>6th, 18th, 30th</td>
<td>8th, 20th</td>
<td>2nd, 14th, 26th</td>
<td></td>
</tr>
<tr>
<td>November</td>
<td>11th, 23rd</td>
<td>6th, 18th, 30th</td>
<td>7th, 19th</td>
<td></td>
</tr>
<tr>
<td>December</td>
<td>5th, 17th, 29th</td>
<td>7th, 19th, 31st</td>
<td>1st, 13th, 25th</td>
<td></td>
</tr>
</tbody>
</table>

3.2.1.1 SAR data pre-processing

Within the GEE platform, all Sentinel-1 products used for this study were already automatically pre-processed using the following steps implemented by the European Space Agency’s Sentinel-1 toolbox (ESA (b), 2021; Google developers, 2021):

- **Apply orbit file:** Updates orbit metadata with a restituted orbit file.
- **GRD border noise removal:** Removes low intensity noise and invalid data on scene edges
- **Thermal noise removal:** Removes additive noise in sub-swaths to help reduce discontinuities between sub-swaths for scenes in multi-swath acquisition modes.
- **Radiometric calibration:** Computes backscatter intensity (to sigma naught) using sensor calibration parameters in the GRD metadata.
- **Range-Doppler geocoding**: Converts data to ground range geometry using the SRTM 30 meter DEM or the ASTER DEM for high latitudes (greater than 60° or less than -60°).

Besides these steps, additional pre-processing steps were applied to further enhance the data. First, data were converted from dB to linear scale since the following pre-processing steps require the data to be in linear scale (Mullissa *et al.*, 2021). Image subset was applied to focus the analysis on the region of interest. Subsequently, speckle noise reduction was applied using a circular average filter of 35-meter radius. Alternative speckle filters, Refined Lee (7x7 window size) and Perona-Malik (5x5 window size) (Servir-Mekong, 2021), were tested, and were shown to provide significantly lower performance in signal noise suppression and delineation of flooded areas than the selected average boxcar (see Figure 20). This filter makes use of moving windows to change the intensity of the central pixel depending on the intensities of all the pixels within the window (ESA 2020). This filter generated smoother images and a notable reduction of noise which subsequently contributed to reducing false positives. Lastly, the final products were converted back to dB and projected to WGS84 / Pseudo-Mercator (EPSG: 3857) at 10-meter pixel spacing.

![Image](image1.jpg)  
**Figure 20.** Speckle filter comparison. Comparison of the products derived from the application of the circular boxcar mean filter (top-right), Refined Lee (bottom-left), and Perona-Malik (bottom-right) for a Sentinel-1 GRD (VH-pol) acquired on 04/06/2020 on the Amoko lake region.
3.2.2 Open water edges ground truth data

To support the accuracy assessment of the surface water detection, ground measurements were collected by a field team on a regular basis (12-day) coinciding with the Sentinel-1 passes. This dataset contains information about the surface water dynamic of six distinct sites, representing different hydrological sub-catchments within the North Rupununi wetlands. The ground team collected information on the land/water edge over transects of ±600 m in length for each sampling site, using mobile and handheld GPSs with a position accuracy of (±5 m). A total of eight fieldwork campaigns were conducted from 20th October 2020 to 1st January 2021, accounting for a total of 2761 points and more than 27,000 m of surveyed transects (Figure 21). These regular fieldwork campaigns allowed to validate, by the use of proximity analysis, the detector's performance when monitoring the hydrological dynamics of temporary floods.

Figure 21. Example of the land/water edge ground truth transects used for validation. Three Mile Bush water body, 02/10/2020 (yellow), 14/10/2020 (red), 26/10/2020 (blue), 07/11/2020 (purple), 19/11/2020 (brown) and 01/12/2020 (green); Basemap: Bing aerial.

3.3 Area of study

3.3.1 The North Rupununi wetlands

The North Rupununi wetlands are situated in the southern interior of Guyana, South America (04° N 05’, 59° W 02’) (Figure 22). The region straddles the watershed divide between the Amazonian basin and the Essequibo river catchment. The area is dominated by three large rivers: the Rupununi, the Takatu, and its tributary, the Ireng. In this area, the three rivers pass within approximately 30 km of each other, separated by savanna, crisscrossed by a network of wetlands,
small rivers, creeks, and lakes. As for most tropical region, the climate of the North Rupununi region is dominated by two well marked wet and dry seasons. The principal rainy period is from mid-April to September, while dry season peak runs from November to March. The dry season is generally interrupted by a brief period of precipitation events, known as cashew rains, which runs from December to January. These seasons have a significant year-to-year variation based on the position of the Inter-Tropical Convergence Zone (ITCZ) (Simpson et al., 2020). The total annual rainfall varies from 1,400 – 3,000mm, of which 50 to 70% falls during the main wet season, transforming approximately 8,000 km² of savanna and grasslands into wetlands during most of the wet season. The temperature and humidity remain fairly constant throughout the year with mean annual temperatures between 27.5 °C and 33 °C (Weather and Climate, 2022).

![Reference map of the region of study, the North Rupununi natural wetlands, Guyana.](image)

This natural ecosystem supports a high terrestrial and freshwater biodiversity, supplying Indigenous communities with a range of livelihood activities, including subsistence fishing and ecotourism.

### 3.4 Methods

The methodology used for the detection and classification of flooding is an adaptation of the original CuSum algorithm used to monitor forest disturbances. The notable difference in the nature of the changes to be monitored, from permanent to temporary, has required the transformation of fundamental parameters such as the reference period, the iteration time window or the post-processing steps.
3.4.1 Land Use and Land Cover classification map

To investigate the hydrological dynamics of the study area, it was necessary to have a land cover map that provided information on the different habitats. An updated land cover map, that classified the study area based on diverse land cover types, was required to perform a thorough investigation of the radar signal behaviour for each ecosystem.

The most up-to-date Land Use and Land cover maps for the North Rupununi region date from 2013. This update of the national Land Use map was framed within the Guyana National Land Plan project (Guyana Lands and Surveys Commission, 2013) and carried out by the Guyana Lands and Surveys Commission supported by the European Commission. The new Guyana's Land Use map was computed by combining data from Global Land Cover Network (FAO, 2006) together with vegetation maps from the Guyana Forestry Commission - Monitor, Report and Verify (MRV) project. Unfortunately, the outdated and large-scale nature of this product did not provide enough information for the habitat characterization, at a necessary spatial resolution, so it was decided to perform a new land cover classification analysis for the region of interest.

To do so, a new land cover map was generated using ground truth information and applying machine learning classifiers to cloud-free Landsat images composite computed from eight Landsat 8 - Tier 1 calibrated top-of-atmosphere (TOA) (Chander, Markham and Helder, 2009) images acquired during the 2015 and 2016 dry periods. The ground truth data used for training the classifiers consisted of a total of 250 points (30m pixels), equally distributed among all land classes. This training data was extracted from manual digitalization from the North Rupununi District Development Board (NRDDB) ground truth team and Unmanned Aerial Vehicle (UAV) fieldwork surveys carried in 2019. To test the accuracies of the classification algorithms, the ground truth data was distributed following a 75-25% random selection clause, where 75% of the total sample (188 points) was randomly selected to train the models, while the remaining 25% (62 points) was used to validate the classification results. Three supervised classification algorithms, Classification and Regression Trees (CART) (Breiman et al., 1984), Support Vector Machine (SVM) (Drucker et al., 1997) and Random Forest (RF) (Breiman, 2001) were tested. Among the three classification algorithms tested (SVM - OA = 60.6%; CART - OA = 90.1%), the Random Forest classifier (RF [50 estimators] - OA = 91.8%) was the one that showed the best performance for the classification of land covers of the study area. (see Figure 23). The Land use and land cover (LULC) analysis was performed on the Google Earth Engine platform (Google developers (b), 2021).

Table 8. Acquisition dates of the Landsat 8- T1_TOA images used for computing the reference image composite. Image properties WRS Path (232) and WRS rows (57,57).

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>11th September 2015</td>
<td>24th January 2016</td>
</tr>
<tr>
<td>4th October 2015</td>
<td>6th October 2016</td>
</tr>
</tbody>
</table>
Chapter 3

The final map provided information, at a 30m spatial resolution, on the location and extent of five land cover classes: Forest, Grassland, Savanna, Wetland, and Water.

- **Forest**: Dense-canopy tropical rainforest, dominated by woody vegetation type with trees taller than 5m.
- **Grassland**: Herbaceous ecosystems formed by permanent and seasonal herbaceous and shrub plants located in the lowlands. This includes agricultural farms under rice cultivation.
- **Savanna**: Mixed low-density woodland-grassy plain located in the lowland region affected by periods of flooding during the wet season.
- **Wetland**: Open flat area that is flooded by water, either permanently or seasonally.
- **Water**: Permanent in-land water bodies (e.g. Freshwater lakes, rivers, and streams).

![Figure 23. Final land cover map of the Southwestern region of the North Rupununi wetland used to develop and test the DETECT system resulting from the Random Forest (RF) classification analysis.](image)

3.4.2 Adaptation of CUSUM for flood detection

3.4.2.1 Selection of the reference period for the CUSUMs

The first aspect to consider in the adaptation of the Ker-CuSum approach to the detection of temporary disturbances is the selection of the reference period. Permanent changes where monitored using a reference image obtained over a long period of time (Ruiz-Ramos et al., 2020). However, the adoption of this methodology for the study of highly dynamic environments, such as seasonal wetlands, required an investigation of seasonality to identify the reference period to be used in the change detection analysis.
To do so, a timeseries analysis was performed to evaluate the radar signal behaviour over the dry and wet season. The different behaviours and patterns observed in the backscatter helped identify the annual wet and dry period. Both the VH and VV polarisation channels showed a progressive increase in the backscatter intensity from April to June which illustrates the start of the wet season. This trend, observed in all the years of the timeseries, reaches its major peak around mid-May or beginning of June, corresponding to the annual peak flood period. Similarly, ‘cashew rain’ events were clearly identifiable in all years, showing slight increases in backscatter during the months of November and December. Finally, stable low-intensity values were observed for all the dry periods. Both the co- and cross-polarised channels showed a progressive decrease in intensity from September-October, sustained until the beginning of the dry season in April, only being interrupted by occasional cashew rainfall events (see Figure 24).

![Sentinel 1 – VH polarisation channel signal backscatter timeseries](image)

Figure 24. Sentinel 1 – VH polarisation channel signal backscatter timeseries. Top figure illustrates the complete timeseries (01/01/2017 – 01/04/2020); Bottom shows the 2019 timeseries (01/01/2019 – 31/12/2019). Analysis performed for entire region of study. As a reference, annual hydrology is shown by the bars below the graphs; Blue illustrates the wet periods while the dry periods are represented in green.

This signal analysis enabled the classification of the timeseries based on seasonal periods. Considering that most of the temporary disturbances to be studied (e.g. seasonal floods) occur during the rainy season, the period used to calculate the mean reference values corresponded to the dry
season. In this context, the reference mean composite used for this investigation was computed using the three driest images of each year, which were acquired at the end of each annual dry season (mid-March to end of April).

3.4.2.2 Assessing CUSUM-SAR monitoring capabilities for highly dynamic environments

A preliminary analysis was performed to explore the capabilities of the original CUSUM-SAR method for monitoring temporary environmental disturbances. The original detection principle of the Cumulative Sum (CUSUM-SAR) method, which relies on the progressive integration of all the differences in the time series, makes it especially suitable for the detection of permanent changes. However, its use for continuous monitoring of environmental disturbances of a temporary nature has not yet been explored. The analysis of the behaviour of the CuSum timeseries and its comparison with the backscatter radar values obtained for the different land classes studied, served to assess potential capabilities of this method for flood monitoring.

As can be seen in Figure 25, comparing the behaviour of the pre-processed Sentinel-1 radar backscatter (A) with the CuSum values obtained from the CUSUM-SAR method (B), the continuous accumulation strategy leads to a progressive separation of the values from the reference mean. This behaviour illustrates the poor capabilities of the original CUSUM-SAR method for identifying environmental changes that only last a short amount of time (e.g. temporary flood events). This is because, once the CuSum has diverged and passed the threshold, it will not go back to zero and every instance after that will also pass the threshold. Hence, the use of the original Cumulative Sum method in highly dynamic ecosystems will lead to significant false alarms associated with the fact the CuSum is not resetting after the anomaly has concluded (i.e. after the flood has passed).
Modifying the original CUSUM to work with cyclical disturbances integrating ancillary data: A natural wetland study case

Figure 25. Evaluation of the behaviour of the CUSUM-SAR method to seasonal variations in the study region. Comparison of A) polarization ratio (VH / VV) of Sentinel-1 preprocessed backscatter intensity (dB) with B) CUSUM-SAR values; period (01/01/2020 - 07/31/2021). Please note the progressive decrease of the CUSUM-SAR values for the ‘wetland’ class after the first floods of 2020 (May, 2020). As a reference, annual hydrology is shown by the bars below the graphs; Blue illustrates the wet periods while the dry periods are represented in green.

In next section we propose a comprehensive transformation of the original CUSUM method in order to adapt it for the monitoring of temporary environmental disturbances.

3.4.2.3 The KerCuSum change detection approach

The core of the new KerCuSum change detection approach stream off the same principle as the previous version (Ruiz-Ramos et al., 2020), where we try to improve the detector statistics by cumulating multiple differences. Specifically, this adaption can be done after generalising the formalism for the ordinary CuSum interpreting it as an integral transform. In this new formalism it is possible to add some useful new functionalities.

Before proposing the new mathematical formalism, in the following, it is provided an intuitive understanding of the differences between the algorithms. The principle of the KerCuSum method remains similar, thus relying on a two-step process: a) on the first step, a reference mean value is subtracted to each image of the time-series, subsequently, b) on the second step, consecutive
difference images are added, enhancing any possible persistent variation which takes place over time (Figure 26). It is in the time span of the cumulative function of this second step where both methods differ. The CUSUM-SAR uses all the values of the time series, while the new KerCuSum integrates a kernel operator that limits the cumulation to a certain number of images. This allows the algorithms to improve the statistics by cumulating differences, but also reset to zero once the anomaly has been removed.

This generalisation has been performed using an integral transform formalism. The easiest way to see this is by considering time series as continuous functions instead than discrete signals. The integral transform maps the function (i.e. the time series of differences) into an integral space.

The ordinary CuSum (in a continuous space approximation) can be represented by the equation:

\[
CuSum(t) = \int_0^t (I(r) - \bar{I}_r) \, dr
\]  
(14)

This equation can be generalised as an integral transform:

\[
KerCuSum(t) = \int_0^t (I(r) - \bar{I}_r) \, Ker(y - r) \, dr
\]  
(15)

\(Ker()\) is a function that in theory can be set arbitrarily as long as it is integrable. Image \(I\) can be a VV, VH polarisation or a ratio image, \(t\) is time domain, \(r\) is the convolutional delay variable and \(y\) represent the time variable before the convolution. A common use of this function is to have a \(Rect()\) (or \(Box()\)) function where the signal is equal to zero everywhere except for an interval of interest and the integral is unitary.

\[
Rect(t) = \begin{cases} 
1 & \text{when } t \in [t_1, t_2] \\
0 & \text{otherwise} 
\end{cases}
\]  
(16)

Please note, the \(Rect\) function is the same used in Boxcar filter and the integral transform is a convolution between the signal and the \(Rect\) function.

The CuSum expression is a particular result of the general KerCuSum expression when \(Ker\) is a constant unitary function \(U(t)\).

\[
U(t) = 1 \quad \forall \quad t \in ] - \infty, \infty[
\]  
(17)

That is,

\[
CuSum(t) = \int_0^t (I(r) - \bar{I}_r) \, U(y - r) \, dr
\]  
(18)
Since we are working with discrete signal, the integral transformation can be rewritten as:

\[ \text{KerCuSum}_i = \sum_{j=0}^{i} (I_j - \langle I_j \rangle) \text{Ker} (j - t) \]  

(19)

\( \text{KerCuSum}_0 = 0 \) and \( i \) is an iteration over the temporal domain. Image \( I \) can be VV, VH polarisation or their ratio while \( \langle I \rangle \) is the reference composite computed for the dry season.

For this investigation it was decided to constrain the kernel function to a box of only 2 images due to the dynamic nature of flood and the gap of 12 days between images. Thus, the CuSum timeseries is formed by the accumulation of the values of the image \( t \) and its previous \( t-1 \).

The standardization of the CuSums, obtaining the Z-scores, allowed to add a statistical rational to the selection of the thresholds. Unlike the version used for permanent disturbances, Z-scores were not transformed to probability. This is because there is a deterministic monotonic link between the Z-score and the probability (provided the differences are Normal) and therefore there is no loss of generality to set the threshold directly on the Z-score. Using the Landsat-8 derived reference land cover map, a radar backscattering analysis based on the comparison of multiple images acquired over the dry and wet seasons was performed for each land cover type. This provided information on the detection capabilities of each polarisation channel for the different types of floods studied (open water, flooded vegetation), allowing the identification of the most suitable channel based on their flooded/non-flooded separability (Figure 27). To fully exploit the polarimetric information of the time-series, the change detection analysis was carried out using both the co-polarisation (VV), the cross-polarisation channel (VH) and their Ratio (VH/VV).
3.4.3 Post-processing: Result refinement from ancillary datasets

Additional EO datasets were used to refine the ‘open water’ and ‘flooded vegetation’ masks with the aim of reducing the presence of false alarms. This process followed five steps:

- 1. Forest penalty: A penalty score was applied to the Z-score values of forest areas. The forest reference map was obtained from the Landsat-8 land cover classification analysis. The use of this penalty is based on the assumption that floods occurring at under-canopy levels are undetectable due to the limited penetration of C-band Sentinel-1 radar signals.

- 2. HAND map analysis: Reclassification of the flood masks using the Global (30m) Height Above Nearest Drainage (HAND) dataset (Donchyts et al., 2016). The implementation of the HAND method (Nobre et al., 2011; Johnson et al., 2019) allowed to mask out all regions located at a height greater than five meters from the closest drainage network of the study area.

- 3. Permanent water bodies addition: The 30-meter resolution JRC global surface water map (Pekel et al., 2016) was used for adding all permanent water bodies (>10 months/year) to the open water masks.

- 4. DEM-slope analysis: The WWF Hydrological data and maps based on SHuttle Elevation Derivatives at multiple Scales (HydroSHEDS) (WWF, no date; Lehner, Verdin and Jarvis, 2008) was utilised to remove all flooded pixels located in steep terrain (slope >5%), since we assume that water must flow on terrains with such characteristics.
• 5. Sieve filter: The sieve connectivity filter helped us to eliminate those smaller and isolated flooded areas, generally caused by noise. All flooded pixels connected to 20 8-connected pixels (minimum mapping unit of 0.2 ha) or fewer neighbours were removed.

3.4.4 Validation

3.4.4.1 Accuracy Assessment

The final Ker-CuSum flood maps were validated using high-resolution optical satellite data. The initial plan established for validating the results focused on the use of very high-resolution (VHR) UAV drone data, but unfortunately, the international travel restrictions and regulations associated with the Covid-19 global pandemic precluded the drone fieldwork campaigns. Therefore, coincidental or near-coincidental cloud-free multi-spectral (blue, green, red, near-infrared) PlanetScope (3m spatial resolution) (Planet Team, 2021) imagery was used for assessing the performance of the detector (Table 9). Following the same approach considered in previous studies for the validation of near-real time classification maps (Hardy, Oakes and Ettritch, 2020; Reiche et al., 2021), equalised stratified random sampling (Stehman, 1999, 2014; Stehman et al., 2003) was used, generating a total of 150 accuracy sample points distributed along three strata (‘open water, ‘flooded vegetation’ and ‘non-flooded’). Each sample location was visually examined using the ‘Class Assessment validation plugin’ (Buntig, 2020) on QGIS, comparing the predicted and reference values to derive the confusion matrix and overall accuracies.

Table 9. Reference information of the products used for the accuracy assessment analysis.

<table>
<thead>
<tr>
<th>Sentinel1 acq. date</th>
<th>Planet acq. date</th>
<th>Cloud cover (%)</th>
<th>Season description</th>
</tr>
</thead>
<tbody>
<tr>
<td>10th July 2020</td>
<td>9th July 2020</td>
<td>2.0</td>
<td>Peak flood</td>
</tr>
<tr>
<td>24th September 2020</td>
<td>19th September 2020</td>
<td>4.6</td>
<td>Late wet season</td>
</tr>
</tbody>
</table>

Standard accuracy metrics (Overall Accuracy, User Accuracy, Producer Accuracy and Kappa Score) were calculated for each class. Nonetheless, as explained in Pontius and Millones (2011) the limitation in the Kappa Score for addressing disagreement between maps in terms of the quantity and spatial allocation of the categories, led to the consideration of using additional accuracy components such as the quantity and allocation disagreement. The author who introduced these terms define ‘quantity disagreement’ as the “amount of difference between the reference map and a comparison map that is due to the less than perfect match in the proportions” and ‘allocation disagreement’ as “the amount of difference between the reference map and a comparison map that is due to the less than optimal match in the spatial allocation of the categories, given the proportions of the categories in the reference and comparison maps” (Pontius and Millones, 2011, p.4409). There is a growing acceptance in the use of the quantity and allocation disagreement metrics for land classifications as
they provide more detailed information about the spatial agreement between the mapped areas and validation data (Hardy, Oakes and Ettritch, 2020).

3.4.4.2 Proximity analysis to water bodies edges

A spatial proximity analysis was performed to assess the accuracy of the Ker-CuSum flood detector in delineating the edges of open water bodies. To do this, actual waterside terrain data collected by the NRDDB on open water bodies was compared with Ker-CuSum derived open water flood maps. Distances were calculated using the spatial analysis tool ‘Near’ (ArcMap 10.6.1 toolbox) which extracts the geodesic distance and the proximity information (angle) between the input features (Ker-CuSum ‘Open water’ edge result) and the closest entity in the reference layer (actual water edge of the ground). To obtain more information on the distance between features, it was decided to increase the sample by transforming the coincident edges of the Ker-CuSum open water maps to points at fixed intervals of 15 meters (Figure 28). Distance metrics, maximum distance, minimum distance, mean distance and standard deviation were calculated for each site and date.

Figure 28. Illustration showing the water body edge ground truth data and the Ker-CuSum open water edge points used for the proximity analysis over Three Mile Bush on the 14th October 2020. The ground truth edge line (yellow) was created using the ground truth points and subsequently smoothed (PAEK – 10m) in order to reduce sharp angles between adjacent samples.
3.5 Results

3.5.1 Seasonal floods change detection

Wetland areas, characterised by large extensions of open water, showed a significant decrease in the backscatter intensity of both the cross-polarised channel (VH) and the combined ratio (VH/VV) during the wet period. This low intensity values are typical of open water areas due to the dominance of specular surface scattering mechanism. Between the two, the ratio combination showed larger signal variations between dry and wet conditions while a greater separation, thus it was chosen as the best product for the mapping of open water areas (Figure 29). Open water regions showed a recurring trend for all the years of the study period characterized by a progressive decrease in intensity at the beginning of the wet season (early May), remaining stable during the peak flood season (Figure 30).

![Figure 29. Comparison of the backscatter radar for the dry and wet season, showing, in black, the reduction in intensity for the open water zones. Sentinel-1 Ratio (VH / VV) (dB) pre-processed composites; A) Reference dry mean and B) Mean composite computed from 2020 peak-wet season acquisitions (07/01 - 09/15).](image)

In contrast, vegetated floodplains (e.g. savanna and grassland) showed significant increases in the co-polarised (VV) signal intensity coinciding with severe precipitation events and temporary floods that occur during both the main wet period (May-October) and the cashew rains, at the end of the year (Figure 30).
Figure 30. Timeseries of the Z-score values for the land cover classes. Top graph A) illustrates the ratio combination (VH/VV) while bottom B) shows the values for the co-polarised VV channel. Results obtained for the period from 01/01/2020 to 06/07/2021. As a reference, annual hydrology is shown by the bars below the graphs; Blue illustrates the wet periods while the dry periods are represented in green.

Once the most-suitable polarization for each type of flood had been determined, a subsequent investigation of the Z-score trend over the dry and humid periods served to select the specific threshold values used for the final mapping and characterization of floods. The histograms in Figure 31 show the distribution of wetland Z scores for the wet and dry seasons. Frequency distribution analyses were carried out in several sampling areas, of diverse size and random locations within the studied land classes (Wetlands and Grasslands). Wetland areas showed a change in Z-score distribution towards low values during the wet season. Contrarily, flooded grassland displayed a significant increase. Based on the histogram analysis, it was decided to use a threshold of $Z_{\text{ratio}} \leq 12.5$ on the ratio (VH divided VV) for the identification of surface water areas and a value of $Z_{\text{VV}} \geq 22.5$ on the co-polarized channel VV for the mapping of flooded vegetation regions.
Figure 31. Example of a comparison of the Zscore values on different land cover classes for dry and wet conditions. Dry condition values (left) extracted from the peak dry image acquire on 05/04/2020 while wet condition values were obtained from the peak flood image acquired on 03/08/2020. The red lines correspond to the threshold values used to map the open water (top) and flooded vegetation (bottom).

The final classification maps were used to evaluate the hydrological dynamics in terms of extent, typology and periodicity of floods. As shown in Figure 32, the hydrological dynamics observed for the study area were very similar for all the years studied, showing minimal interannual variations in the flooding patterns. The annual variation in the flooded area extension during the peak wet season was around 1%, not exceeding 2% in any of the years studied.

![Figure 32](image)

Figure 32. Interannual variation of the flood area for the natural wetlands of northern Rupununi. Comparison of the flooded extension during the wet season (01/05 - 30/09) for both Classes of open water (Top left) and flooded vegetation (Top right). N refers to the number of Sentinel-1 images acquired during each annual maximum flood season in the study area and considered for this analysis.
The total area for open water and flooded vegetation regions showed a predominance of flooded areas characterized by shallow waters with emergent vegetation, typical of the great alluvial plains of the study region (see Figure 33, May-October period). Using the values obtained for the year 2020 as a reference for the description of the observed trends, the previously described annual seasons can be clearly differentiated. The dry season runs from the beginning of the year to the beginning of May, a period in which the flooded area detected was very low (≈3300 ha / 1.29% study area) (Figure 33). Similarly, the wet season, which begins with the first rains in May and reaches its peak at the end of July, showed large areas of flooding, reaching the greatest extent (≈72,500 ha / 28.4% study area) in the period between 07/22/2020 and 08/03/2020. The total flooded area remained above 60,000 ha for much of the wet period (06/04/2020 to 08/27/2020).

![Figure 33. CUSUM-SAR derived flood area calculation. Timeseries extracted for The North Rupununi natural wetlands for the entire 2020 period.](image)

Finally, a second wet season characterized by short periods of precipitation scattered over time (cashew rains) were observed during the final months of the year. This irregular precipitation events commonly results in the development of sudden or flash floods which can extend over large areas of floodplains (≈40,000 ha) for short periods of time.

### 3.5.2 Validation results

The accuracy assessment yielded consistent good results, showing a high performance in the detection and characterization of flood dynamics for the study area. A first validation analysis performed for the ‘open water’ classification map revealed a very high Overall Accuracy (OA=0.93; Kappa=0.87) with a high detection performance on surface water bodies and a neat delineation of the edges. Results obtained for the combined (‘open-water’ & ‘flooded-vegetation’) classification
maps show a lower overall performance (OA = 0.79) yet providing confident detections of flooded areas (Table 10).

Table 10. Summary of accuracy assessment performed for the combined flood classification map: Overall accuracy % (OA); kappa coefficient; Q: Quantity disagreement; A: Allocation disagreement; C: Overall agreement; D: Overall disagreement.

<table>
<thead>
<tr>
<th>Date</th>
<th>OA (%)</th>
<th>Kappa</th>
<th>Q</th>
<th>A</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>09/07/2020</td>
<td>81.33</td>
<td>0.72</td>
<td>0.06</td>
<td>0.11</td>
<td>0.82</td>
<td>0.17</td>
</tr>
<tr>
<td>20/09/2020</td>
<td>77.33</td>
<td>0.66</td>
<td>0.03</td>
<td>0.15</td>
<td>0.81</td>
<td>0.18</td>
</tr>
<tr>
<td>Mean</td>
<td>79.33</td>
<td>0.69</td>
<td>0.045</td>
<td>0.13</td>
<td><strong>0.815</strong></td>
<td>0.175</td>
</tr>
</tbody>
</table>

Assessing the additional accuracy metrics suggests a good detection performance with an Overall agreement of C=0.81 and equally low values for the quantity (Q=0.045) and allocation (A=0.13) disagreements metrics. These values, where the difference between the quantity and allocation disagreements is low, suggests that there has been no significant bias in the placement of predicted or mis-classified classes.

As shown in Table 11, the observed lower overall performance for the combined classification map responds to an overestimation of the flooded vegetated areas. The increase of backscattering could be for instance caused by increased wet biomass in wetter periods, and an increase in soil moisture content. Most of these changes are below the threshold used to detect flooded vegetation, since the
introduction of the double bounce component (due to water under vegetation) is expected to have more backscattering than the vegetation on its own (in theory doubling the backscattering of vegetation), or the soil moisture increase. Yet, the high producer accuracies obtained for both ‘open-water’ (PA=91.2%) and ‘flooded-vegetation’ (PA=74.1%), corroborate the high capabilities of the Ker-CuSum method for monitoring seasonal variations in natural wetlands.

Table 11. Combined error matrix for the combined flood map (% of N = 300) where: OW = Open Water; FV = Flooded vegetation; NW = Non-Flooded.

<table>
<thead>
<tr>
<th></th>
<th>OW</th>
<th>FV</th>
<th>NW</th>
<th>User (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>OW</td>
<td>27.30</td>
<td>5.29</td>
<td>1.33</td>
<td>81.90</td>
</tr>
<tr>
<td>FV</td>
<td>0.94</td>
<td>22.94</td>
<td>9.11</td>
<td>68.82</td>
</tr>
<tr>
<td>NW</td>
<td>1.63</td>
<td>2.58</td>
<td>28.98</td>
<td>86.95</td>
</tr>
<tr>
<td>Producer (%)</td>
<td>91.21</td>
<td>74.11</td>
<td>74.78</td>
<td>79.33</td>
</tr>
<tr>
<td>OA (%)</td>
<td>79.33</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kappa</td>
<td>0.69</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 35. Ker-Cusum derived flood map for the region of study of the North Rupununi natural wetlands for the 20th September 2020 using a Bing composite as base map. Area indicated in the map compares in detail C) the combined flood map with B) the reference high-resolution (3m) Planet image acquired on 20/09/2020.
3.5.3 Proximity analysis

Results obtained for the water edge proximity analysis showed good performance in the delineation of open water bodies. The proximity analysis was focused on two sites; Three Mile Bush and Diamond-D, which presented a low density of vegetation at the edges. The rationale behind this site selection responds to the difficulties to identify the limits of the water bodies when there is a dense vegetation cover. A total of 333 points and 4995m of transects were investigated for both sites on four different dates (Table 12).

Table 12. Proximity analysis results for Three Mile Bush and Diamond D water bodies. All distance units are expressed in meters.

<table>
<thead>
<tr>
<th>Date</th>
<th>N Points</th>
<th>Transect (m)</th>
<th>Max Distance</th>
<th>Min Distance</th>
<th>Mean Distance</th>
<th>Stan. Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Three Mile Bush</td>
<td>14th October 2020</td>
<td>26</td>
<td>390</td>
<td>21.89</td>
<td>0.26</td>
<td>11.23</td>
</tr>
<tr>
<td></td>
<td>7th November 2020</td>
<td>28</td>
<td>420</td>
<td>35.68</td>
<td>2.49</td>
<td>15.1</td>
</tr>
<tr>
<td></td>
<td>19th November 2020</td>
<td>16</td>
<td>240</td>
<td>16.81</td>
<td>1.49</td>
<td>4.93</td>
</tr>
<tr>
<td></td>
<td>1st December 2020</td>
<td>26</td>
<td>390</td>
<td>16.48</td>
<td>0.23</td>
<td>8.61</td>
</tr>
<tr>
<td>Diamond D</td>
<td>14th October 2020</td>
<td>56</td>
<td>840</td>
<td>66.84</td>
<td>0.01</td>
<td>28.78</td>
</tr>
<tr>
<td></td>
<td>7th November 2020</td>
<td>56</td>
<td>840</td>
<td>100.72</td>
<td>2.1</td>
<td>37</td>
</tr>
<tr>
<td></td>
<td>19th November 2020</td>
<td>61</td>
<td>915</td>
<td>96.63</td>
<td>0.43</td>
<td>43.41</td>
</tr>
<tr>
<td></td>
<td>1st December 2020</td>
<td>64</td>
<td>960</td>
<td>90.82</td>
<td>1.35</td>
<td>28.16</td>
</tr>
</tbody>
</table>

Although significant variation was observed between the analyzed areas, the average proximity distances, Three Mile Bush (μ: 9.96 m, σ: ± 5.72 m) and Diamond D (μ: 34.33 m, σ: ± 23.60 m), demonstrate the capability of the detector to map the edges of bodies of water with a spatial error of maximum 60 meters (Figure 36).

Figure 36. Open water edge delineation analysis for Amoko lake open water body. Comparison of Open water flood mask (19/09/2020) and reference Planet image acquired on 20/09/2020.
Considering the Sentinel-1 sensor spatial resolution (i.e. the ability to separate between adjacent target objects on the ground) is approximately 20 m × 22 m, these results demonstrate that the identification of water-no water boundary ranges remains within the range of 1 to 2 pixels. The visual exploration of additional open water bodies distributed across the study areas showed an accurate delimitation of the edges, agreeing with the results obtained for the surveyed areas (Figure 36).

### 3.5.4 Ancillary data for flood mapping optimization

The incorporation of auxiliary data into the final optimization of the flood change detection analyses has been crucial in improving the maps. The use of additional data sources that provide useful and relevant information on the ecology, environmental characteristics, management, or historical disturbances played an important role in the enhancement and optimization of the Ker-CuSum Sentinel-1 derived flood maps. A final quantitative assessment was performed to better understand the specific contribution of each of the post-processing steps in the reduction of false positives. By extracting the values resulting from each process for the entire time series, it was possible to investigate the total number of pixels and extension removed or added to the open water masks (Figure 37).

![Figure 37. Comparison of the total flooded extensions derived from each of the post-processing steps. The values represented correspond to the Open water masks for the entire Sentinel-1 time series of 2020 extracted for the entire study region. The sub-figure on the right shows a close-up view of the values obtained for three flood maps generated for the peak-flood period.](image)

The low penetration capabilities of the C-band radar electromagnetic signal significantly hindered the detection of flooded areas under the dense forest canopy cover. Therefore, the application of the penalty score to the forest areas served to eliminate all those low confidence false detection calls that may be associated with phenological variation of the vegetation. Slight changes in weather conditions (e.g. rain events, strong wind, wind gusts) which may have produced variations in the radar
backscatter signal of the forested areas may have also been responsible for some misclassification errors in the detection of flood events.

The addition of the JRC global permanent water body layer served to incorporate those specific permanent water body features, that remained undetected by the proposed approach, to the final open water maps (Figure 38). The change detection principle of the CUSUM method relies on differences, therefore, any permanent feature (e.g. lake, river) whose environmental characteristics remain unaltered throughout the period of study will not be detected as a disturbance. This step is significantly important in products aimed at generating accurate and reliable descriptions of the hydrological status of the wetlands, without making any distinctions between the temporary or permanent nature of the bodies water. The implementation of permanent water bodies resulted in the addition of a total of 293 ha to the open water maps.

Figure 38. Illustration of surface water flood masks before (left) and after (right) the application of the permanent water bodies refinement. A) Lagoa de Cheirosa, B) Ireng and Tacutu confluence.

The implementation of the HAND method and the slope correction provided an important topographical based optimization of the final result. Considering the assumption that water must flow over steep terrain, the occurrence of flood events in these areas was considered null. The impact of this process was not particularly great in terms of false positive reduction over a large part of the study region studied (large extensions of flat savanna plains). However, a significantly higher impact was observed in those areas characterised by steeper and irregular terrains in which most of the false
positives caused by radar geometric distortions (NRCan, 2015; ESA, 2020) (e.g. foreshortening, layover, and radar shadow) were eliminated from the flood maps (Figure 39).

Figure 39. Illustration of the effect of DEM slope refinement on the surface water flood macks. False positives driven by radar geometric distortions (left) and post-processing refined flood mask (right).

Lastly, the use of the sieve morphological image process helped to reduce the number of isolated false positive pixels. Among all the processes implemented for the refinement of the final results, the sieve filter accounted for the higher quantitative reduction in the rates of false positive. The use of a larger neighbor window would have resulted in the elimination a larger number of wrongly classified isolated regions. In this study, it was decided to adopt a less restrictive approach, by adopting a small filtering windows size (20 pixels), in order to preserve a finer spatial resolution on the final flood maps.

### 3.5.5 DETECT | CUSUM Web App

The DETECT | CUSUM web-App stands out as the first continuous remote sensing-based monitoring tool developed for the North Rupununi region. The developed Ker-CuSum system provided, for the first time, near-real time information about the extent and typology (open water or flooded vegetation) of temporal flood events in the North Rupununi. Although previous research had proven the capabilities of Sentinel-1 data to study flood dynamics in wetland ecosystems (Cazals et al., 2016; Twele et al., 2016; Plank et al., 2017; Tsyganskaya et al., 2018a; Hardy et al., 2019; Alexandre et al., 2020; Gulácsi and Kovács, 2020; Landuyt, Verhoest and Van Coillie, 2020), no reported efforts had been made for Guyana natural wetlands, and no remote sensing operational system has ever been in place in Guyana.
Developed with the goal of reducing user interaction with the code and the multiple variables analysed, this user-friendly tool automatically generates a flood map for each new Sentinel-1 image acquired for the study area. In this way, the user's interaction will focus only on the visualization of the results from the selected date (see Figure 40).

The design of the web-App user interface was developed in collaboration with the communities, relying on continuous communication to acquire valuable feedback from numerous potential users when optimizing the final tool. The system has already been tested, proving that it can be accessed and run by anybody with an internet connection. Since this application was developed as a user-oriented system, several performance tests were carried out in order to ensure that the current bandwidth in the North Rupununi was sufficient to be able to handle the system. The NRDDB fieldwork team assisted in the final design and functionality of the application. Continuous communications with the members of the NRDDB ground team were used for optimization tasks, adapting the computational requirements of the web-app to the communication infrastructures of the region. The current low-bandwidth network of the North Rupununi region resulted in a notable increase of the data processing and map display times. Future upgrading of communication networks will have a significant impact on the use and accessibility of this and other Earth Observation Environmental monitoring tools.
3.6 Conclusions

This investigation demonstrates the capabilities of the CUSUM change detector for monitoring temporal disturbances. The adaptation of the original CUSUM-SAR algorithm has resulted in a new SAR-based flood monitoring product for studying seasonal flood events on highly dynamic wetland ecosystems. The results showed an optimum performance in detecting and characterising ‘open water’ and ‘flooded vegetation’ regions, providing rapid and continuous information on the hydrological dynamics of the North Rupununi wetlands. The development of this new tool in the Google Earth Engine environment has resulted in a significant enhancement of the detector performance as well as in an expansion of the range of use for wetland monitoring at a global level. In addition, the ability of Sentinel-1 radar mission of acquiring consistent (6- and 12-day intervals) and high resolution (10m) imagery combined with the low data ingestion latency of GEE (1-2 days), makes it a reliable source of information for the near-real-time investigation of natural dynamics, particularly in areas with frequent high cloud coverage. Yet, the uncomplicated nature and low computational requirements of the proposed code make this method easily adaptable for other SAR missions and environmental applications.

The primary limitations of the presented method are; 1. The high sensitivity of the proposed method to subtle variation together with the limited capabilities of C-band radar signal to penetrate moderate vegetation covers caused a significant number of false detections for flooded vegetation regions. And 2. The multiplicative factor associated with the continuous addition of values over the time series may also contribute to higher false-positive rates during the wet-to-dry transition period. This particular feature, inherent to the cumulative sum statistical approach, has to be considered as a potential significant driver of false detections, particularly when working in highly dynamic environments characterized by sudden changes in their environmental conditions. The implementation of the kernel formalism significantly contributed to the control and mitigation of the impact associated with this feature.

This study has served to further refine the understanding of the hydrological mechanisms for flooding and water movement across the North Rupununi Wetlands. Until the appearance of the DETECT project and the development of the Ker-CuSum flood monitoring tool, there was no operational continuous monitoring system for the Northern Rupununi region. Despite the majority indigenous communities of this region are highly exposed to frequent and extensive flooding, most of the previous efforts had been primarily dedicated to the post-disturbance characterization of these events. The Ker-CuSum provides a solution to this problem, helping in determining the extent of inundation and flow pathways in a continuous and near-real time basis. In addition, the identification of the main hydrological mechanisms and flow pathways has significantly contributed to the conservation of the wetlands, providing valuable environmental information which can now be used to preserve these
ecologically important areas for water and food supply, species migration, fish spawning or species movement.

The new Ker-CuSum flood monitoring system was made publicly available through a Google Earth Engine platform web-App. This operational open-user tool contributes to increasing the base knowledge on the natural dynamics of the North Rupununi region, providing Indigenous communities and stakeholders with a useful near-real time tool that could be integrated into rapid response and wetland conservation management plans. Preliminary explorations have been performed with the aim of investigating the adaptation of the methods proposed in this chapter to multi-orbit and data fusion monitoring approaches. Appendix A details the analyses carried out in collaboration with the Laboratory of Geographic Information Systems and Remote Sensing of the Doñana Biological Station (CSIC), providing an insight into the capabilities of the Ker-CuSum for monitoring the complex flood dynamics of Doñana's wetlands, Spain.
4 Chapter

Enhancement of the Ker-CuSum for non-stationary environments: Current deforestation trends in Tropical forests of the North Rupununi region.
In this Chapter, the performance of the Ker-CuSum for monitoring permanent changes in tropical rainforests is investigated. A new fully unsupervised and automatic tropical forest change detector, the ‘ Constant False Alarm Rate – KerCuSum’ (CFAR-KerCuSum) is developed, optimising the previous Ker-CuSum approach while taking advantage of the work carried out in Google Earth Engine in the previous chapter. Additionally, the aim of this chapter is to analyse the contribution of new advanced features such as multitemporal filtering and occurrence analysis to the performance of the proposed change detection algorithm as well as the capabilities of this approach for assessing tree biomass loss on a regional scale.

This work demonstrates the capabilities of the proposed CFAR-KerCuSum for detecting natural and anthropogenic forest disturbances in tropical forested areas. The adaptation and enhancement of this algorithm to a simpler and more automatic version has resulted in a new EO forest monitoring tool with great exporting capabilities for its implementation in other tropical areas of the planet.

This research has served to study both current deforestation trends and the main causes of forest changes in the North Rupununi region. The enhanced user-friendly and automatic characteristics of this new approach, which does not require any supervision, make it a relevant forest monitoring tool for tropical forest conservation.
4.1 Introduction

Deforestation and forest degradation have been recognised as the most important human-induced land transformations during the last half century, being responsible for 12–20% of the global anthropogenic greenhouse gas (GHG) emissions in the 1990s and early 2000s (Dixon et al., 1994; Rudel, 2009; Schrope, 2009; van der Werf et al., 2009; Saatchi et al., 2011). The type of forest is an important consideration when assessing contribution to the global carbon cycles. For example, tropical and subtropical forests contribute the most, accounting for 78% of gross emissions (6.3 ± 2.4 GtCO$_2$e y$^{-1}$) and 55% of gross removals (−8.6 ± 7.6 GtCO$_2$e y$^{-1}$) (Harris et al., 2021).

Detecting deforestation activities using traditional methods, such as human patrol surveillance, can be very expensive and ineffective, especially in highly dense tropical forests. Hence, satellite-based deforestation monitoring systems, such as the well-known GLAD annual global forest cover loss map (Hansen et al., 2013), embedded in the Global Forest Watch (GFW) platform (GFW, no date), are generally considered as the best solutions due to their global coverage and the open and user-friendly GFW interface (non-GIS expertise required) (Bos et al., 2019). However, despite the great technological advancements made in the Earth observation field during the past decades, current operational systems still present significant limitations when it comes to their use as they rely predominantly on inconsistent and coarse resolution (30-500 m) optical satellite imagery (Reiche et al., 2017). Technical and environmental aspects such as the recurrent cloud coverage (e.g., Tropical areas) or the inability to obtain information from sub-canopy forest layers, considerably limit the use of optical sensors for monitoring small-scale deforestation events in a rapid and continuous manner (Ruiz-Ramos et al., 2020). Satellite-based high-resolution radar sensors stand out as the best alternative to overcome these limitations. This work will take advantage of synthetic aperture radar (SAR) monitoring capabilities to address the issues with current operational optical-based deforestation products.

Guyana has one of the largest intact old-growth tropical rainforest of the world, with an estimated national forest cover of 88% [18.9 million ha, year 2000; (GFC, 2018)]. This makes Guyana to be considered as a critical test case for emission-reduction initiatives, such as the REDD+ program (Roopsind, Sohngen and Brandt, 2019). Deforestation rates have increased in the past decade from 0.056% y$^{-1}$ (10,652 ha·y$^{-1}$) during the Norway–Guyana REDD+ program (2010 to 2015) to more than double 0.122% y$^{-1}$ (22,985 ha·y$^{-1}$) over the 2 year after the end of Norway–Guyana REDD+ program (2016 to 2017) (Roopsind, Sohngen and Brandt, 2019). This increase in the deforestation rates at national level highlights the need for developing new forest monitoring systems that allow a more detailed assessment of the forest degradation activities at lower spatial scales. In this study, dense timeseries of Sentinel-1 high-resolution radar data will be used to investigate the current...
deforestation trends at a regional level, analysing the annual forest changes of tropical rainforests of the North Rupununi (Guyana).

This chapter focuses on assessing the capabilities of the Ker-CuSum for monitoring small-scale forest degradation in highly dynamic tropical forests. This study builds on the foundations of the previous chapter, deepening the research, development and optimization of Ker-CuSum for the monitoring of temporary disturbances, focusing efforts on the generation of new forest monitoring tools. Under the premise of automating the detection process, a new thresholding approach based on the principle of the Constant False Alarm Rates (CFAR) adaptive algorithm is developed. By the thorough reformulation of the original CuSum change detection principle and the integration of auxiliary data into the Google Earth Engine platform, this chapter aims to achieve the following main objectives:

- Develop a new automatic and fully-unsupervised version of the Ker-CuSum change detector, CFAR-KerCuSum, and evaluate its performance for the detection of forest changes in tropical forests.
- Investigate the current deforestation dynamics in the North Rupununi region through the generation of annual forest change maps.
- Integrate the new forest change monitoring tool with new Above Ground Biomass products for the estimation of carbon stock losses at regional level.

4.2 Study Area

The study area is located in the North Rupununi region situated in the southern interior of Guyana, South America. The North Rupununi extends from the Siparuni River to the Kanuku Mountains and from the Essequibo River to the Brazilian border (Ozanne, Cabral and Shaw, 2014). The total area studied (638,600 ha) encompasses a wide variety of natural ecosystems distributed among the four main rivers of this region, from west to east, the Essequibo, Rewa, Rupununi and Ireng rivers (Figure 41). These natural landscapes range from large extensions of floodplains and natural wetlands, studied in Chapter 3, to the old-growth secondary tropical forest that is the focus of this chapter. The forest area covers 62.72% (400,534 ha) of the total area of study and encompasses several types of forest ecosystems, ranging from the low density savanna-scrubland mixed forest to the protected closed natural tropical forests areas of the southern border of the Iwokrama Wilderness Reserve.
As described in Chapter 3, the climate of the North Rupununi region is dominated by two well-marked wet and dry seasons. The annual dry season generally runs from September to March-April. The wet season is composed by two distinct rainy seasons: a prolonged period from May to mid-August and a brief period of precipitation events, known as cashew rains, which runs from December to January. The study area contains a total of 10 Amerindian communities that make extensive use of the forest and wetland resources for a wide range of livelihood activities including farming, hunting and gathering practices and in trading or work for cash payment (Ozanne, Cabral and Shaw, 2014; Mistry et al., 2021). Small-scale agricultural farming, mining activities and wildfires are considered as the main drivers of deforestation and forest degradation for the region of study.

4.3 Data

4.3.1 Sentinel-1 data timeseries

Forest change detection was carried out using ESA Sentinel-1 timeseries downloaded from the Google Earth Engine data archives. Similar to the previous chapter, the timeseries used were composed of dual-polarised (VV, VH) high resolution GRD-H products. Using the same sensor technical specifications (Level 1 product - Interferometric wide swath, unique orbit path (164) and ascending pass direction) for the composition of the time series, the images utilised presented identical characteristics to those used for the study of hydrological dynamics of the North Rupununi
wetlands (12-day revisit time, 10 x 10-meter pixel spacing, 20 x 22-meter spatial resolution) (Torres et al., 2012; Filipponi, 2019; ESA (a), 2021). However, this investigation also used additional images acquired during the dry season of 2021 (see Table 13). The final output resulted in a timeseries formed by 133 Sentinel-1 images.

Table 13. Acquisition dates of Sentinel-1 imagery used for the forest change detection analyses.

<table>
<thead>
<tr>
<th></th>
<th>2017</th>
<th>2018</th>
<th>2019</th>
<th>2020</th>
<th>2021</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>15th</td>
<td>10th, 22nd</td>
<td>5th, 17th, 29th</td>
<td>12th, 24th</td>
<td>6th, 18th, 30th</td>
</tr>
<tr>
<td>February</td>
<td>8th</td>
<td>3rd, 15th, 27th</td>
<td>10th, 22nd</td>
<td>5th, 17th, 29th</td>
<td>11th, 23rd</td>
</tr>
<tr>
<td>March</td>
<td>4th, 16th, 28th</td>
<td>11th, 23rd</td>
<td>6th, 18th, 30th</td>
<td>12th, 24th</td>
<td>7th, 19th, 31st</td>
</tr>
<tr>
<td>April</td>
<td>9th, 21st</td>
<td>04th, 16th, 28th</td>
<td>11th, 23rd</td>
<td>5th, 17th, 29th</td>
<td>12th, 24th</td>
</tr>
<tr>
<td>May</td>
<td>3rd, 15th, 27th</td>
<td>10th, 22nd</td>
<td>5th, 17th, 29th</td>
<td>11th, 23rd</td>
<td>6th, 18th, 30th</td>
</tr>
<tr>
<td>June</td>
<td>8th, 20th</td>
<td>3rd, 15th, 27th</td>
<td>10th, 22nd</td>
<td>4th, 16th, 28th</td>
<td>11th, 23rd</td>
</tr>
<tr>
<td>July</td>
<td>02nd, 14th, 26th</td>
<td>9th, 21st</td>
<td>4th, 16th, 28th</td>
<td>10th, 22nd</td>
<td>-</td>
</tr>
<tr>
<td>August</td>
<td>7th, 19th, 31st</td>
<td>2nd, 14th, 26th</td>
<td>9th, 21st</td>
<td>3rd, 15th, 27th</td>
<td>-</td>
</tr>
<tr>
<td>September</td>
<td>12th, 24th</td>
<td>7th, 19th</td>
<td>2nd, 14th, 26th</td>
<td>8th, 20th</td>
<td>-</td>
</tr>
<tr>
<td>October</td>
<td>6th, 18th, 30th</td>
<td>1st, 13th, 25th</td>
<td>8th, 20th</td>
<td>2nd, 14th, 26th</td>
<td>-</td>
</tr>
<tr>
<td>November</td>
<td>11th, 23rd</td>
<td>6th, 18th, 30th</td>
<td>1st, 13th, 25th</td>
<td>7th, 19th</td>
<td>-</td>
</tr>
<tr>
<td>December</td>
<td>5th, 17th, 29th</td>
<td>12th, 24th</td>
<td>7th, 19th, 31st</td>
<td>1st, 13th, 25th</td>
<td>-</td>
</tr>
</tbody>
</table>

4.3.1.1 SAR data pre-processing

All Sentinel-1 products used in this study have gone through the automatic pre-processing chain, implemented using the European Space Agency’s Sentinel-1 toolbox. This process was composed of the following steps: (1) Apply orbit files, (2) GRDH border noise removal, (3) thermal noise removal, (4) radiometric calibration, and (5) Range Doppler geocoding using the Shuttle Radar Topography Mission (SRTM) 30 m digital elevation model (DEM) (ESA (b), 2021; Google developers, 2021). Furthermore, two additional pre-processing steps; (1) radiometric angular-based slope correction (Vollrath, Mullissa and Reiche, 2020) and (2) speckle filtering (using a circular average filter, 35-meter radius) were applied in order to reduce the image speckle. The implementation of the additional radiometric terrain normalisation contributed to mitigate the effects of topography on the SAR backscatter signals. Based on the angular relationship between the SAR image and the terrain geometry (Mullissa et al., 2021), this angular-based radiometric terrain normalisation corrects the backscattering in all those areas affected by geometric distortions induced by the terrain slope (e.g. layover or shadow) (see Figure 42). This is important since it affects the calculation of the reference value for the spatial forest mean. Although this is not tested in this study, the implementation of the radiometric terrain normalisation could expand the use of the proposed change detection using multi-orbit approaches, overlapping imagery from ascending and descending orbits or even different sensors. The use of these data combination strategies (e.g. multi-orbit or multi-frequency) is an important topic that deserves a study on its own and is therefore left out of this chapter. The next
Chapter (Chapter 5) will offer a first insight into the use of the Ker-CuSum method with multi-orbits strategies.

Figure 42. Comparison of the effect of the Angular-based radiometric slope correction. Zoom overview of the mountainous region of the Alto tatuku-Alto Esequibo located between the Wowetta and Peropo communities. Co-polarised (VV) Sentinel-1 image acquired on the 15th January 2017; (A) Original pre-processed scene, (B) Corrected scene after the radiometric slope normalisation.

### 4.3.1.2 Multitemporal averaging – Monthly Composites

Figure 43 presents a preliminary exploration of the backscatter timeseries of various forested areas randomly distributed within the region of study. This analysis served to identify a noticeable variation in the radar signal. This signal variation is characteristic of vegetated surfaces and is usually driven by a wide range of environmental variables. Slight variations in environmental variables produced either by external factors such as climatology (e.g. temperature, precipitation, humidity) or the physical parameters inherent to the vegetation (e.g. phenology) can lead to changes in the backscatter mechanisms which can be misinterpreted as structural forest changes. Multi-temporal filtering techniques were employed to mitigate the potential influence that this statistical variation could exert on the final detection performance. A temporal averaging procedure was applied to the pre-processed Sentinel-1 time series within specified time window (1-month). The resulted image collection was reduced to 54 dual-polarised (VV, VH) images containing the monthly composites from January 2017 to June 2021. As shown in Figure 43, the implementation of the temporal reduction significantly scaled down the statistical variation.
Enhancement of the Ker-CuSum for non-stationary environments: Current deforestation trends in Tropical forests of the North Rupununi

4.4 Methods

This chapter focuses on investigating the monitoring capabilities of the new ‘CFAR-KerCuSum’ detector for the detection of forest disturbances in highly dynamic environments, the old-growth tropical forests of the North Rupununi region, Guyana.

4.4.1 CFAR - Kernel Cumulative Sum (CFAR-KerCuSum) change detection

One of the main priorities of this chapter has been to develop a new forest monitoring tool building on the advances made in Chapter 3 to monitor disturbances of a temporary nature. Here, the original Ker-CuSum is modified to develop a new fully unsupervised and automatic tool that aims to be easily exportable to other tropical forested areas. Hence, although the change detection principle of the original Ker-CuSum method remains similar, several modifications have been performed to make it automatic. Among the diverse changes implemented, the new way to set the threshold automatically is one of the main modifications. Similarly, substantial adaptations of the post-processing chain were performed. All these modifications will be explained in more detail below.

![Figure 43. Comparison of the paired sums values for time series composed of daily images (every 12 days) (Top) and monthly composites (Bottom). The study area corresponds to a forest plot (4°01'13.6"N 59°02'12.2"W) near Wowetta, which was deforested in October 2019.](image)
4.4.1.1 Selection of the temporal forest reference

The selection of the reference period to use for the land classification is one of the most important points to consider when tuning the detector. The use of dense timeseries allows the adoption of different strategies when choosing the reference period, which can be selected based on the specific characteristics of the environment to be studied. Stable environments that present little variation in conditions allow the adoption of long reference periods. However, highly dynamic ecosystems with temporal variations (e.g. seasonality) that influence the radar signal need a more careful selection in order to eliminate the potential false alarms that these variations could introduce. Taking into account the particularly high dynamic of the North Rupununi region, special attention has been paid to seasonality when selecting the reference period.

Chapter 3 highlights significant differences in the radar signal between the images acquired in the wet and dry season. Seasonal environmental variations (e.g. temporal floods, rainfall events) cause important alterations to the physical properties of the vegetation which result in a significant variation of the backscatter. Despite dense forested areas generally present lower variations than other land covers, such as floodplains or low-vegetated land, they still need to be carefully considered when selecting the reference time period. Most deforestation processes that occur in the North Rupununi take place during the last months of the dry season (from February to April), coinciding with the better state of roads and infrastructures (Jafferally, D., NRDBD; personal communication, 20th January 2021, Mistry et al., 2021). The prolonged adverse weather conditions throughout the wet period considerably limit the access and exploitation of forests. For these reasons, it was decided to focus the analysis on the dry period, thus reducing the potential influence that seasonal changes may exert on the final detection performances.

The value for the forest reference was computed using the monthly composites generated from the images acquired during the driest period of 2017 (January, February, March and April 2017). To focus the analysis exclusively on forests, all non-forest areas were masked out using the GLAD – Hansen Tree cover map generated for the year 2000 (Hansen et al., 2013) (Figure 44). A ‘≥ 90%’ canopy coverage clause was used in order to discard those particular low density or shrubland areas which may lead to subsequent misclassification errors.
Enhancement of the Ker-CuSum for non-stationary environments: Current deforestation trends in Tropical forests of the North Rupununi

The final reference mean value was computed following the same rationale used for the mean calculation used in the CUSUM-SAR (Chapter 2 (Ruiz-Ramos et al., 2020)). This is done by averaging the radar signal values over the forested areas over a specific period of time (the reference time). Therefore, this is a temporal average of pixels.

4.4.1.2 CFAR-KerCuSum forest change detection

The operational principle of the Kernel CuSum method remained identical to the original version in Chapter 3, where the cumulative sum paired timeseries were computed by following a two-step process: a) the forest reference mean value is subtracted to each image of the pre-processed Sentinel-1 time-series and, b) each of the resulting difference images are added to the previous one (but not to the full stack of differences) (Figure 45).

The largest modification to the algorithm was made in the selection of the detection threshold. This new approach was adopted with the aim of developing a more automated version, which did not require any supervision from the user when selecting the detection thresholds. In the following, it will be shown that the CuSum forest reference dataset was distributed as a Gaussian zero mean with standard deviation $\sigma$. Standard deviation values are calculated averaging the CuSum values spatially and temporally over all forest pixels. This provides a mean and standard deviation for each pixel analysed, which allows to fully characterise the gaussian probability distribution function pdf.
This allows the adoption of order-statistics-based two-parameter change detection methods such as the Constant False Alarm Rate (CFAR) detection (Novak and Hesse, 1991).

In Normal distributions, there is a direct link between the standard deviation and the probability that a sample is larger than a multiple of the standard deviation. Such probability can be calculated using the Bienaymé – Chebyshev inequality probability theorem (Bienaymé, 1853; Chebichef, 1867). Chebyshev’s inequality states that no more than $1/k^2$ of the distribution’s values can be $k$ or more standard deviations away from the mean (Routledge, 2011). In this framework, Table 14 shows the values of probability for several values of $k$. Since the reference is assumed to be not affected by changes, the probability coming from the Chebyshev’s inequality corresponds to the probability of false alarm one would experience using the respective value of $k$.

<table>
<thead>
<tr>
<th>Reference Forest standard deviation</th>
<th>$k$</th>
<th>Max. % beyond k standard deviations</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.75</td>
<td>5.5</td>
<td>3.3057%</td>
</tr>
<tr>
<td>3.0</td>
<td>6</td>
<td>2.7778%</td>
</tr>
<tr>
<td>3.25</td>
<td>6.5</td>
<td>2.3668%</td>
</tr>
<tr>
<td>3.5</td>
<td>7</td>
<td>2.0408%</td>
</tr>
<tr>
<td>3.75</td>
<td>7.5</td>
<td>1.7777%</td>
</tr>
<tr>
<td>4.0</td>
<td>8</td>
<td>1.5625%</td>
</tr>
<tr>
<td>4.25</td>
<td>8.5</td>
<td>1.3840%</td>
</tr>
<tr>
<td>4.5</td>
<td>9</td>
<td>1.2346%</td>
</tr>
</tbody>
</table>

This adaptation of the thresholding approach converts the original Ker-CuSum algorithm into a fully unsupervised version since the threshold is automatically set after the value for the probability of false alarms is selected (generally following some high-level user design). Likewise, the automatic nature of the threshold selection is expected to enhance the adaptability of the Ker-CuSum method to other tropical forest areas. The following diagram (Figure 45) shows the operational block diagram of the proposed CFAR Kernel Cumulative Sum (CFAR-KerCuSum) change detection tool.
Forest disturbance was here defined as the complete or partial elimination of tree cover within the Sentinel-1 pixel spatial resolution (10 x 10 meters | ~0.01 ha). This follows a similar definition approach adopted by previous operational satellite-based forest change products (Hansen et al., 2013, 2016; Vargas, Montalban and Leon, 2019; Ruiz-Ramos et al., 2020; Reiche et al., 2021). Similarly, this methodology does not distinguish between types of forest changes or inducing factors, as for the Hansen map.

4.4.2 Post-Processing – Sieve filtering and Occurrence confidence analysis

Radar backscattering are highly sensitive to variations in target parameters (e.g. surface roughness, geometry, moisture content). The highly dynamic nature of vegetation results in a continuous alteration of these parameters that may lead to significant misclassifications and estimation errors when performing change detection studies. Hence, the use of post-processing techniques stands out as a crucial step to refine the final classification maps. As in previous chapters, post-processing techniques were used with the aim of both increasing the levels of confidence in the detection and minimising the possible influence of false positives. The final annual forest change maps were derived following a two-step process (a) Sieve morphological filtering and (b) Occurrence analysis.

a) **Sieve filtering**: A conservative minimum mapping unit of 0.4 ha (40 Sentinel-1 pixels on a 10m grid) was applied to eliminate the smaller and isolated detected regions, aiming to reduce
the false alarm rate. The decision to use a larger-scale mapping unit responds to the fact that, as previously stated by (Bouvet et al., 2018; Reiche et al., 2018, 2021; Hirschmugl et al., 2020), the adoption of very fine-scales for forest change monitoring with SAR data will lead to higher false detection rates caused by speckle noise or moisture fluctuations. All change pixels connected to 40 8-connected pixels (minimum mapping unit ~0.04 ha) or fewer neighbours were removed using the GEE ‘connectedPixelCount’ image tool (Google, 2021a).

b) Occurrence analysis: An assumption was made that any forest change sustained over time is likely due to a real disturbance. Therefore, investigating the persistence over time, it is possible to increase the confidence in the detection. A new occurrence analysis process, inspired by the Bayesian updating approach (Reiche et al., 2015), was implemented into the post-processing chain. The confidence about the forest disturbance was calculated based on the number of times it repeated itself. Annual forest change maps, containing the forest disturbance alerts detected during the dry season (September to April) were classified according to the following clauses:

- **Mid-confidence** ($t_1$): It considers all the disturbances detected, without evaluating their occurrence. That is, any change observed for one time during the annual period analysed (September to April).

- **High-confidence** ($t_2$): It considers only those disturbed pixels which are called twice during the annual period analysed.

- **Very High-confidence** ($t_3$): It considers only those disturbed pixels which are called three or more times during the annual period analysed.

The implementation of the forest change occurrence analysis required some post-processing of the detection maps. In particular, a change is called only if this is persistent over a sorter number of consecutive detection maps. The number of times that a change needs to persist is a parameter ($t$) of the occurrence analysis. For example, in the context of this study, if a forest disturbance occurs in April (the last month of the considered period of study (dry season)), the following month (May) will need to be included for the $t_2$ investigation, as its persistence over the next month needs to be evaluated. In the same way, the next two months (May and June) will be required for the $t_3$ investigation. In this regard, the annual timeseries were adapted, containing the following periods: $t_1$ (September to April), $t_2$ (September to May), $t_3$ (September to June) (Figure 46).
4.4.3 **Accuracy Assessments (spatial validation)**

The objective was to evaluate the detection performance of the proposed CFAR-KerCuSum method to discriminate between forest disturbances and intact forest areas. The analysis focused on three regions of interest (ROI), which presented different environmental characteristics but similar deforestation rates for the study period. The sample validation regions were individually selected according to their specific environmental characteristics, prioritizing: a) the generation of a heterogeneous population in terms of possible environmental factors of influence (e.g. flood events) and b) their specific location within the study area. A preliminary visual exploration of the study area, using multispectral Planet optical imagery, served to identify those areas with higher rates of forest changes. Subsequently, a more thorough investigation on the environmental characteristics and the temporal and spatial distribution of forest changes occurred in these deforestation hotspots served to determine the final regions of interest. The three regions of interest, of rectangular shape and size 2.5 x 2.5 km (6.25 km2), were located in the vicinity of three indigenous communities of the northern (Wowetta), central (Yupukari) and southern (Katoka) region of the North Rupununi (Figure 47).
Figure 47. Illustration of the validation sites used for the validation assessment. A) Yupukari region (central), B) Katoka region (south) and C) Wowetta region (central). Reference forest change areas were obtained by visual investigation of Planet imagery acquired before and after the period of study (2018-2019).

The forest change validation areas were manually digitised using photointerpretation of high-resolution multi-spectral (blue, green, red, near-infrared) PlanetScope (3m spatial resolution) optical images acquired by Planet (Planet Team, 2021). The forest change validation analyses were performed for assessing the forest disturbances that occurred in 2018 and 2019. Contrary to 2018 dry season, which showed low levels of deforestation, the 2019 dry season presented a significantly higher deforestation rate providing a larger area of disturbed forests which could be used for the performance evaluation. Consequently, the ground truth forest change areas contained all forest disturbances that had occurred since the end of the reference period (1st May 2017) until the end of the dry season 2019 (1st May 2019). The high cloud-cover present in the study area hindered the utilisation of images acquired on coincident or near-coincident dates of the end of the dry season.
For this reason, the images used for the photointerpretation of forest changes date from the beginning of the following dry season (September 2019) (Table 15). Additional supporting Planet images were used to verify those areas that presented a higher level of uncertainty regarding the date of disturbance, thus minimizing the potential inclusion of specific changes that could have occurred at the beginning of the following dry season.

Table 15. Planet optical imagery used for the digitalisation of the 2019 forest changes of the three validation sites of the North Rupununi region.

<table>
<thead>
<tr>
<th>Reference period</th>
<th>Reference period</th>
<th>Reference period</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Katoka</strong></td>
<td><strong>Yupukari</strong></td>
<td><strong>Wowetta</strong></td>
</tr>
<tr>
<td>20th August 2017</td>
<td>20th August 2017</td>
<td>20th August 2017</td>
</tr>
<tr>
<td>2019 dry season</td>
<td>28th August 2019</td>
<td>25th August 2019</td>
</tr>
<tr>
<td></td>
<td>15th September 2019</td>
<td></td>
</tr>
</tbody>
</table>

Accuracy assessments were separately performed for each of the sample sites. The separate evaluation of each area of interest allowed to obtain more detailed information on the performance of the algorithm over different environments. This analysis served to assess the performance of each of the combinations of confidence intervals and occurrences, thus evaluating the accuracy of a total of 24 products (K = 5, 5.5, 6, 6.5, 7, 7.5, 8, 9) with 3 levels of occurrence (t_o = 1, t_o = 2 and t_o = 3) for each of the detector studied.

The performance was assessed by using standard accuracy metrics: Overall Accuracy, User Accuracy, Producer Accuracy and F-score. Accuracy confusion matrices were extracted by comparing the CFAR-KerCuSum classification masks against the validation map.

### 4.5 Results

#### 4.5.1 Testing the Assumptions: Normality

A required step to adopt the proposed automatic threshold selection is to test the assumption that the forest CuSums obeys a Gaussian zero mean distribution. Data normality was tested by investigating the data distribution of 20 polygons (316 ha | 13904 pixels) of varying size, randomly distributed across the forest reference image. The Anderson-Darling test for normality was used (Anderson and Darling, 1954), the null hypothesis (normality) was accepted as the p-value was well higher than 0.05 (P-value = 0.222) (Figure 48).
Chapter 4

Figure 48. Distribution analysis of CuSums over the Forest reference image. The sample data used for the Anderson-Darling normality test (right) was obtained using 20 randomly distributed polygons across the forest mask.

4.5.2 Best Polarisation

Previous studies have shown disagreement between researchers in the choice of the most suitable polarisation channel for monitoring forest disturbances (Ruiz-Ramos et al., 2020). The complexity and heterogeneity of structural properties of vegetation lead to differences in performance of polarization channels when it comes to detect forest disturbance. Therefore, the sensitivity of each polarisation channel was studied by comparing the detection performance of both the co-polarised (VV) and cross-polarised (VH) channel for 5 probabilities (K = 6, 6.5, 7, 7.5, 8) (Figure 49).

Figure 49. Comparison of the change detection performance of each polarisation channel. Combined accuracy metrics (True positives = TP; False positives = FP) extracted from the 2019 annual forest change analysis performed over Wowetta, Yupukari and Katoka.
The performance comparison showed a greater sensitivity of the co-polarised channel to forest changes. The higher performance of the VV channel was consistent for all the level of false alarm tested, where the Overall Accuracy and Fscore values were on average OA ≈ 1.2 and F1 ≈ 1.89 over the results obtained for the VH channel. As shown in Figure 48, the VV channel provided a higher performance both in the detection of true positives and in the discrimination of false positives. These results coincide with previous studies (Green, 1998; Eriksson et al., 2012; Rüetschi et al., 2019) which observed a greater sensitivity of the co-polarized backscatter to forest changes. Based on these findings, it was decided to focus the analyses on the VV polarisation, thus exclusively considering this channel as the most suitable for the subsequent comparison with the alternative methodologies explored.

4.5.3 CFAR-KerCuSum forest disturbance detection

Results obtained for the proposed CFAR-KerCuSum algorithm showed high performance in detecting forest disturbances with accuracy values ranging from OA = 80.1% (F1 = 77.7%) to OA = 72.31% (F1 = 65.35%) for the products derived from the combination of the occurrences t1, t2 and probabilities K = 5.5 - 8. Although there is variability in the values for each of the validation regions, the combined figures showed consistent high User Accuracy (UA) values situated around UA = 90.5% for the same products (Table 16).

Table 16. Combined Accuracy metrics extracted from the 2019 annual forest change analysis performed over Wowetta, Yupukari and Katoka using the CFAR-KerCuSum over the VV pol-channel. TP = true positives, TN = true negatives, FP = false positives, FN = false negatives, OA = overall accuracy, PA = producer accuracy, UA = user accuracy.

<table>
<thead>
<tr>
<th></th>
<th>TP</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
<th>UA</th>
<th>PA</th>
<th>OA</th>
<th>Fscore</th>
</tr>
</thead>
<tbody>
<tr>
<td>K 5.5</td>
<td>T1</td>
<td>66.10</td>
<td>87.26</td>
<td>12.74</td>
<td>33.90</td>
<td>84.29</td>
<td>66.10</td>
<td>76.68</td>
</tr>
<tr>
<td></td>
<td>T2</td>
<td>65.04</td>
<td>90.16</td>
<td>9.84</td>
<td>34.96</td>
<td>87.14</td>
<td>65.04</td>
<td>77.60</td>
</tr>
<tr>
<td></td>
<td>T3</td>
<td>39.53</td>
<td>97.25</td>
<td>2.75</td>
<td>60.47</td>
<td>93.36</td>
<td>39.53</td>
<td>68.39</td>
</tr>
<tr>
<td>K 6</td>
<td>T1</td>
<td>62.48</td>
<td>90.07</td>
<td>9.93</td>
<td>37.52</td>
<td>86.75</td>
<td>62.48</td>
<td>76.28</td>
</tr>
<tr>
<td></td>
<td>T2</td>
<td>61.39</td>
<td>92.19</td>
<td>7.81</td>
<td>38.61</td>
<td>89.01</td>
<td>61.39</td>
<td>76.79</td>
</tr>
<tr>
<td></td>
<td>T3</td>
<td>35.84</td>
<td>97.95</td>
<td>2.05</td>
<td>64.16</td>
<td>94.46</td>
<td>35.84</td>
<td>65.90</td>
</tr>
<tr>
<td>K 6.5</td>
<td>T1</td>
<td>59.04</td>
<td>92.62</td>
<td>7.38</td>
<td>40.96</td>
<td>89.29</td>
<td>59.04</td>
<td>75.83</td>
</tr>
<tr>
<td></td>
<td>T2</td>
<td>57.44</td>
<td>94.05</td>
<td>5.95</td>
<td>42.56</td>
<td>90.85</td>
<td>57.44</td>
<td>75.74</td>
</tr>
<tr>
<td></td>
<td>T3</td>
<td>30.99</td>
<td>98.58</td>
<td>1.42</td>
<td>69.01</td>
<td>95.40</td>
<td>30.99</td>
<td>64.78</td>
</tr>
<tr>
<td>K 7</td>
<td>T1</td>
<td>56.39</td>
<td>94.56</td>
<td>5.44</td>
<td>43.61</td>
<td>91.52</td>
<td>56.39</td>
<td>75.48</td>
</tr>
<tr>
<td></td>
<td>T2</td>
<td>54.42</td>
<td>95.54</td>
<td>4.46</td>
<td>45.58</td>
<td>92.55</td>
<td>54.42</td>
<td>74.98</td>
</tr>
<tr>
<td></td>
<td>T3</td>
<td>25.87</td>
<td>99.03</td>
<td>0.97</td>
<td>74.13</td>
<td>95.82</td>
<td>25.87</td>
<td>62.45</td>
</tr>
<tr>
<td>K 7.5</td>
<td>T1</td>
<td>53.15</td>
<td>95.84</td>
<td>4.16</td>
<td>46.85</td>
<td>93.00</td>
<td>53.15</td>
<td>74.49</td>
</tr>
<tr>
<td></td>
<td>T2</td>
<td>50.66</td>
<td>96.57</td>
<td>3.43</td>
<td>49.34</td>
<td>93.66</td>
<td>50.66</td>
<td>73.61</td>
</tr>
<tr>
<td></td>
<td>T3</td>
<td>21.20</td>
<td>99.23</td>
<td>0.77</td>
<td>78.80</td>
<td>94.52</td>
<td>21.20</td>
<td>60.21</td>
</tr>
<tr>
<td>K 8</td>
<td>T1</td>
<td>48.65</td>
<td>96.80</td>
<td>3.20</td>
<td>51.35</td>
<td>94.08</td>
<td>48.65</td>
<td>72.72</td>
</tr>
<tr>
<td></td>
<td>T2</td>
<td>46.44</td>
<td>97.20</td>
<td>2.80</td>
<td>53.56</td>
<td>94.35</td>
<td>46.44</td>
<td>71.82</td>
</tr>
<tr>
<td></td>
<td>T3</td>
<td>19.12</td>
<td>99.40</td>
<td>0.60</td>
<td>80.88</td>
<td>95.41</td>
<td>19.12</td>
<td>59.26</td>
</tr>
</tbody>
</table>

These results demonstrate the high reliability of the CFAR-KerCuSum tool for forest monitoring since despite providing a medium to high accuracy the detection of true positives (TP = \( \bar{x} \) 60.29%
Chapter 4

[\{t1, t2 \mid K = 5.5 - 7\}], it provides significantly low false alarm rates (FP = \bar{x} 7.9\% [\{t1, t2 \mid K = 5.5 - 7\}]). This significantly enhances the potential usability of the product as it ensures very high levels of confidence when detecting changes in tropical forests.

The investigation of distinct validation areas (with diverse environmental characteristics) allowed to analyse the influence of environmental fluctuations on the performance. Both the areas located in the northern (Wowetta) and southern (Katoka) regions showed a similar performance characterized by high true detection rates (TP = \bar{x} 60.5\% [\{t1, t2 \mid K = 5.5 - 7\}] and low false alarm (FP = \bar{x} 5.38\% [\{t1, t2 \mid K = 5.5 - 7\}] rates (Table 17.1 and Table 17.2). This is a consequence of the forests in Wowetta and Katoka to be less affected by environmental variations such as seasonal floods. The central region (Yupukari) showed the opposite result, with a lower overall performance directly associated with a higher presence of false positives (FP = \bar{x} 13.08\% [\{t1, t2 \mid K = 5.5 - 7\}] (Table 17.3). Yupukari indigenous community is located on the banks of the Turantsink creek and the Rupununi river, the main contributor to the inundations during the wet season. As observed in previous research (Hoekman et al., 2020), seasonal floods have been identified as an important source of misclassification errors over wetland forests, as some of these flooded vegetated areas have been erroneously classified as forest change. The majority contribution to this error occurred during the first (September-October) and the last months (April-May), coinciding with the dry to wet season transitional periods (Figure 50).

Table 17. Region specific accuracy assessment results extracted from the 2019 annual forest change analysis performed over (1) Wowetta – North region, (2) Katoka – South region and (3) Yupukari – Central region; using the CFAR-KerCuSum over the VV pol-channel. TP = true positives, TN = true negatives, FP = false positives, FN = false negatives, OA = overall accuracy, PA = producer accuracy, UA = user accuracy.

<table>
<thead>
<tr>
<th>Region</th>
<th>TP</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
<th>UA</th>
<th>PA</th>
<th>OA</th>
<th>Fscore</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wowetta</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>K 5.5</td>
<td>t1</td>
<td>62.64</td>
<td>93.32</td>
<td>6.68</td>
<td>37.36</td>
<td>90.36</td>
<td>62.64</td>
<td>77.98</td>
</tr>
<tr>
<td></td>
<td>t2</td>
<td>62.45</td>
<td>95.03</td>
<td>4.97</td>
<td>37.55</td>
<td>92.63</td>
<td>62.45</td>
<td>78.74</td>
</tr>
<tr>
<td></td>
<td>t3</td>
<td>36.17</td>
<td>98.77</td>
<td>1.23</td>
<td>63.83</td>
<td>96.72</td>
<td>36.17</td>
<td>67.47</td>
</tr>
<tr>
<td>K 6</td>
<td>t1</td>
<td>57.62</td>
<td>95.04</td>
<td>4.96</td>
<td>42.38</td>
<td>92.07</td>
<td>57.62</td>
<td>76.33</td>
</tr>
<tr>
<td></td>
<td>t2</td>
<td>57.32</td>
<td>96.25</td>
<td>3.75</td>
<td>42.68</td>
<td>93.86</td>
<td>57.32</td>
<td>76.78</td>
</tr>
<tr>
<td></td>
<td>t3</td>
<td>32.07</td>
<td>99.23</td>
<td>0.77</td>
<td>67.93</td>
<td>97.67</td>
<td>32.07</td>
<td>65.65</td>
</tr>
<tr>
<td>K 6.5</td>
<td>t1</td>
<td>53.22</td>
<td>96.70</td>
<td>3.30</td>
<td>46.78</td>
<td>94.15</td>
<td>53.22</td>
<td>74.96</td>
</tr>
<tr>
<td></td>
<td>t2</td>
<td>52.76</td>
<td>97.40</td>
<td>2.60</td>
<td>47.24</td>
<td>95.30</td>
<td>52.76</td>
<td>75.08</td>
</tr>
<tr>
<td></td>
<td>t3</td>
<td>27.74</td>
<td>99.56</td>
<td>0.44</td>
<td>72.26</td>
<td>98.43</td>
<td>27.74</td>
<td>63.65</td>
</tr>
<tr>
<td>K 7</td>
<td>t1</td>
<td>51.11</td>
<td>97.77</td>
<td>2.23</td>
<td>48.89</td>
<td>95.82</td>
<td>51.11</td>
<td>74.44</td>
</tr>
<tr>
<td></td>
<td>t2</td>
<td>50.65</td>
<td>98.03</td>
<td>1.97</td>
<td>49.35</td>
<td>96.26</td>
<td>50.65</td>
<td>74.34</td>
</tr>
<tr>
<td></td>
<td>t3</td>
<td>25.75</td>
<td>99.74</td>
<td>0.26</td>
<td>74.25</td>
<td>98.99</td>
<td>25.75</td>
<td>62.74</td>
</tr>
<tr>
<td>K 7.5</td>
<td>t1</td>
<td>48.74</td>
<td>98.73</td>
<td>1.27</td>
<td>51.26</td>
<td>97.47</td>
<td>48.74</td>
<td>73.73</td>
</tr>
<tr>
<td></td>
<td>t2</td>
<td>48.51</td>
<td>99.05</td>
<td>0.95</td>
<td>51.49</td>
<td>98.08</td>
<td>48.51</td>
<td>73.78</td>
</tr>
<tr>
<td></td>
<td>t3</td>
<td>22.03</td>
<td>99.87</td>
<td>0.13</td>
<td>77.97</td>
<td>99.42</td>
<td>22.03</td>
<td>60.95</td>
</tr>
<tr>
<td>K 8</td>
<td>t1</td>
<td>44.56</td>
<td>99.49</td>
<td>0.51</td>
<td>55.44</td>
<td>98.88</td>
<td>44.56</td>
<td>72.03</td>
</tr>
<tr>
<td></td>
<td>t2</td>
<td>44.10</td>
<td>99.55</td>
<td>0.45</td>
<td>55.90</td>
<td>99.00</td>
<td>44.10</td>
<td>71.83</td>
</tr>
<tr>
<td></td>
<td>t3</td>
<td>19.12</td>
<td>99.89</td>
<td>0.11</td>
<td>80.88</td>
<td>99.43</td>
<td>19.12</td>
<td>59.50</td>
</tr>
</tbody>
</table>
Enhancement of the Ker-CuSum for non-stationary environments: Current deforestation trends in Tropical forests of the North Rupununi

## 2 - Katoka

<table>
<thead>
<tr>
<th></th>
<th>TP</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
<th>UA</th>
<th>PA</th>
<th>OA</th>
<th>Fscore</th>
</tr>
</thead>
<tbody>
<tr>
<td>K 5.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t1</td>
<td>69.69</td>
<td>88.32</td>
<td>11.68</td>
<td>30.31</td>
<td>85.64</td>
<td>69.69</td>
<td>79.00</td>
<td>76.85</td>
</tr>
<tr>
<td>t2</td>
<td>69.32</td>
<td>91.06</td>
<td>8.94</td>
<td>30.68</td>
<td>88.58</td>
<td>69.32</td>
<td>80.19</td>
<td>77.77</td>
</tr>
<tr>
<td>t3</td>
<td>48.51</td>
<td>97.44</td>
<td>2.56</td>
<td>51.49</td>
<td>94.99</td>
<td>48.51</td>
<td>72.98</td>
<td>64.22</td>
</tr>
<tr>
<td>K 6</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t1</td>
<td>66.58</td>
<td>91.64</td>
<td>8.36</td>
<td>33.42</td>
<td>88.84</td>
<td>66.58</td>
<td>79.11</td>
<td>76.11</td>
</tr>
<tr>
<td>t2</td>
<td>66.34</td>
<td>93.45</td>
<td>6.55</td>
<td>33.66</td>
<td>91.01</td>
<td>66.34</td>
<td>79.89</td>
<td>76.74</td>
</tr>
<tr>
<td>t3</td>
<td>44.55</td>
<td>98.25</td>
<td>1.75</td>
<td>55.45</td>
<td>96.22</td>
<td>44.55</td>
<td>71.40</td>
<td>60.91</td>
</tr>
<tr>
<td>K 6.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t1</td>
<td>63.73</td>
<td>93.50</td>
<td>6.50</td>
<td>36.27</td>
<td>90.75</td>
<td>63.73</td>
<td>78.62</td>
<td>74.88</td>
</tr>
<tr>
<td>t2</td>
<td><strong>63.36</strong></td>
<td><strong>95.00</strong></td>
<td><strong>5.00</strong></td>
<td><strong>36.64</strong></td>
<td><strong>92.69</strong></td>
<td><strong>63.36</strong></td>
<td><strong>79.18</strong></td>
<td><strong>75.27</strong></td>
</tr>
<tr>
<td>t3</td>
<td>39.85</td>
<td>98.71</td>
<td>1.29</td>
<td>60.15</td>
<td>96.87</td>
<td>39.85</td>
<td>69.28</td>
<td>56.47</td>
</tr>
<tr>
<td>K 7</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t1</td>
<td>60.83</td>
<td>95.26</td>
<td>4.74</td>
<td>39.17</td>
<td>92.77</td>
<td>60.83</td>
<td>78.04</td>
<td>73.48</td>
</tr>
<tr>
<td>t2</td>
<td>60.39</td>
<td>96.22</td>
<td>3.78</td>
<td>39.61</td>
<td>94.10</td>
<td>60.39</td>
<td>78.30</td>
<td>73.56</td>
</tr>
<tr>
<td>t3</td>
<td>34.24</td>
<td>99.06</td>
<td>0.94</td>
<td>65.76</td>
<td>97.32</td>
<td>34.24</td>
<td>66.65</td>
<td>50.65</td>
</tr>
<tr>
<td>K 7.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t1</td>
<td>58.12</td>
<td>96.40</td>
<td>3.60</td>
<td>41.88</td>
<td>94.17</td>
<td>58.12</td>
<td>77.26</td>
<td>71.88</td>
</tr>
<tr>
<td>t2</td>
<td>57.51</td>
<td>97.18</td>
<td>2.82</td>
<td>42.49</td>
<td>95.32</td>
<td>57.51</td>
<td>77.34</td>
<td>71.74</td>
</tr>
<tr>
<td>t3</td>
<td>32.10</td>
<td>99.33</td>
<td>0.67</td>
<td>67.90</td>
<td>97.95</td>
<td>32.10</td>
<td>65.72</td>
<td>48.36</td>
</tr>
<tr>
<td>K 8</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t1</td>
<td>53.96</td>
<td>97.58</td>
<td>2.42</td>
<td>46.04</td>
<td>95.71</td>
<td>53.96</td>
<td>75.77</td>
<td>69.01</td>
</tr>
<tr>
<td>t2</td>
<td>52.81</td>
<td>98.00</td>
<td>2.00</td>
<td>47.19</td>
<td>96.35</td>
<td>52.81</td>
<td>75.40</td>
<td>68.22</td>
</tr>
<tr>
<td>t3</td>
<td>28.86</td>
<td>99.54</td>
<td>0.46</td>
<td>71.14</td>
<td>98.44</td>
<td>28.86</td>
<td>64.20</td>
<td>44.63</td>
</tr>
</tbody>
</table>

## 3 - Yupukari

<table>
<thead>
<tr>
<th></th>
<th>TP</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
<th>UA</th>
<th>PA</th>
<th>OA</th>
<th>Fscore</th>
</tr>
</thead>
<tbody>
<tr>
<td>K 5.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t1</td>
<td>65.98</td>
<td>80.15</td>
<td>19.85</td>
<td>34.02</td>
<td>76.87</td>
<td>65.98</td>
<td>73.06</td>
<td>71.01</td>
</tr>
<tr>
<td>t2</td>
<td>63.34</td>
<td>84.38</td>
<td>15.62</td>
<td>36.66</td>
<td>80.21</td>
<td>63.34</td>
<td>73.86</td>
<td>70.78</td>
</tr>
<tr>
<td>t3</td>
<td>33.91</td>
<td>95.54</td>
<td>4.46</td>
<td>66.09</td>
<td>88.38</td>
<td>33.91</td>
<td>64.72</td>
<td>49.01</td>
</tr>
<tr>
<td>K 6</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t1</td>
<td>63.25</td>
<td>83.52</td>
<td>16.48</td>
<td>36.75</td>
<td>79.34</td>
<td>63.25</td>
<td>73.39</td>
<td>70.39</td>
</tr>
<tr>
<td>t2</td>
<td>60.50</td>
<td>86.88</td>
<td>13.12</td>
<td>39.50</td>
<td>82.18</td>
<td>60.50</td>
<td>73.69</td>
<td>69.69</td>
</tr>
<tr>
<td>t3</td>
<td>30.90</td>
<td>96.37</td>
<td>3.63</td>
<td>69.10</td>
<td>89.49</td>
<td>30.90</td>
<td>63.63</td>
<td>45.93</td>
</tr>
<tr>
<td>K 6.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t1</td>
<td>60.15</td>
<td>87.66</td>
<td>12.34</td>
<td>39.85</td>
<td>82.98</td>
<td>60.15</td>
<td>73.91</td>
<td>69.75</td>
</tr>
<tr>
<td>t2</td>
<td><strong>56.20</strong></td>
<td><strong>89.74</strong></td>
<td><strong>10.26</strong></td>
<td><strong>43.80</strong></td>
<td><strong>84.57</strong></td>
<td><strong>56.20</strong></td>
<td><strong>72.97</strong></td>
<td><strong>67.52</strong></td>
</tr>
<tr>
<td>t3</td>
<td>25.39</td>
<td>97.46</td>
<td>2.54</td>
<td>74.61</td>
<td>90.91</td>
<td>25.39</td>
<td>61.42</td>
<td>39.69</td>
</tr>
<tr>
<td>K 7</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t1</td>
<td>57.23</td>
<td>90.66</td>
<td>9.34</td>
<td>42.77</td>
<td>85.97</td>
<td>57.23</td>
<td>73.94</td>
<td>68.71</td>
</tr>
<tr>
<td>t2</td>
<td>52.24</td>
<td>92.39</td>
<td>7.61</td>
<td>47.76</td>
<td>87.28</td>
<td>52.24</td>
<td>72.31</td>
<td>65.36</td>
</tr>
<tr>
<td>t3</td>
<td>17.64</td>
<td>98.29</td>
<td>1.71</td>
<td>82.36</td>
<td>91.14</td>
<td>17.64</td>
<td>57.96</td>
<td>29.56</td>
</tr>
<tr>
<td>K 7.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t1</td>
<td>52.58</td>
<td>92.40</td>
<td>7.60</td>
<td>47.42</td>
<td>87.37</td>
<td>52.58</td>
<td>72.49</td>
<td>65.65</td>
</tr>
<tr>
<td>t2</td>
<td>45.96</td>
<td>93.48</td>
<td>6.52</td>
<td>54.04</td>
<td>87.58</td>
<td>45.96</td>
<td>69.72</td>
<td>60.28</td>
</tr>
<tr>
<td>t3</td>
<td>9.47</td>
<td>98.48</td>
<td>1.52</td>
<td>90.53</td>
<td>86.19</td>
<td>9.47</td>
<td>53.97</td>
<td>17.06</td>
</tr>
<tr>
<td>K 8</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t1</td>
<td>47.42</td>
<td>93.32</td>
<td>6.68</td>
<td>52.58</td>
<td>87.66</td>
<td>47.42</td>
<td>70.37</td>
<td>61.54</td>
</tr>
<tr>
<td>t2</td>
<td>42.43</td>
<td>94.06</td>
<td>5.94</td>
<td>57.57</td>
<td>87.72</td>
<td>42.43</td>
<td>68.24</td>
<td>57.19</td>
</tr>
<tr>
<td>t3</td>
<td>9.38</td>
<td>98.76</td>
<td>1.24</td>
<td>90.62</td>
<td>88.35</td>
<td>9.38</td>
<td>54.07</td>
<td>16.96</td>
</tr>
</tbody>
</table>
Figure 50. Map illustrating the influence of temporal flooding events on the 2019 annual Forest change map obtained using the CFAR-KerCuSum t2-K6.5 product combination. Significant commission errors can be observed in the banks of the Turantsink creek associated with the presence of flood events during the period of study.

4.5.3.1 Closer look at forest changes

In this subsection, a visual investigation of forest disturbances was carried out in regions not covered by the previous validation. These additional forest changes were initially identified by visually investigating cloud-free single-acquisition and monthly composites of Planet imagery and subsequently compared to the CFAR-KerCuSum forest change masks. The exploration of these disturbances, distributed across the study area, provided a better picture of the detection capabilities of the detector, showing a high performance in the identification of small-scale forest disturbances of diverse nature (e.g. wildfires, farming clear-cuts) (Figure 51). Figure 51 illustrates two examples of these areas located outside the validation regions. The upper image succession shows the detection of a large fire event that occurred in September 2019 near the Crashwater community, while the lower images illustrate a deforestation event driven by the expansion of a small-scale agricultural farm located in the western region of Anai during the 2019 dry season. Both disturbances were successfully identified by the CFAR-KerCuSum detector, demonstrating high performance in edge delineation and versatility in the detection of diverse types of changes.
4.5.3.2 Validation with ground data

A final validation assessment was performed to investigate the most recent forest disturbances that occurred in the study area. A ground-team from the North Rupununi District Development Board (NRDDDB) undertook a field campaign to map as many recently deforested areas during the last months of the 2021 dry season (April and May). A total of 34 recently deforested sites were mapped. Forest disturbances’ GPS coordinates were directly compared against CFAR-KerCuSum results to assess the classification performance of the latter. Comparisons demonstrated that all the 34 sites had indeed been identified by the CFAR-KerCuSum change detector (see examples in Figure 52). However, comparison with Planet imagery suggested that some omission or miss-detection has occurred in highly challenging regions such as grasslands and forest-scrub transitional zones. Most of these miss-detections mainly respond to the direct exclusion of these dispersed forest areas from the analysis by not matching the ‘≥ 90%’ canopy coverage clause used for the forest mask. Therefore, a more detailed and comprehensive ground-truthing campaign, monitoring deforestation over extensive time periods and in different habitat types, will be required in order to further optimise the detector.
Among all the products evaluated the T2 K6.5 was selected as the most suitable forest change detection product. The results obtained for this combination showed a high performance, matching some pre-established accuracy criteria (OA ≥ 75%, UA ≥ 90% , TN ≤ 5%) while providing an optimum compromise between the true detection and false alarm rates (F1 ≥ 70%).

4.5.3.3 Occurrence analysis contribution to detection performance

The occurrence postprocessing analysis is an effective procedure to reduce false positives. False alarm mitigation strategies commonly rely on the use of minimum mapping units (MMU) or morphological filters (e.g. neighbourhood, sieve filters) that seek to reduce the number of false detections at expenses of spatial resolution (Bouvet et al., 2018). In this work, an alternative approach is implemented that does not entail a cost in the spatial resolution of the final maps since it relies on temporal information. It may therefore influence temporal resolution. The analysis showed that this processing step led to a reduction in false detections, yet the contribution in true detection remained minimal, thus having a positive impact on overall performance (Table 18).

Table 18. Table showing the influence of the temporal occurrence analysis on the True positive (*TP) and False positive (*FP) detection rates. Results obtained from the subtraction of the values resulting from t2 to those obtained for t1. It can be observed that the contribution to the reduction of false positives is greater for most of the probabilities evaluated. Katoka validation area, CFAR-KerCuSum derived 2019 annual forest change map.

<table>
<thead>
<tr>
<th>Probability</th>
<th>TP</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td>K 5.5</td>
<td>-0.372</td>
<td>-2.745</td>
</tr>
<tr>
<td>K 6</td>
<td>-0.237</td>
<td>-1.809</td>
</tr>
<tr>
<td>K 6.5</td>
<td>-0.372</td>
<td>-1.502</td>
</tr>
<tr>
<td>K 7</td>
<td>-0.440</td>
<td>-0.954</td>
</tr>
<tr>
<td>K 7.5</td>
<td>-0.609</td>
<td>-0.781</td>
</tr>
<tr>
<td>K 8</td>
<td>-1.150</td>
<td>-0.418</td>
</tr>
</tbody>
</table>
The results obtained for the $t_3$ variant showed a much lower performance suggesting that the use of long temporal windows may be counterproductive for the detection performance due to the fast dynamics of the ecosystem. The filtering clause utilised for '$t_3$' variant considers a 3-month time window, a period in which the ‘alerting’ response in the backscatter signal may be affected by the recovery processes of the vegetation. Unlike Temperate forests, previously investigated in Chapter 2 (Ruiz-Ramos et al., 2020), vegetation in Tropical forests show a significantly higher recovery rate. Past land use history strongly affects recovery rate, with untouched/secondary tropical forests being one of the natural systems with the fastest recovery rates to human-induced disturbances. (Holl, 2013). Large areas that have been used for industrial scale agriculture may recover more slowly that those used for shifting agriculture over shorter periods of time (Holl, 2007, 2013). Future research will focus on investigating the interrelationship between the time window of the occurrence analysis and the vegetation recovery periods using radar timeseries.

4.5.3.4 Deforestation trends in the North Rupununi Region

The evaluation of multiple combinations of the algorithm parameters generated a wide variety of products with diverse performances, providing different trade-offs between true detection and false alarm rates. The analysis in the previous section helped set the parameters of the detector. The following step was to investigate the current deforestation trends of the North Rupununi region. To do this, annual estimations of both the forest area loss and Above Ground Biomass loss were computed using the novel CFAR-KerCuSum tropical forest change detector.

When developing a new change detection monitoring tool, it is important to aim for a final performance that provides an optimal balance between the detection of disturbance events and the levels of false positives. Hence, the choice of the monitoring strategy is always a complex decision which is generally subject to 1. the nature of the environmental application to be studied and 2. the interpretation of the specific users or stakeholders that will make use of the tool. One of the most notable advantages of the CFAR-KerCuSum approach is that it allows the user to adjust various parameters such as the probability and confidence of detection, temporal or spatial resolution in a simple manner, thus generating a tool according to their specific preferences.

4.5.3.5 Annual Tropical forest area loss

Areas affected by annual forest change were calculated by merging all the disturbed areas detected during the annual study periods, during the dry seasons (September to April). For the annual deforestation area investigation, it was decided to use the forest change maps resulting from the CFAR-KerCuSum product with probability of false alarms 0.024 ($K = 6.5$) and Occurrence = $t_2$ (2
months). This specific product was selected as it provided a high confidence detection of true changes with false alarm rates within acceptable ranges. Once the annual change maps for each year (2018 - 2021) were extracted, they were exported to ESRI’s ArcMap GIS software (v. 10.6.1) where, after being geocoded, the final annual extension figures were extracted.

4.5.3.5.1 Redundancy post-processing analysis

The forest change redundancy analysis was implemented to deal with specific areas that were detected as experiencing changes on several occasion during the years. The land cover recovery periods (e.g. vegetation regrowth) can vary significantly depending on the typology of the disturbance (e.g. agricultural conversion, wildfire, clear-cuts) and the intensity of the event. This results in some forest disturbed areas being detected as changing over multiple years. Therefore, to eliminate potential errors associated with the inclusion of these changing/recovering areas in subsequent years, all following changes were not added to the analysis. Using the Erase tool (ArcMap 10.6.1) each annual mask was subtracted from its previous one (Figure 53). Figure 53 presents a graphical example of the redundancy analysis performed for the generation of the 2019 annual forest change map. Both the image (53.A) and (53.B) show the annual preliminary maps obtained for 2018 and 2019 respectively. Image (53.C) displays both masks together, where the detection of the same disturbance in both years can be observed (e.g. top polygon). Finally, image (53.D) shows the post-processed final map resulting from the elimination of redundant areas.

Figure 53. Annual forest change map - Erase tool graphical illustration. A) Forest Change map 2018, B) Initial Forest Change map 2019, C) Overlap Forest Change maps 2018 & 2019 and D) Final Forest Change map 2019: Erased | Elimination of Forest change 2018.
4.5.3.5.2 North Rupununi deforestation trends

The results of the annual forest change showed an increase in deforestation activity in the tropical forest of the North Rupununi for the past four years (2018 – 2021). These findings are consistent with the results obtained by previous studies (Roopsind, Sohngen and Brandt, 2019; WWF, 2020) that evidence an increasing deforestation trend at national level (Guyana). The results also demonstrate the influence of annual environmental and climatological patterns on deforestation rates. As shown in Table 19, the annual forest change area decreased in the last season analysed, 2021. This drastic reduction in forest disturbance is directly related to the climatological phenomena of 'La Niña'. La Niña is an oceanic and atmospheric phenomena, characterized by a large-scale cooling of surface temperatures in the central and eastern equatorial Pacific Ocean that generates higher than average rainfall events, which in turn cause prolonged catastrophic flooding events (Muñoz, 2017; NOAA, 2021a). This highly variable climatological phenomena generally occur every seven years in the North Rupununi region, with 2021 being the third most intense 'La Niña' year in the last two decades, after 2005 and 2006 (Kester, C., Civil Defense Commission Guyana; personal communication, 28th August 2021). Unlike in previous years, the 2021 wet season began much earlier, with important precipitation events from end February - March that coincides with the peak logging/fire season. The early-start of the wet season had a notable impact on activities for forest resources exploitation. It is highly likely that the hampered access and work in the forests, due to the impractical environmental conditions and poor state of the infrastructures (e.g. flooded areas, destroyed roads, torrential rains), has caused the reduction in logging activities.

Table 19. Total annual forest change for the tropical forests of the North Rupununi study region for the years 2018, 2019, 2020 and 2021. Values extracted from the CFAR-KerCuSum product with probability of false alarms 0.024 (K = 6.5) and Occurrence = r2 (2 months). Normalised percentages were calculated including forest area losses from previous years.

<table>
<thead>
<tr>
<th>Year (dry season)</th>
<th>Net area loss (ha)</th>
<th>Normalise forest annual loss (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2018</td>
<td>4007.792</td>
<td>-1.001</td>
</tr>
<tr>
<td>2019</td>
<td>5271.698</td>
<td>-1.329</td>
</tr>
<tr>
<td>2020</td>
<td>6953.971</td>
<td>-1.777</td>
</tr>
<tr>
<td>2021</td>
<td>2310.359</td>
<td>-0.601</td>
</tr>
</tbody>
</table>

The distribution of forest change showed a greater density of small-area (1-5 ha) disturbances in the vicinity of the majority of indigenous communities contiguous or surrounded by tropical forests. In Guyana, small-scale agriculture is also a primary driver of deforestation (Simpson et al., 2020). Most of the small new forest gaps located in the vicinity of these settlements correspond to small family farms which provide economic sustenance to the members of these communities (Mistry et al., 2021). The spatio-temporal analysis of these small-scale agriculture plots has shown a progressive growth of these areas during the total study period (see Figure 54). A significant expansion of the edges of these farms was observed during the 2020 period, coinciding in time with the appearance of the Covid-19 global pandemic. According to Mistry et al., 2021, many communities decided to expand
their farming activities in order to mitigate the economic impact derived from the pandemic. The influx of people into rural areas driven by job destruction and lockdown policies resulted in an increased population needing to farm for survival. In addition, many communities, especially those with easy access to main roads (e.g. Georgetown to Lethem road) felt vulnerable, leading many families to retreat to their farms for safety. These factors led to a transformation of consumption model during the pandemic period, with most communities experiencing a drop in commercial farming activities and an increase in subsistence farming (Mistry et al., 2021). Similarly, the results obtained in this study coincide with the conclusions obtained by Mistry et al., 2021, that indicate that farm size have progressively increased over this 2012-2021 time-period and that 71% of households surveyed grew a greater amount of crops in 2020 compared to previous years.

![Figure 54. Example of the annual forest changes for the Wowetta validation sites. Please note the progressive expansion of the small agricultural farms.](image)

Larger disturbances (> 5-10ha) appeared generally distributed in open areas of savanna or low scrubland located at a greater distance from urban settlements. These vast altered areas are mainly related to controlled wildfire events caused by members of these indigenous communities. The use and management of fire is highly integrated into the traditional knowledge of most of the indigenous communities living in this territory, where more than 90% of fires are caused by humans (Bilbao et al., 2019). The fire management system adopted by these communities is highly complex, integrating a wide variety of uses (e.g. domestic use, medicinal/healing and spiritual use, safety, animal
husbandry, fishing, agricultural use) and timings according to the season, times of the day, type of ecosystem and type of livelihood practice (Rodriguez et al., 2011; Mistry, Bilbao and Berardi, 2016). Although this study has not been able to extract the specific contribution of these fire events to the total annual forest changes, the results have shown a high occurrence rate of these events throughout all the years analysed, thus being recognised as one of the most relevant deforestation drivers for this region (Mistry, Bilbao and Berardi, 2016; Mistry et al., 2021).

In terms of the impact of these forest changes on the carbon stock, there was an annual reduction of \( \approx 1.2\% \) of the total forest area in the study area, which resulted in an estimated loss of 3931 Gg of carbon stock during the study period (Appendix B). As discussed further in Appendix B, the growing trend observed during the period investigated evidence a concerning deforestation rate that threatens the integrity of natural ecosystems as well as generates a direct impact on the natural carbon assets of the North Rupununi region.

4.5.3.5.3 Challenges and limitations

The interannual comparison of the final forest change maps allowed the identification of some anomalies that may have introduced errors in the classification maps. Despite the significant increase in deforestation activity for 2020, the forest change masks obtained for this year also showed higher false alarm rates mainly related to issues with the co-registration process of some images acquired during the 2020 dry season (September 2019 to May 2020). Google Earth Engine (GEE) platform's automatic image co-registration process uses a "rubber sheet" technique that stacks images together, allowing for slight translation differences between images (Google, 2021b). This co-registration process had implications for the final classification performance. Some images belonging to the 2020 time series showed an increase in false positive detections in near forest edges where the transition between forest and non-forest is sharp and co-registration error may result in the algorithms thinking the edge of the forest was removed (Figure 55). Transitional areas in which the forest-vegetation edge is more gradual did not show this issue. This finding suggests that minor co-registration issues can be a potential source of errors. Future optimizations will focus on the implementation of a more robust co-registration proceeding. Alternative approaches such as the utilisation of image displacement techniques or offline data processing, outside the GEE environment, will be investigated.
River borders and banks also appeared as challenging areas for the classification of forest changes. These regions showed higher false positive rates, especially in 2020 and 2021. The highly dynamic nature of these rivers, subjected to major flooding events and water level variation, cause significant transformations of the river basin. Transformations of the river basin can, in fact, result in significant modifications of the riverside vegetation, resulting in detection errors. Several masking processes, such as the elimination of riverbank areas by the application of an exclusion buffer, of variable radius, were considered. Nonetheless, it was finally decided to maintain these areas, since as indicated in GFC, 2021; these areas are generally subject to a high incidence of forest changes driven by small-scale mining activities. The generation and use of more accurate and updated water body maps will play a key role in the enhancement of confidence levels in these particularly challenging areas.

4.6 Conclusions

This Chapter demonstrates the capabilities of the Ker-CuSum change detection methodology for monitoring forest disturbances in highly dynamic Tropical forested areas. The development of the this automatic version of the algorithm (CFAR-KerCuSum) in the Google Earth Engine platform, resulted in a novel EO deforestation monitoring tool for tropical areas with enhanced functional characteristics (e.g. fully-unsupervised approach, higher spatial and temporal resolution, higher detection performance, user-friendly and easily implementable in other areas). The proposed CFAR-KerCuSum approach showed a high degree of accuracy in the detection of forest changes with Overall Accuracy values ranging from OA = 80.1% (F1 = 77.7%) to OA = 72.31% (F1 = 65.35%) and consistent high User Accuracies situated around UA = 90.5%. The integration of auxiliary data on forest Above Ground Biomass allowed expanding the research on the impact of current deforestation trends in the North Rupununi region, providing information on the rates of loss of forest
Enhancement of the Ker-CuSum for non-stationary environments: Current deforestation trends in Tropical forests of the North Rupununi

carbon stocks. Results obtained in this Chapter showed a progressive increase in deforestation rates in the North Rupununi region for the study period (2018 - 2021). Likewise, the results obtained in this chapter showed a progressive increase in deforestation rates in the North Rupununi region for the study period (2018 - 2021). Furthermore, this research identified an increase in forest degradation events caused by small-scale agriculture, directly associated with the expansion and opening of new farm sites as a measure to alleviate the economic damage derived from the Covid-19 pandemic. CFAR-KerCuSum appears as the first continuous SAR-based forest monitoring system for the North Rupununi region, providing accurate and continuous information on the conservation status of forests and deforestation patterns in this region.

4.6.1 CFAR-KerCuSum optimization

The novel CFAR-KerCuSum change detection algorithm emerges as an effective change detection algorithm for monitoring forest disturbances in highly dynamic tropical environments. The investigation of Sentinel-1 image timeseries showed significant differences in the SAR signal between the altered and intact forested areas, which were in fact enhanced by the value’s cumulative strategy of the Ker-CuSum method. Both polarized channels showed a clear decrease in intensity values for the affected areas, being the co-polarized channel (VV) the one that showed a greater sensitivity to structural forest changes. The automatization of the thresholding approach, using the Constant False Alarm Rate (CFAR) method and the post-processing occurrence analysis must be recognised as the most remarkable optimizations, having a significant impact on the final detection performances. The new thresholding strategy played a crucial role in the transformation of the previous Ker-CuSum version into a fully unsupervised tool. Similarly, the occurrence analysis proved its effectiveness in the reduction of the false alarms as well as in the enhancement of the detection confidence rates.

4.6.2 The North Rupununi deforestation trends

The annual forest change analyses performed for the North Rupununi indicated a rise in the forest degradation rates in recent years. These results agree with previous studies (Roopsind, Sohngen and Brandt, 2019) which found a growth in the national deforestation activity since the completion the REDD + program, mainly related to the reduction of the aid provide by this project. Similarly, the high density of small new forest gaps in areas adjacent to indigenous communities point to small-scale agriculture as the main driver of forest disturbance for this region. Likewise, the social and economic setbacks derived from the global Covid-19 pandemic led to a notable growth in
agricultural activity, resulting in an expansion of many of the existing pre-pandemic agricultural areas. This progressive growth in forest degradation rates was also reflected in the Above Ground Biomass annual loss figures, accounting a total of 3931.61 Gg of carbon stock loss for the 2018-2021 period (Appendix B).

This research served to highlight the importance of having access to consistent and reliable forest monitoring systems that allow not only the assessment of current forest conservation health and status, but a detailed analysis of the forest degradation and deforestation trends and patterns supported by accurate long-term environmental data. The findings of this study significantly contributed to the Mistry et.al, 2021 Darwin Initiative - Covid-19 Rapid Response project, helping to investigate the short-term biodiversity, traditional knowledge, and livelihood impacts of the Covid-19 pandemic in Indigenous forest-based rotational farming.

### 4.6.3 Limitations and future improvements

Despite the overall high performance shown by the CFAR-KerCuSum detector, certain limitations were identified. The highly dynamic nature of the region of study presented a challenge in the monitoring of forest disturbances with low false positive rates. The great inter- and intra-annual environmental variability of the North Rupununi region significantly conditioned the study of natural landscape transformations. Temporal flooding events had an influence on the classification performance since they were responsible for large part of the commission errors, especially during the transitional/interseasonal periods close to the end and start of the wet season. High false positive rates were observed on extensive vegetated flood plains as results of seasonal flood events misclassified as forest changes. The main contribution to this error comes from the input land cover data source used for extracting the reference forest mask. The utilisation of more accurate land cover data can potentially contribute to mitigate these classification errors. Updated Land cover and Land use global maps, such as the recently published ESRI’s Global High Resolution (10 m) Land Cover 2020 map (Karra et al., 2021), would provide reliable information on the environmental characteristics of the study areas, thus allowing the use of diverse land cover-based filtering processes (e.g. land cover penalty scoring) that favour the reduction of high the false positive rates. Incorporating these updated land cover maps into the Google Earth Engine environment will have a significant impact on the implementation, use and performance of the CFAR-KerCuSum change detector in other tropical forest regions of the world.

Future research will continue exploring the potential capabilities of the Ker-CuSum tool, focusing on the investigation of forest change detection performance in other tropical regions of the planet. Similarly, the adaptation of this method to single acquisition timeseries will allow its direct
comparison with some recently published high-performance forest monitoring tools such as the GLAD-S2 or the Sentinel-1 based RADD alerts.
5 Chapter

Conclusions
5.1 Main Results

There is a need for satellite-based environmental monitoring to adapt to the latest advances in remote sensing in order to provide rapid and accurate information on the dynamics and changes of natural ecosystems. The development of new environmental monitoring strategies that exploit the high monitoring capacities of current satellite data stands as a crucial point in the global fight against environmental degradation and climate change (Vorovencii, 2011; Pettorelli, Safi and Turner, 2014). Optical remote sensing has historically dominated Earth Observation (EO) research, being commonly used to investigate the environmental dynamics of natural ecosystems. The large imagery archive generated by some long-running optical satellite programs such as the Landsat program which stretches from 1972 to the present, provides researchers with unique resources for global-change studies and long-term environmental investigations (Wong et al., 2021). Nonetheless, optical remote sensing has limited applicability for continuous or near-real-time environmental monitoring, especially in regions with persistent cloud cover (e.g. tropical regions). This makes SAR sensors a highly valuable solution for large-scale environmental monitoring as they provide consistent and continuous data, regardless of weather conditions, cloud cover, or absence of daylight. Nonetheless, most current SAR-based change detection systems present certain limitations. Sparse data frequencies, single-event investigation, site-specific approaches or high computational requirements are examples of hindrances to the use of these systems for continuous environmental monitoring.

To mitigate these limitations, this thesis aims to advance SAR dense time series based methods based, exploiting the high detection capabilities of cumulative sum strategies for near-real time and continuous monitoring of permanent and temporary environmental disturbances. This Chapter focuses on summarising the key results of the four main research questions that have been addressed in previous data chapters. In Section 5.2 an overall reflection is provided on the continuous process of design and development of the proposed methodologies and their contribution to environmental dynamic monitoring. This section also pays attention to the main research limitations encountered and provides an insight into some of the current and future research lines. The final Section 5.3 presents a summary on the contribution of this PhD research to environmental remote sensing science.

1. How can we exploit the advantages of multi-temporal SAR dense timeseries and cumulative sum strategies for detecting historical forest structural disturbances?

Forest degradation is recognized as a major environmental threat on a global scale (Rudel, 2009; Defries, 2013). The recent rise in natural and anthropogenic degradation of forested ecosystems highlights the need for developing new, rapid, and accurate RS monitoring systems, which capture
forested land transformations. Optical RS sensors have been commonly used for detecting forest degradation processes (Hansen et al., 2013), however, the requirement of certain technical and environmental conditions (e.g., sunlight, not cloud-coverage) significantly restrict their use for continuous monitoring of forest ecosystems (Verbyla, Kasischke and Hoy, 2008; Rüetschi et al., 2019; Tanase et al., 2019). For European temperate forests, most forest degradation events are primarily driven by natural disasters such as fires and windstorms (Schelhaas, Nabuurs and Schuck, 2003; Seidl et al., 2014). For our study site in the western forest of Scotland, recurrent Atlantic windstorms have significant ecological and economic impacts on managed forest areas (Forest Research, 2018). However, the detection and monitoring of these small-scale forest disturbances through common optical imaging photointerpretation is restricted due to persistent cloud cover. In contrast, Sentinel-1 C-band SAR emerged as the best choice to overcome these limitations due to its capability to provide reliable information on forest degradation processes in a consistent and rapid way. Nonetheless, there is still lack of continuous monitoring methods that fully exploit the potential monitoring capabilities of Sentinel-1 dense timeseries (Hostert et al., 2015).

To overcome the latter limitations, Chapter 2 presented a novel C-band SAR-based change detection methodology for mapping permanent forest structural changes in a continuous and near-real-time manner using dense Sentinel-1 time-series. Our cumulative sum (CUSUM-SAR) algorithm is based on cumulative sum statistical analysis and allows to monitor permanent forest structural changes. Taking advantage of the high temporal resolution of the Sentinel-1 (S-1) constellation, we used ground range detected (GRD) dual (VV and VH) polarisations timeseries. This resulted in a total of 84 images acquired between 01 January 2018 and 30 September 2019, to monitor clear-cutting operations carried out in a Scottish forest plantation during 2019. The lack of reliable information on small windthrow events led to consider controlled logging activities as the best scenario for testing the new methodology. In addition to the implementation of the CUSUM method proposed by Manogaran and Lopez, 2017, we presented an innovative version of the original approach based on the modification of the reference period calculations. The new CUSU-SM (as called in the published article) uses the spatial domain to calculate the reference values, contrary to the CUSUM, which calculates the forest reference values from a temporal aggregation of the time series. Using the forest type classification from the 2018 Scottish National Forest Inventory, we investigated the behaviour of the SAR signal for the time series. The comparative analysis of the backscatter signal for both approaches served to identify the constant divergence of the CuSums values for the CUSUM-SM strategy. This constant divergence, especially observed for 'broadleaves' forests, responds to forest pixels having a natural higher (or lower) backscatter than the forest reference mean value, thus causing a constant change that acts as a bias and accumulates over time forming a ramp. To overcome this issue, we developed a bias correction strategy, where the constant temporal change was removed from the timeseries. The proposed correction improved the final detection performance (OA = +5%; F = +4.3%), as a result of a significant reduction of false positives (FP = -6.7%) . Regarding the
Conclusions

detection strategies, similar overall performances were observed for both the CUSUM (OA = 73.6%; F = 69.5%) and the CUSU-SMC (OA = 65.7%; F = 68.0%). With the cross-polarized channel (VH) consistently showing higher sensitivity to forest structural changes (OA_{CUSUM}: VH = 73.6%; VV = 62.1%), the CUSUM method appeared as the most conservative strategy, providing a medium-high performance in the detection of true positives (TP = 60.2%) and high performance in the rejection of false positives (FP = 13.0%). Contrary, the CUSU-SMC offered higher true detection rates (TP = 72.4%) but significantly higher false alarm rates (FP = 40.6%), thus standing as a more permissive/tolerant approach. Postprocessing morphological filtering techniques added between 3.6 - 5.0% to the overall accuracies and 3.5 - 7% to F-score values as a result of the significant reduction of false alarms.

Compared to commonly adopted pairwise image change detection methods, both CUSUM and CUSU-SMC showed significantly higher performance in the detection of forest logging activities (Figure 56).

![CuSum - Pairwise comparison](image)

Figure 56. The CUSUMs approaches were the ones for conservative (*C) and tolerant (*T) strategies. TP = true positives, TN = true negatives, FP = false positives, FN = false negatives, OA = overall accuracy, PA = producer accuracy, UA = user accuracy.

Results of Chapter 2 demonstrated the high capabilities of the CuSum method for monitoring permanent environmental disturbances. The new CuSums algorithms proved to provide fast detection rates (early warning/rapid response), standing out as a valuable monitoring tool for foresters/forest managers; reducing both the current response times of optical-based products and the costs and efforts, when evaluating forest damage.

This work appears as the first adaptation of the cumulative sums’ method for continuous monitoring of forest disturbances. These results revealed the high versatility of this method, showing its potential suitability for monitoring other environmental disturbances in highly dynamic environments.
2. **How can we expand/adapt the capabilities of the CUSUM detector to other (highly dynamic) environmental monitoring scenarios?**

Wetlands are some of the most important and valuable ecosystems on Earth. They perform important eco-hydrological functions, providing a wide range of ecosystem services while play a key role in global carbon cycles. Socio-economic pressures exerted by large-scale mining and agricultural development together with the high vulnerability of these fragile ecosystem to environmental disturbance, such as climate changes, are leading to a rapid degradation and loss of these landscapes on a global scale (Davidson, 2014; Finlayson et al., 2018; Salimi, Almuktar and Scholz, 2021). The management and conservation of these wetlands require robust and operational satellite-based monitoring systems that provide near-real-time and accurate information on their environmental conditions. Optical satellite data (e.g. Landsat mission) have been sparsely used for flood and wetland mapping (Guo et al., 2017). However, the use of optical satellite data for operational monitoring of wetlands is restricted due to atmospheric disturbances such as cloud cover and intense precipitation events, that in some regions (e.g. tropical, sub-tropical) last for long periods of time because of the monsoon cycles. The current C-band SAR mission Sentinel-1 provides more consistent data acquisition schemes due to its high temporal resolution (6 - 12 days).

Since Chapter 2 focused on the monitoring of permanent forest disturbances, the potential capabilities of the CuSum method for monitoring non-permanent disturbances remained unexplored. Moving from the temperate forest of Scotland (Chapter 2) to the North Rupununi wetlands in central Guyana (Chapter 3), the test of the CuSum approach for monitoring temporary environmental disturbances in highly dynamic scenarios (seasonal wetland ecosystem) was attempted.

Chapter 3 presented an adaptation of the original CUSUM-SAR (Chapter 2) algorithm for detecting seasonal open-water and flooded-vegetation areas. Using a dense Sentinel-1 time series composed of 118 dual (VV and VH) polarization GRDs images acquired for the years 2017 to 2020, we investigated the performance of the CUSUM approach for flood mapping. The assessment of the original CUSUM-SAR method (Chapter 2) for temporary disturbances demonstrated the poor capabilities of this approach to identify environmental changes that only last a short amount of time (e.g. temporary flood events). Hence, Chapter 3 proposes a new way of looking at the CUSUM-SAR, interpreting it as an integral transformation of the differences between acquisitions and a reference. The new Ker-CuSum approach was successfully used for the detection and characterization of 'open water' and 'flooded vegetation' regions. The ratio combination (VH / VV) showed the best performance for the identification of 'open-water' areas. This is due to a significant decrease in the backscatter intensity associated with specular scattering mechanisms. The co-polarized (VV) channel performed better for the derivation of 'flooded-vegetation' areas, showing significant increases in the signal intensity coinciding with growth of wet vegetation during the rainy season. These results are consistent with previous C-band wetland mapping studies (Twele et al., 2016; Landuyt, Verhoest
Conclusions

and Van Coillie, 2020) that found VV channel as the most sensitive to double-bounce mechanism and VH channel to specular reflection. Conversely, these results disagree with Tsyganskaya et al., 2018a, who identified the VV as the most suitable polarisation for 'open-water'. These discrepancies suggest that environmental site-specific parameters (e.g. wetland typology, vegetation typology and structure, qualitative water parameters) may exert an important influence on the dominant signal scattering mechanisms.

The proposed Ker-CuSum demonstrated that both ‘open-water’ and ‘flooded-vegetation’ areas can be continuously mapped with a high degree of accuracy, providing classification performances similar to previous studies (Twele et al., 2016; Tsyganskaya et al., 2018a, 2018b; Hardy et al., 2019; Alexandre et al., 2020; Landuyt, Verhoest and Van Coillie, 2020). For the ‘open-water’ class, results revealed a very high overall accuracy (OA= 0.93; Kappa= 0.87) with a high detection performance on ‘open-water’ bodies and a neat delineation of the edges. However, when we add the flooded-vegetation class, we obtain a lower overall performance (OA = 0.79). The results for the combined classification drop due to the significant overestimation of ‘flooded-vegetation’ areas. These lower performance agree with previous studies which also identified the detection of ‘flooded-vegetation’ areas with C-band as a major challenge due to overlap in the signal backscatter values between the ‘dry-land’ and ‘flood-vegetation’ classes (Cazals et al., 2016; Plank et al., 2017; Hardy et al., 2019). Despite this, the quantity and allocation disagreement metrics showed a good overall agreement between the classification map and validation data (mean C = 0.81). The high producer accuracies obtained for both ‘open-water’ (PA= 91.2%) and ‘flooded-vegetation’ (PA= 74.1%), demonstrated the high capabilities of the Ker-CuSum method for monitoring seasonal variations in natural wetlands. The inclusion of ancillary data into the postprocessing chain had a significant impact on the final results, playing a crucial role in the enhancement and optimization of the Ker-CuSum Sentinel-1 derived flood maps.

Chapter 3 represents the first effort to map and monitor in a near-real-time and continuous manner the hydrological dynamics of the North Rupununi wetland using only data from Sentinel-1, providing a useful tool which could be integrated into rapid response and wetland conservation management plans.

3. **How can we development a new user-friendly and fully operational SAR-based environmental tool?**

SAR data processing involves a great deal of time-consuming computation due to the numerous data processing steps involved (Gulácsi and Kovács, 2020). This often makes it difficult to translate monitoring systems into operational real-time monitoring tools. Furthermore, remote sensing (RS) systems have been collecting massive volumes of data sets for decades, which have been commonly managed and analysed using common software packages and desktop computing resources (Amani et al., 2020). Cloud-computing science has revolutionized the world of RS since its appearance in
2010 as a strategy to speed up processing and share huge amounts of digital data (so-called Big Data). Cloud-computing allows scientists and users alike to store, access and analysis large datasets in a more efficient and faster way (Chi et al., 2016; Amani et al., 2020). Google Earth Engine (GEE) emerges as one of the most recognised cloud-computing platform (Gorelick et al., 2017; Mullissa et al., 2021). Designed specifically to facilitate the processing of big geo data on large scales and for long periods of time, GEE aims at: (i) speed up satellite data processing, (ii) upscale it to a planetary scale, and (iii) help researchers to easily disseminate their results (Gorelick et al., 2017; Gulácsi and Kovács, 2020). One advantage of the GEE platform is that it allows the rapid adaptation of the processing chain when it comes to location and data types. In this context, the large RS data archive hosted on Google servers together with the extensive embedded catalog of scientific-libraries and custom-build functions represented a notable asset when testing and performing algorithm optimizations. These platforms significantly contribute to saving time and effort in the algorithm’s development since no download and basic pre-processing of raw imagery is required.

One of the main objectives of this thesis has been the search and development of systemic and solution-focused approaches for environmental monitoring. Once the high performance of Ker-CuSum was proven, we focused on the design and development of an operational tool on a cloud-computing environment (GEE)

Taking advantage of the implementation of the new Ker-CuSum method into the Google Earth Engine platform, we proceeded to develop a web mapping tool that would serve both community members and environmental institutions to map location and extent of the North Rupununi floods. The competitive advantage of our GEE-CUSUM App resides in the robust statistical framework of the Ker-CuSum capable of including information coming from long time series of data in a semi-supervised fashion which therefore does not require building time-consuming ad-hoc models. An important consideration in the development of this application was the participation of potential users (indigenous communities) in the design of the web application. Since this web-app was intended to be used as a real-time environmental information tool, a user-oriented interface (e.g. user-friendly, non-expertise requirements, user-oriented interpretability) was needed. Continuous communication with potential (product-testers) users and diverse Guyanese stakeholders (e.g. NRDB, Iwokrama International centre, Civil Defence Commission) provided us with valuable feedback on the user’s and functional requirements, and technical specifications. The final web-application was the first continuous automatic wetland monitoring tool for the North Rupununi wetland, providing automatic and near-real-time information (12-date updating period) on the ‘open-water' and 'flood-vegetation' areas.

Compared to other computer Deep Learning solutions, our tool provides a less computational demanding and more scalable solution, allowing solutions to be adapted to a range of contrasting
environments relatively quickly and without the need to re-build training data sets or changing architectures through:

i) **No labelling** - The algorithm can automatically identify the reference backscattering by looking at the time series and ancillary climatological information. The cost of image analysis is thus reduced since introducing a new region will not require hiring an EO-analyst to label flooded areas either by performing ground measurements or using eventual (and maybe expensive) cloud free high-resolution optical images.

ii) **Reduced processing time** - since we do not use numerical optimisations (only analytical solutions for extracting probabilities), the processing time is quick and does not require high computational requirements, enabling its usability over regions with poor communication infrastructure.

iii) **Adaptability** - The high adaptability of the CuSum method for monitoring environmental dynamics and disturbances of various types (e.g. temporary or permanent), which has already been assessed in various ecosystems (e.g. wetland, forest), represents an important cost advantage when integrating this solution into new regions or new applications. Its implementation as a fully operational system within a cloud-computing environment such as GEE together with the uncomplicated and robust nature of the algorithm will help reduce costs and efforts when integrating this tool into other environmental monitoring systems.

Utilizing cloud processing platforms such as GEE, that provides users with pre-processed and analysis-ready-data, helped to speeding up the geoprocessing and analysis of Sentinel-1 C-SAR data. To date, the CUSUM flood application has been used by numerous communities in the region exposed to recurring seasonal floods. Likewise, Guyanese environmental institutions such as the Civil Defence Commission and the Environmental Protection Agency have shown their interest in this tool, highlighting its usefulness for the conservation of these natural ecosystems and considering its inclusion in the monitoring, management, alert and damage assessment programs.

It is expected that cloud-computing solutions continue growing during the next years and that platforms such as GEE will be utilized by more users from different fields to resolve their big data processing challenges (Amani et al., 2020). Numerous EO data science projects and programs are moving towards integrating their data sets on cloud computing platforms, such as Google Earth Engine, to exploit the wide research possibilities offered by the multi-petabyte on-line catalogue of satellite imagery and geospatial datasets (Amani et al., 2020; GEO, 2020). The recent announcement of the integration of Planet into GEE, is one of these examples, that may be of relevance to researchers who could perform validation analyses in the GEE platform, making this more efficient. This current trend in the migration of big data analysis to cloud computing solutions favours the use
Chapter 5

of the algorithms developed in this thesis since this will facilitate the application of these methods for a wider range of datasets.

4. How can we modify the CUSUM algorithm for fully-unsupervised tropical forest monitoring and above ground biomass loss estimations?

Chapter 4 presented the third adaptation of the CUSUM algorithm, the CFAR-KerCuSum, which is designed to perform historical deforestation monitoring in a fully unsupervised and automatic way.

To address the limited availability of RS based forest monitoring systems that accurately detect forest degradation and small forest changes over tropical regions (Hirschmugl et al., 2020), Chapter 4 presents a modification of the Ker-CuSum (Chapter 4) approach to mapping tropical forest disturbances improving the temporal resolution (monthly) of the current operational forest monitoring systems available for the study region. The North Rupununi tropical forests appeared as an ideal scenario for the evaluation of the proposed methodology given the lack of updated systems that provide rapid and accurate information on forest degradation events. As part of the REDD+ reporting framework, Guyana's current forest monitoring systems relies on the Multi-year Monitoring Verification and Reporting System (MRVS). Guyana's MRVS tracks forest change, both deforestation and degradation, through outdated and time consuming methods, visually interpreting and digitizing a national coverage of high resolution optical satellite imagery (GFC, 2018, p. 33).

To perform this final modification, we took advantage of the previous work carried out in the GEE platform (Chapter 3), making use of dense GRD-dual polarisation Sentinel-1 time series available for the North Rupununi region - same data used in Chapter 3. A temporal (monthly) average was applied to the pre-processed Sentinel-1 image collection to scale down the forest random signal variation. The new CFAR-KerCuSum focuses on the automation of the disturbance detector through adaptation of 3 main aspects: i) implementation of radiometric terrain correction, ii) reinterpretation of the thresholding approach and, iii) post-processing change occurrence analysis. The addition of the radiometric angular-based slope correction (Small, 2011; Vollrath, Mullissa and Reiche, 2020) significantly contributed to enhance the usability of the algorithm, enabling its use on sloped terrain and allowing eventually adoption of multi-orbit approaches. The new Constant False Alarm Rate (CFAR) thresholding strategy represented the larger change to the Ker-CuSum (Chapter 3) performed in Chapter 4. This allows the detection of forest changes in an automatic and fully unsupervised way. Lastly, the change occurrence analysis reduced false alarms, accounting for an improvement of the detection performance of \( \approx + 1.2\% \) in OA. In Ygorra et al., 2021, the authors combine the CUSUM-SAR method (Chapter 1), with the (Kucera, Barbosa and Strobl, 2007; Kellndorfer, 2019) bootstrapping validation strategy to achieve an automatic system for tropical forest monitoring. However, the computational time of this approach is expected to be more demanding as a result of the greater computational requirements of the validation method. Similarly, the development of the CFAR-KerCuSum in cloud-computing environments (GEE) enhances the
versatility of this method as it may significantly reduce the time and cost when applying it to other forest regions.

CFAR-KerCuSum showed similar accuracies to previous Sentinel-1 time-series based forest detectors (Reiche et al., 2017; Bouvet et al., 2018; Hoekman et al., 2020; Ballère et al., 2021; Ygorra et al., 2021), standing as the best version of the all CuSum strategies developed in this thesis. The co-polarized channel (VV) showed the highest accuracy for the detection of forest structural changes, obtaining consistent high User Accuracy (UA) values situated around UA = 90.5% and Overall accuracy up to OA = 80.1% (F1 = 77.7%). Moreover, the integration of auxiliary data on above ground biomass allowed the evaluation of the annual loss of carbon stocks, thus obtaining information on the impact / consequences of these landscape alterations (Appendix B).

The adaptation of the Ker-CuSum method for the investigation of tropical forested disturbances in North Rupununi reveals the high capacities and great versatility of the CuSum strategy for continuous environmental monitoring, allowing the study of various environmental dynamics (e.g. seasonal-flooding and forest-changes) from a unique monitoring tool.

Table 20 presents an overview of the overall contribution of this thesis to environmental remote sensing monitoring, classifying these contributions for each of the different algorithms developed in this work.

### Table 20. Main types of contribution to satellite environmental remote sensing monitoring. Classification of the various methods and modifications presented in this thesis.

<table>
<thead>
<tr>
<th>Algorithm version</th>
<th>Demonstrated in</th>
<th>Contribution</th>
<th>Dissemination</th>
</tr>
</thead>
<tbody>
<tr>
<td>CUSUM-SAR</td>
<td>Chapter 2</td>
<td>Continuous forest monitoring tool First implementation of CUSUM method to SAR timeseries</td>
<td><em>Rem. Sensing</em> Journal article ESA Living Planet 2019</td>
</tr>
<tr>
<td>CUSUM-SMC</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ker-CuSum</td>
<td>Chapter 3</td>
<td>Adaptation to temporary environmental disturbance detection Adaptation to wetland mapping and characterisation applications Development of cloud-based operational NRT flood mapping service</td>
<td>InGARSS 2020 PolInSAR 2021 IGARSS 2021 Journal article (In process)</td>
</tr>
<tr>
<td>CFAR-KerCuSum</td>
<td>Chapter 4</td>
<td>Optimization to fully unsupervised change detection Adaptation to Tropical forest context Detection confidence enhancement by occurrence analysis Integration of auxiliary data for annual estimates of AGB</td>
<td>ESA Living Planet 2022 Journal article (In process)</td>
</tr>
</tbody>
</table>
5.2 Reflection & outlook

This section presents a comprehensive reflection on the environmental monitoring capabilities of the methods proposed in this thesis, paying attention to the main limitations encountered in this research and providing an insight into some of the current and future research lines.

5.2.1 Method comparisons

This thesis presents the developments of the CuSum method for environmental monitoring using dense SAR timeseries. From the first implementation of the CuSum algorithm for permanent forest disturbance monitoring (Chapter 2) to the final adaptations to highly dynamic environments (Chapter 3 and 4), this thesis presents a series of SAR-based change detection tools whose performance needed to be compared. Therefore, taking advantage of the work carried out in the North Rupununi study area for tropical Forest monitoring (Chapter 4), the next section presents a final comparison of some of the methods proposed in this thesis. Specifically, we compare the latest modification in this thesis, the CFAR-KerCuSum with previously developed methods such as CUSUM and direct Pair-wise (Chapter 2). Similarly, the performance of all Sentinel-1-based methods was compared to the annual GLAD forest, commonly used by most global forest monitoring initiatives such as REDD +.

The detection performance of each method (CFAR-KerCuSum, Pairwise, CUSUM-SAR) was assessed by using standard accuracy metrics (Overall Accuracy, User Accuracy, Producer Accuracy and F-score). Accuracy confusion matrices were extracted by comparing the method’s derived classification forest change masks against the reference ground-truth map.

5.2.1.1 CUSUM and Pairwise change detection comparison

To gain a better insight into the capabilities of each approach for tropical forest monitoring, it was decided to investigate both the a) static Pairwise and b) CUSUM-SAR (Ruiz-Ramos et al., 2020) change detection algorithms, presented in Chapter 2.

a) Pairwise method: This methodology follows the common direct pairwise change detection, by which two acquisitions acquired at different times are directly compared.

\[ \text{Pairwise}_i = I_i - I_{\text{ref}} \text{ for } i = 1, 2, ..., N \]  \hspace{1cm} (20)

where, \( i \) is an iteration over time. \( N \) is the total number of acquisitions used in the training dataset. \( I_{\text{ref}} \) is the reference image computed for the comparison. The image \( I \) used for the analysis corresponds to a pre-processed monthly composite image.
b) **CUSUM-SAR**: As stated in (Ruiz-Ramos *et al.*, 2020), this method is the cumulative sum of the differences between the values and the reference average image. This is:

\[
\Sigma_d = \sum_{t=0}^{N} I_t - I_{ref}
\]  

(21)

Where \(N\) is the total number of temporal samples, \(I_t\) represents a sample take at time \(i\).

### 5.2.1.2 Global Land Analysis and Discovery (GLAD) deforestation data

An additional optical-based product for loss of tree cover was used to assess the detection performance of each algorithm. The annual Tree Cover Loss map, developed by the Global Land Analysis & Discovery (GLAD) laboratory at the University of Maryland in collaboration with Google, United States Geological Survey (USGS), and NASA, measures areas of tree cover loss across all global land at approximately 30 × 30 meter resolution (Hansen *et al.*, 2013). Annual forest masks were generated using multispectral satellite imagery from the Landsat mission (Landsat-5 (TM) and Landsat-7 (ETM +), Landsat-8-9 (OLI)), defining 'tree cover' as all areas covered by vegetation greater than 5 meters in height, without distinguishing between the form of natural forests or plantations across a range of canopy densities (Hansen *et al.*, 2013; Global Forest Watch, 2021). The updated 1.8 version of the GLAD global forest change product, containing the annual forest loss masks from 2001 to 2020 year, was downloaded from the GLAD-Google servers, using the 0-10N-50-60W 10 x 10 degree tile covering the area of study (Hansen/UMD/Google/USGS/NASA, 2021). Lastly, both the tree canopy cover map for the year 2000 and the forest loss masks for years 2018 and 2019 were extracted, down-sampling the rasters to 10-meter pixel resolution using the bilinear interpolation resampling tool contained in the data management toolbox of ESRI ArcGIS Desktop 10.6.

### 5.2.1.3 Method’s comparison validation analysis

The detection performance of each method (CFAR-KerCuSum, Pairwise, CuSum-SAR) was assessed by using standard accuracy metrics (Overall Accuracy, User Accuracy, Producer Accuracy and F-score). Accuracy confusion matrices were extracted by comparing the method’s derived classification forest change masks against the reference forest change ground-truth map. Lastly, the performance of the optical-based GLAD annual forest loss mask was also evaluated and subsequently compared with the rest of-Sentinel1-based detectors.

The validation analyses were carried out using the same forest change maps used in Chapter 4. Hence, the detection performance of each method was assessed for the identification of forest disturbances, which occurred during the 2018 and 2019 dry seasons, over the three regions of interest (Wowetta,
Yupukari and Katoka). Similarly, all detectors were tested using the same Sentinel-1 (monthly composite) timeseries used in Chapter 4. The same pre- and post-processing steps were used for all SAR methodologies. The thresholds were all applied using the Constant False Alarm Rate (CFAR) with the same probability of false alarm (0.027; $K_6$) except for the CuSum approach, where a manual threshold (CuSum value ≤ 5) was used as it provided better results.

5.2.2 Methods performance discussion

5.2.2.1 CFAR-KerCuSum vs alternative change detectors

Figure 57 shows a comparative analysis of the different SAR-based change detection methods: CFAR-KerCuSum, PairWise, CuSum) and optical-based products (GLAD annual forest map). Among all the methods tested, the CFAR-KerCuSum approach stood out as the best product for monitoring forest changes (PA= 61.4%, OA= 76.8%, F1= 0.73), providing a significantly higher detection performance than those obtained for the rest of the approaches.

5.2.2.1.1 Pairwise method

The Pairwise showed significantly lower performances compared to CFAR-KerCuSum. As shown in Figure 57, the pairwise approach provided a notable underestimation of true detections (PA = 49.7%) demonstrating the limited detection capabilities of this method. Despite the Overall Accuracy figures are similar (Pairwise OA = 73.07%; CFAR-KerCuSum OA = 76.78%), the values obtained for the F-score (Pairwise F1 = 0.64; CFAR-KerCuSum F1 = 0.73) showed a remarkably better trade-off between precision and recall for the CFAR-KerCuSum method.

![Change detection performance comparison](image)

Figure 57. Reference comparison of the main accuracy metrics obtained for the CFAR-KerCuSum (red), pairwise (yellow), CuSum (green), Sentinel1-based change detectors, and GLAD-based annual forest map Landsat (blue). Results extracted for the product combination K6 t2 (CFAR-KerCuSum, Pairwise) and CuSum value (THD ≤ 5) (CuSum). OA = overall accuracy, PA = producer accuracy, UA = user accuracy and F1= F-score.
5.2.2.1 CuSum method

The results obtained for the original CuSum approach support the idea that the greater integral time makes it ideal for monitoring more static/stable environments in which the targets to be studied show less dynamics (e.g. mono-species plantation forests, urban areas). Nonetheless, the utilization of the CuSum in highly dynamic environment, as in the case of the North Rupununi region, may lead to poor detection performances. With the worst performance of all the evaluated methods (PA = 45.2%, OA = 61.6%, F1 = 0.54), the results obtained for CuSum suggests that the high heterogeneity in the structure and plant typology of these forests has negatively impacted the detection performance. This forest heterogeneity has led to the continued change over time generated by the difference existing between specific pixel values and the forest reference mean composite, a fact that has consequently resulted in notable classification errors associated with high false positive rates (See FP, Figure 58).

![Change detection method comparison](image)

Figure 58. Detailed accuracy metrics obtained for the CFAR-KerCuSum (red), pairwise (yellow), CuSum (green), Sentinel1-based change detectors, and GLAD-based annual forest map Landsat (blue). Results extracted for the product combination K6 t2 (CFAR-KerCuSum, Pairwise) and CuSum value (THD ≤ 5) (CuSum). TP = true positives, TN = true negatives, FP = false positives, FN = false negatives, OA = overall accuracy, PA = producer accuracy, UA = user accuracy and F1 = Fscore.

5.2.2.1.3 GLAD annual map

The investigation of the detection performance of the optical-based GLAD annual forest map (Hansen et al., 2013) demonstrated the higher capabilities of the CFAR-KerCuSum approach (OA = +4.08%, F1 = +8.6%) for the detection and evaluation of forest changes. The results obtained for the Landsat-based forest change detector showed figures very similar to those obtained for the pairwise method, characterized by a low detection capacity, with true detection (TP = 48.6%) and false positives (FP = 3.2%). With 38.6% of omission error, the CFAR-KerCuSum method provides a better detection of the deforestation pixel than GLAD (51.4% of omission error). On the other hand,
the GLAD alert generates fewer false detections (3.2% of commission error), versus the 7.8% of the CFAR-KerCuSum. These results coincide with recent research which also identified substantial omission errors in the GLAD detector (up to 80%) (Perbet et al., 2019; Price and Elsner, 2022). These results differ significantly from the accuracy metrics proposed by Tyukavina et al. (2015), where the omission error for the GLAD forest loss detection tool over tropical region was estimated in 16.9%. These high commission errors place the GLAD tool within the group of conservative approaches, characterised by lower detection capability but higher detection confidence.

Another important factor to consider when comparing near-real-time monitoring approaches is their detection responsiveness. The use of SAR data by the CFAR-KerCuSum allows continuous and consistent assessment of the forest habitat while the operability of the GLAD tool depends on environmental conditions, a fact that can lead to significant time delays in the detection, especially in areas subject to high cloud cover.

These results are of crucial importance given the global nature of this product, which is commonly used not only for regional deforestation research but also for assessment of compliance with various climate change mitigation policies, such as REDD+ initiative. The results obtained points to a significant underestimation of GLAD outputs, and therefore the annual deforestation figures considered by these initiatives could be subject to notable errors.

5.2.2.1.4 Post-disturbance recovery monitoring

This comparison also served to highlight the limited capabilities of the CuSum method for monitoring the post-disturbance recovery stages. Despite the investigation of the vegetation recovery processes after the disturbance is not within the scope of this study, a brief exploration of some natural disturbances (e.g. wildfire) allowed to compare the capabilities of both approaches to monitor natural recovery. As it can be observed in Figure 59, contrary to CuSum, the CFAR-KerCuSum timeseries was able to catch the post-fire vegetation recovery process, being this noticeable by the progressive return of the radar signal to pre-event values. This finding is particularly important as it shows the potential capabilities of the new CFAR-KerCuSum not only for the detection of forest changes but also for assessing the natural recovery processes after the disturbances.
5.2.2.2 Main findings

The CFAR-KerCuSum has proven to improve the performance obtained by other forest change monitoring products, such as the widely used GLAD-Hansen global forest change map. The performance comparison between the optical-based GLAD forest change map (Hansen et al., 2013) and the proposed CFAR-KerCuSum served to identify some potential limitations of the first. Apart from the better performance offered by the KerCuSum in terms of spatial and temporal resolution, and data acquisition consistency, the accuracy assessments highlighted the lower detection capabilities of GLAD's global forest change product, leading to a notable underestimation of forest change areas for the study region.

5.2.2.3 Further assessments

When first developed in May 2021, the CFAR-KerCuSum appeared as the first Sentinel-1 based continuous forest monitoring operational tool for the North Rupununi region, being a novel
alternative to well-established optical-based deforestation products such as GLAD annual forest maps. However, in December 2021 the RADD tool was presented for the Humid tropical forest in South America, which to date had only been presented for sub-Saharan Africa and insular Southeast Asia tropical regions (Reiche et al., 2021). RADD then appeared as the first operational alternative to the CFAR-KerCuSum, as its near-real-time forest disturbance alert system is also based on the investigation of dense Sentinel-1 time-series. Nonetheless, the recent publication of this product for the forest region investigated in this thesis and its limited span of the sentinel-1 archive (2020 onwards), hampered the accurate comparison of both detector performances.

Specifically, the changes in the validation forest used for the performance assessment occurred during the 2018 and 2019 dry seasons (September to April), dates for which RADD alerts were not available. Similarly, the short data span of the GLAD-S2 product also did not allow a performance comparison as its archive only dates back to January 2019. Despite these obstacles, an initial visual assessment was performed over the forest validation sites used in Chapter 4 for the 2020 year. Results derived from the RADD alert showed similar values to those obtained for the GLAD product (Figure 60). Both the GLAD and RADD tools use a similar detection strategy based on the direct pairwise image analyses, so this may explain the similarities in the results.

![Figure 60. Comparative image illustrating the results of the GLAD and RADD alerts for changes in forests for the year 2020. Visual exploration carried out to assess the detection performances in the detection of forest disturbances that occurred in the period between September 2019 and September 2020 in northern tropical forests of the Annai region, near the Wowetta settlement. Data collected from Global Forest Watch (Global Forest Watch, 2021).](image)

The advantage of the new RADD alert over similar products is its high temporal resolution (every 6-12 days), improving on the previous global-scale or reduced (optical-based) temporal resolution deforestation products. Future research will focus on the exhaustive comparison of the proposed CFAR-KerCuSum with the new GLAD-S2 and RADD, in which both the detection performance and the temporal resolution of each product will be evaluated in depth.
5.2.3 Contribution to Environmental monitoring and future research

Prior to this research, the Cumulative Sum strategy had only been tested by in a limited number of studies to monitor historical climate anomalies (Manogaran and Lopez, 2017) or single-date land disturbances (Kucera, Barbosa and Strobl, 2007; Kellndorfer, 2019; Eric L Bullock, Woodcock and Holden, 2020). Yet, the use of the CUSUM model for the development of continuous and operational environmental monitoring systems remained unexplored.

The methods proposed in this thesis have contributed to expanding knowledge in the field of dense time-series based anomaly detection algorithms. The growing number of Earth Observation missions together with the easier access to multiple historical data catalogues has led to the emergence of numerous break or anomaly detection models for environmental monitoring, among which stand out models such as the Continuous Change Detection and Classification – ‘CCDC’ (Zhu and Woodcock, 2014; Olofsson et al., 2016; Arévalo et al., 2020; Bullock et al., 2022), the Continuous monitoring of Land Disturbance – ‘COLD’ (Zhu et al., 2020), the Continuous Monitoring of Forest Disturbance Algorithm – ‘CMFDA’ (Zhu, Woodcock and Olofsson, 2012), the Breaks For Additive Season and Trend monitor – ‘BFAST’ (Hamunyela et al., 2020; Wu et al., 2020), the Yet Another Time Series Segmentation Algorithm – ‘YASA’ (Martí et al., 2014), or the Anomaly Vegetation Change Detection – ‘AVOCADO’ (Decuyper et al., 2022) Most of these detectors have been developed using optical satellite imagery for the identification of forest disturbances at sub-annual scale, thus lacking the consistent time resolution to provide near-real-time detections, especially in areas with high cloud cover. Likewise, as described by Hamunyela et al. (2020), despite the benefits that these methods bring to environmental monitoring, there is a current lack of operational monitoring systems since most of these change detection methods have not yet been integrated into operational monitoring tools; remaining confined to the research domain or only available in highly specialized computational platforms which, in most cases, are too challenging for many current and potential users.

This research was conducted with the objective of fulfilling this research gap, focusing efforts on both developing a new continuous, consistent, and full operational monitoring algorithm based on the use of SAR data, and ensuring the integration of the final operational products on freely available web-based platforms, accessible to all users. Due to its similarity with this work regarding the data used (SAR-Sentinel-1) and the development environment, it is worth noting the recent integration of the BFAST model in GEE for the detection of forest changes (Hamunyela et al., 2020). With high performance in continuous monitoring of land changes (OA = 97%), this research stands out as it shares some of the core principles of this thesis, implementing state-of-the-art monitoring methods and making freely available to the geospatial community.
Regarding the current trends in time-series based environmental monitoring, there is a growing interest in the field of data fusion and multi-source data approaches. Technical advances made in satellite Remote Sensing during the past decade, which contributed to sharpening resolutions and increasing the availability of high-resolution data, have attracted the attention of the scientific community (Perbet et al., 2019). Recent studies, focused on new multi-sensor data harmonization approaches, have demonstrated substantial improvements in the temporal and spatial resolution of continuous environmental monitoring systems (Xin et al., 2013; Perbet et al., 2019; Nguyen et al., 2020; Shang et al., 2022; Swinnen et al., 2022). The current high availability of satellite imagery data together with the increasing number of new Earth Observation missions scheduled for the coming years (e.g. ALOS-4, TanDEM-L, NISAR, Planet-SuperDoves) favour the development of new multi-sensor monitoring systems that can help to improve current early detection rates as well as advancing the future trends forecasting research (Woodcock et al., 2020). Besides this, the inclusion of different sensors within the algorithm would increase the reliability of the monitoring system, since it can guarantee the operability in case of technical failures of the sensors or unexpected ends of EO missions (e.g. Sentinel-1 B sensor's power supply anomaly).

Following this line of research, some preliminary analyses have been performed, where the implementation of the CuSum methods using multi-orbit and data fusion approaches has been examined. Appendix A describes in detail these exploratory analyses conducted to monitor the hydrologic dynamics of Donana’s natural wetlands. In agreement with previous data fusion studies, preliminary results obtained shown a significant improvement in both temporal and spatial resolution associated with the use of data fusion strategies. We will continue to explore the capabilities of CUSUM for different EO data and applications, with the main goal of further expanding the boundaries of the continuous environmental monitoring research field.

## 5.2.4 Research limitations

During the course of this thesis, various limitations have been found which have influenced the development and final results of the research carried out. Among all the limitations observed, the following points stood out for their influence on this research:

1. The Covid-19 pandemic has had and continues to have a significant impact on research activities around the world, which has also led to extraordinary disturbances of the work carried out in this thesis. Among the numerous difficulties associated with this global crisis, mobility restrictions have been identified as one of the most influential issues for the normal development of research activity. International travel restrictions and recurrent lockdown periods markedly disrupted the ground-truth data collection plans. The cancellation of the one-month UAV data collection campaign aimed at collecting
the High Resolution imagery of North Rupununi wetlands or the cancellation of the annual water quality monitoring activities in the Doñana Wetland are some examples of the challenges encountered during this period which required a redesign of the validation processes.

ii. The exploration of CuSum methods over other commonly used SAR frequencies (X or L-band) has been hampered due to the lack of SAR missions that provide dense time series. Since all change detection methodologies proposed in this thesis require dense time series for continuous monitoring of environmental disturbances, the use of alternative SAR frequencies of relevance for this research (e.g. ALOS-2) was hindered due to current data policies (i.e. data are not free). Nonetheless, these limitations may be overcome with the upcoming SAR missions (ALOS4: 2022; TanDEM-L: 2022, NISAR: early 2023), which will provide access to more consistent data acquisition strategies with significantly improved temporal resolutions (ALOS4: every two weeks; Tandem-L: 16-days and NISAR: 12-days) and some of them will be freely accessible (e.g. NISAR). Future research efforts will focus on adapting CuSum monitoring strategies for different frequencies, paying special attention to L-band data due to its potential for forest and wetlands disturbance monitoring.

iii. The development of robust and fast methodologies has been one of the basis when designing the detection strategies proposed in this thesis. Based on this, the CuSum methods have been developed only for Ground Range Detected (GRD) data, focusing the analyses on the evaluation of amplitude signal values. Although the use of Single Look Complex (SLC) data would have allowed the analysis to be expanded through more advanced interferometry (InSAR) or polarimetry processing, the higher computational requirements associated with the processing of SLC data (typical file sizes of 8 GB / product compared to 1.5 GB of GRD; Wagner et al., 2021) would have impacted the operability of the presented tools. Similarly, a large part of this research (Chapter 3 and 4) has been carried out in cloud-computing platforms such as GEE, which, until the date of presentation of this thesis, do not support SLC data. In light of the growing demand for solutions that enable SLC data analysis, several organizations, such as The Alaska Satellite Facility (ASF) in partnership with NASA’s Jet Propulsion Laboratory, have already explored the functional architectures necessary for the processing, distribution and archival of SAR complex data in preparation for the upcoming NISAR mission (Garron et al., 2019). Given the impossibility of directly adapting the CuSum methods for SLC data in GEE, alternative solutions must be developed for the analysis of SLC data in offline environments.
In conclusion, there were limitations to this thesis due to both external factors and the specific characteristics of the data used. The identification and description of these limitations represented a critical point both to satisfactorily develop the research activities carried out in this thesis but also to generate a framework for future work and improvements.

5.3 Summary

Forests and wetlands are among the most productive and biologically diverse natural ecosystems of the planet. Their importance and ecological value go beyond providing an enormous range of beneficial services such as food and fuel supply, water and air purification, recreational or traditional use as they significantly help to maintain global natural ecological balances, acting as major contributors to climate change mitigation. Nonetheless, increasing socio-economic pressures and demand for resources are threatening/compromising the conservation of these natural landscapes. The continuous exposure of these natural ecosystems to Land Cover and Use Changes (LULCC), either by direct destruction or by degradation and fragmentation processes, is causing a significant loss of these natural ecosystems at a global scale, which is being exacerbated by current climate change trends. Besides this, the implications of these land use and land cover changes on the global carbon cycles are major, representing one of the primary sources of greenhouse gas emission. Spatially, continuous and consistent investigations of these land cover dynamics are essential to accurately assess the conservation status of these ecosystems and the potential implications derived from their alteration.

To assess both the historical and current dynamics of these natural ecosystems, satellite remote sensing emerges as a powerful tool. Most of the current remote sensing-based environmental monitoring approaches are based on medium-resolution optical satellite imagery. Yet, optical-based strategies commonly fail to provide near-real-time and continuous information, hindering the consistent evaluation of the natural dynamics. The dense and quasi-permanent cloud cover present at many regions of the globe, significantly affects the operability and performance of these tools, causing low temporal resolutions, inconsistency in the results (e.g. data-gaps in time series) and misclassification errors. Synthetic Aperture Radar (SAR) based methods have demonstrated their high capabilities for monitoring environmental disturbances over, practically, all different types of natural ecosystems. The active nature of radar sensors, which allows consistent data acquisition under any type of weather condition (e.g. dense cloud cover, rainfall, nighttime), makes SAR the most valuable alternative to optical remote sensing. However, research has indicated that there is still low availability of continuous monitoring methods that fully exploit the potential monitoring capabilities of dense timeseries. This thesis addressed the need for advancing continuous monitoring methods that use SAR dense time series-based methods to investigate the environmental dynamics of natural ecosystems. The main scientific contribution of this thesis includes the introduction of three novel
SAR-based change detection approaches capable of exploiting dense satellite imagery time series for the continuous and near-real-time monitoring of forests and wetlands environments (see Figure 61).

Chapter 2 introduced the design and development of a novel SAR-based change detection algorithm based on the Cumulative Sum statistical test. The novel CuSum approach was applied to dense time-series of radar Sentinel-1 data for monitoring permanent forest structural changes that occurred in mixed temperate forest masses. The outcomes of this chapter demonstrated the high capabilities of the proposed methodology for environmental monitoring, thus laying the foundations of the following chapters.

Chapter 3 presented the first modification of the original CUSUM algorithm, adjusting the original method to seasonal/temporary disturbance monitoring. The new Ker-CuSum approach was adapted to monitor the hydrological dynamics of the North Rupununi seasonal natural wetlands, Guyana. The implementation of the proposed methodology in the Google Earth Engine platform allowed assessing the impact of online geo-mapping platforms and ancillary datasets on the change detection capabilities. A fully-operational online flood mapping web application was developed, emerging as the first SAR-based near-real-time wetland monitoring tool for the North Rupununi natural wetlands.

Chapter 4 focused on the modification of the Ker-CuSum method to an automatic and fully-unsupervised change detection approach for monitoring natural and human forest disturbances in Tropical forests. The new CFAR-KerCuSum algorithm was applied to dense timeseries of Sentinel-1 data to monitor forest degradation processes and Above Ground Biomass losses between 2018 and 2021, at highly-dynamic tropical forests areas in Guyana. A final evaluation on the impact of advanced features such as the radiometric terrain normalisation, multi-temporal filtering and occurrence analysis was performed, demonstrating the greater capabilities of this approach over previous versions.
To address the detection capabilities of each of the methods proposed in this thesis, Chapter 5 presented a method comparison investigation by which the performance of these approaches for tropical forest monitoring was evaluated.

These studies have demonstrated the potential of SAR dense time series approaches for environmental monitoring, highlighting the high capabilities of the CuSum strategies for the continuous investigation of natural and anthropogenic disturbances/dynamics in natural ecosystems.
References


Dyer, O. (2020) ‘African malaria deaths set to dwarf covid-19 fatalities as pandemic hits control efforts, WHO warns’, *BMJ (Clinical research ed.)*, 371, p. m4711. Available at: https://doi.org/10.1136/bmj.m4711.


References


ESA-CCI (no date) ESA - ESA’s Climate Change Initiative. Available at: https://www.esa.int/Applications/Observing_the_Earth/Space_for_our_climate/ESA_s_Climate_Operation_Initiative (Accessed: 21 May 2020).


ESA (2020) Radar Course 3 - Image interpretation: Tone, Speckle - ERS Radar Course 3 - ESA Operational EO Missions - Earth Online - ESA. Available at: https://earth.esa.int/web/guest/missions/esa-operational-eo-missions/ers/instruments/sar/applications/radar-courses/content-3/-asset_publisher/mQ9R7ZVkJg5P/content/radar-course-3-image-interpretation-tone (Accessed: 10 June 2020).


References


References


References


References


Nguyen, M.D., Baez-Villanueva, O.M., Bui, D.D., Nguyen, P.T. and Ribbe, L. (2020) ‘Harmonization of landsat and sentinel 2 for crop monitoring in drought prone areas: Case studies of Ninh Thuan (Vietnam) and Bekaa (Lebanon)’, *Remote Sensing, 12(2). Available at: https://doi.org/10.3390/RS12020281.


References


References


References


Appendices

Appendix A

Multi-orbit and optical data fusion: Doñana wetlands study case

The full exploration of the monitoring capabilities of the tools presented in this thesis appears as one of the most important cornerstones of this work. All the adaptations of the algorithms were carried out with the main aim of investigating their performance under different environments, applications and types of disturbances. Hence, once the high capabilities of the CuSum approach have been assured, new strategies and data have been tested on the CuSum approaches with the objective of further expand the monitoring capabilities of the tools presented in this thesis. The following section presents some preliminary analyses in adapting the Ker-CuSum wetland monitoring for multi-orbit ingestion and fusion with optical data. This can provide an insight into the potential capabilities of this method for improving current wetland monitoring systems.

Doñana natural wetlands are located in the south-west region of Spain and they are considered to be one of the latest and most important biodiversity hotspots in Europe (UNEP-WCMC, 2017; IUCN, 2020). They are characterised by having a great habitat heterogeneity, with low-marshland, lagoons, fixed and mobile dunes and forest patches that host a large number of endangered species and provides habitats for as many as six million migratory birds each year (IUCN, 2020). However, despite its great ecological importance and being protected by several international agreements (e.g. UNESCO world heritage site), the conservation status of this natural space is highly threatened. The socio-economic pressures and harmful industrial activities, including intensive agriculture and river modifications, maintained since the 1970s have resulted in a reduction of the water reaching the wetland by 80 percent (WWF, 2016; Dimitriou et al., 2017; IUCN, 2020). It is estimated that there are over 1000 illegal agricultural wells and 3,000 hectares of illegal farms pumping out water and drying out the natural wetland. Both national and regional policies have failed to safeguard this region, ignoring strict water management plans that contribute to the recovery and conservation of this wetland complex. Therefore, it is essential to have continuous monitoring systems which provide with near real time information about the hydrological dynamics as this would significantly contribute to a better investigation of the evolution and conservation of this protected area.

The current operational monitoring system for the Doñana wetlands, developed by Laboratory of GIS and Remote Sensing at the Doñana Biological Station | LAST-EBD (LAST), uses Landsat satellite imagery (MSS, TM, ETM + and OLI / TIR sensors) since 1972 to the present to generate two indicators, a) a binary Flooded / Non-flooded map, and b) a water turbidity mask. Despite having a great performance in the identification of flooded regions (OA ≈ 93%; Díaz-Delgado et al., 2016), its reliance on optical sensors makes the temporal resolution of this system significantly poorer when
Appendices

compared to alternative Sentinel-1 based strategies such as the proposed Ker-CuSum (Figure A1). As shown in Figure A1, the use of Sentinel-1 time series to monitor this wetland would lead to a notable improvement of temporal resolution of the system, providing a consistent data acquisition (every 3-12 days) and helping to solve the current data-gaps existing during the wet seasons.

Figure A1. Illustration showing an annual data acquisition comparison between the Sentinel-1 mission for 2020 and the Landsat data used by the EBD-LAST system for the same period. As it can be observed, the total number of Sentinel-1 acquisitions (31 using the single orbit approach and 62 using the multi-orbit approach) well exceed the 21 images used from Landsat.

Taking advantage of the work carried out in the North Rupununi wetlands (Chapter 3), an initial exploration of the Ker-CuSum was performed for continuous monitoring of the Doñana natural wetlands. This analysis aimed to a) first test a Multi-orbit strategy for the Ker-CuSum algorithm, by which both the ascending and descending modes were combined into a single timeseries and b) assess the potential capabilities of the CuSum approach for water quality (turbidity) monitoring. As in Chapter 3, SAR signal intensities of both the co (VV), cross (VH) polarization channel and their ratio (VH / VV) combination were investigated for 'open-water' (OW) and 'flooded-vegetation' (FV) regions. The study period comprised all Sentinel-1 images acquired during 2019 and 2020, using a composite of all the images acquired during the dry seasons (August and September of each year) as a reference for the generation of the CuSum timeseries. The validation analysis was performed by comparing the Ker-CuSum flood masks against the Landsat derived flood maps. Two dates on which the Sentinel-1 and Landsat acquisitions were near-coincident (23/02/2020 and 30/12/2020) were used, also utilising additional cloud-free high-resolution Planet imagery for the delineation of the validation areas.

The results showed a good performance of the Ker-CuSum method for mapping temporary flooded areas (UA= 75%, CE< 1%). The ratio combination (VH / VV) showed the highest sensitivity to 'open-water' while the co-polarized (VV) provided the best identification of flooded vegetation areas with both 'near-surface' submerged and emergent vegetation. The method agreement analysis showed
an overall agreement of 64% between both strategies, with a higher performance of the Ker-CuSum over the 'flood-vegetation' areas, which are generally a major challenge for optical sensors (Díaz-Delgado et al., 2016; Kordelas et al., 2018) (see Figure A2). The combination of the flood masks of both methods resulted in a significant improvement of the EBD-LAST detection performance (UA+ 8%), showing the high potential of data fusion strategies.

Figure A2. Illustrative map of the methods agreement analysis carried out for February 2020; Sentinel-1 image acquired on (23/02/2020) and Landsat 8 acquisition (18/02/2020). Ker-CuSum combined flood map ('OW', 'FV', 'High Turbidity') (green), EBD-LAST flood map (yellow) and coincidental/agreement regions (blue).

The high diversity in water turbidity present in the ‘open-water’ areas of the Doñana wetland provided us with opportunity to investigate the influence of this parameter on the radar signal. The characteristic sandy and clayey composition of the Doñana marshes, resulting from the continuous accumulation of sediments contributed by the Guadalquivir and Odiel rivers, generates important variations in composition and turbidity of the waters. These variations in the abundance of water suspended particles and turbidity generate in turn differences in the interactions between the electromagnetic signals of the radar and the water, through differences in the surface roughness. An exploratory SAR signal analysis was performed to investigate the potential capabilities of Sentinel-1 data for the monitoring of water qualities. For this, the EBD-LAST derived turbidity masks, generated from the multispectral analysis of Landsat 7 & 8 images (Díaz-Delgado et al., 2016), were
split into two classes according to the Nephelometric Turbidity Unit values (NTU); low turbidity (lnNTU < 4.5) and high turbidity (lnNTU ≥ 4.5).

Both co- and cross-polarization channels showed a high sensitivity to variations in turbidity, with very low backscatter values, near noise floor, for highly turbid flooded areas. Between the two, the VH polarization showed better separability between turbidity levels with detection yields of between 64-67% for areas of high turbidity (see Figure A3).

These results agree with the hypothesis considered which supports that high turbidity water would present a higher density due to high amounts of sediments and consequently a higher surface tension (Ortiz and Klompmaker, 2015; NOAA, 2021b). This higher water surface tension would be causing a suppression of small superficial waves and consequently a lower influence of possible Bragg scattering caused by wind.

Figure A3. Example comparison map of the Ker-CuSum derived high turbidity map (light blue, figure d) with the Landsat (EBD-LAST) derived turbidity mask (b). The analysis was performed for the Sentinel-1 image acquired on 23/02/2020, and the water turbidity mask was derived from a Landsat8 image acquired on 23/02/2020. a) Planet acquisition used for visual reference acquired on 17/02/2020.

Overall, the investigation of multi-orbit strategies of the CuSum approach for monitoring the hydrological dynamics of fluvial wetlands of Doñana natural region served to confirm the high
capacities of this method for monitoring wetland's hydrological dynamics. This analysis provided a first insight into the possibilities of integration of CuSum methods with optical data. Ker-CuSum can be a complementary solution to optical-based strategies, significantly improving the temporal resolution of the current environmental monitoring system and contributing to the elimination of data-gaps during the wet season. Likewise, the good performance observed in the preliminary analyses for the classification of water quality enhances the potential usability of the proposed methodology for wetland monitoring over regions characterized by high cloudiness. Future research efforts will focus on optimizing the multi-orbit method, working on solving encountered issues (e.g. open sand dunes misclassification errors, lack of water quality ground truth data) and developing a new open cloud-computing (GEE) operational tool.
Appendices

Appendix B

CFAR-KerCuSum - Annual Above Ground Biomass loss estimation

An annual assessment on Above Ground Biomass (AGB) loss was performed in order to better understand the impact that these changes may exert on the natural ecosystems of the North Rupununi region. Identified as one of the 54 essential climate variables (ECVs) by the Global Climate Observing System (GCOS) (World Meteorological Organization, no date), forest biomass information is commonly used to quantify the forest resources, as well as to determine their contribution to the different ecosystem services, climate change mitigation, and biodiversity conservation (Soto-Navarro et al., 2020; Santoro et al., 2021). Biomass assessment provide critical support for investigating and reporting of greenhouse emissions at national or regional scales. Among the global context, Tropical and subtropical forests are considered as major contributor to climate change mitigation, being the forest types that contribute the most to global gross forest fluxes (Harris et al., 2021; Suarez et al., 2021). This manifests the need to have access to updated and accurate information on the carbon stocks of these important ecosystems. Having a system that provides continuous information on forest changes and the loss of carbon stock derived from these land transformations would contribute to a better understanding and modelling of forest degradation trends in these ecologically important forests.

Carbon estimations commonly rely on the use of expensive manual measurements using allometric equations to perform accurate biomass estimation over specific survey plots. The latest advances in airborne and UAV as well as LiDAR technology has significantly improved the range of action in terms of cost-efficiency. Yet, the logistic difficulties associated to tropical forest environments added to the lack or poorly developed systematic sampling strategies of many tropical developing countries greatly reduce the reliability on this technology for forest monitoring. Satellite remote sensing has emerged as a valuable solution to overcome these problems. Although the measurements from remote sensing need to be carefully processed to provide a measure of the forest AGB, the demand for spatially explicit estimates of AGB have fostered the development of a multitude of retrieval models based either on empirical regression techniques, physically based mathematical models, or machine learning algorithms (Lu et al., 2014; Lucas, Mitchell and Armston, 2015; Santoro and Cartus, 2018; Hansen, Mitchard and King, 2020). This has resulted in a wide number of forest Above Ground Biomass (AGB) maps that provide estimations at national, regional and global scale. Among the most recent AGB global maps, the most recognised products were the (1-km spatial resolution) integrated pan-tropical biomass (Avitabile et al., 2016), developed by the Wageningen University Center for Geo-Information, integrating the two existing large-scale biomass maps developed by
Saatchi and Baccini (Saatchi et al., 2011; Baccini et al., 2012) (Figure B1 b,c and d); and the (300-m spatial resolution) harmonized above (AGB) and below (BGB) ground biomass global map published at NASA’s Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC) (Spawn et al., 2020). However, the newly published (March, 2021) AGB global map generated by the ESA’s Climate Change Initiative (CCI) stands as the best global biomass product currently available (Santoro and Cartus, 2021; Santoro et al., 2021). The CCI Biomass map (Figure B1 a) was computed using SAR data, are derived from a combination of ESA-Sentinel-1, Envisar’s ASAR and Jaxa’s ALOS-1&2 SAR missions. Its updated information of AGB (2010, 2017 and 2018 years), global coverage and finest spatial resolution (100 m) led the CCI Biomass map to be considered as the most suitable product for this study.

Figure B1. AGB estimates by (a) Santoro et al. (2021) CCI_Biomass map, (b) Avitabile et al., 2016, (c) Saatchi et al., 2011, and (d) Baccini et al., 2012 for a 1°×1° area in the state of Parà, Brazil. Extracted from (Santoro et al., 2021).

The second version of the CCI Biomass product includes major improvements in the AGB estimations, capturing the higher biomass levels in high density forest tropical areas (ESA-CCI, 2021). Hence, assuming the high levels of uncertainties associated to large-scale forest biomass assessments (Zhang, Liang and Yang, 2019), it was decided to perform an annual estimation of the ground biomass loss for the study region.

To estimate the annual biomass loss, the final forest change maps calculated from CFAR-KerCuSum were combined with the most recent AGB map from ESA’s CCI biomass map, generated for 2018. Special attention needed to be paid to the data fusion process. It was crucial to count on a single geographic framework that would allow the precise association of the various datasets with different specifications such as pixel spatial resolution and geographical projection. Based on this, the spatial
resolution of the CCI’s AGB map was resampled to a new 10 x 10 m pixel size, thus matching the grid of the CFAR-KerCusum’s forest change maps (Figure B2). The resampled technique used for this process was the Cubic interpolation, which is recommended for continuous data (ESRI, 2020). Once both datasets shared the same spatial resolution and projection (EPSG: 32621), a coregistration process was carried out to stack the datasets into the same spatial grid before combining.

Figure B2. Illustration showing the original (100 x 100m) ESA’s Biomass AGB 2018 map for the North Rupununi region and the final resampled (10 x 10m) product used for the annual AGB calculations.

AGB loss values were estimated by multiplying the total extension of each disturbed forest area by the estimated biomass values at the pixel level. The final annual AGB loss figures were extracted by summing all individual disturbed forest area, obtaining the following values for the last 4 years (2018-2021) (Figure B3). The total change in carbon stocks estimated for the period of study accounts for a total of 3931.61 Gg.

Figure B3. Annual Above Ground Biomass (AGB) biomass loss estimations for the forested area of the North Rupununi region.

<table>
<thead>
<tr>
<th>Year</th>
<th>Annual AGB Loss (Gg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2018</td>
<td>808.98184</td>
</tr>
<tr>
<td>2019</td>
<td>1049.41933</td>
</tr>
<tr>
<td>2020</td>
<td>1482.42564</td>
</tr>
<tr>
<td>2021</td>
<td>590.78489</td>
</tr>
</tbody>
</table>
Results for the annual AGB loss showed a progressive growing trend in the AGB loss for the (2018 - 2020) period and a notable reduction in the 2021 year, that we hypothesise as a result of 'la Nina'. These results are consistent with the figures obtained for the annual deforestation areas. The distribution of AGB of the deforested areas is relatively uniform, with a slightly higher frequency being observed for the upper band of the biomass range (see Figure B4). The higher frequency of forest disturbances observed in the old-growth forest band may be related to backscatter intensity differences between different types of forests. Old-growth/primary forests commonly present higher backscatter values as a result of their more complex and dense canopy structure, a fact that could have led to greater post-disturbance backscatter variations than those shown by secondary forests (Imhoff, 2019). These forest disturbances in the upper AGB range are particularly important in ecological terms since these old-growth established forests, rather than any new wooded areas, are predominantly responsible for most of the global carbon capture (Harris et al., 2021). Harris et al. also highlight the substantial but often underappreciated contribution of these intact primary and older secondary forests to carbon dioxide removals warning of the catastrophic impact that the release of carbon stored in these ecosystems would exert at a global level, warming the planet, for generations to come.

Figure B4. Distribution of annual forest changes for the variable Above Ground Biomass. Low AGB values (red) correspond to areas of savanna and sparse vegetation, while high AGB values (green) are characteristic of highly dense secondary old-growth forests.
For the Tropical forest region analysed in this study, the annual reduction of \( \approx 1.2\% \) of the forest cover (\( \approx 4800 \) ha) would account for a loss in sequestration rates of between 15,360 to 48,000 t CO\(_2\) year\(^{-1}\). These figures manifest the great impact that current forest degradation and deforestation trends exert on the carbon absorption and storage cycles at the regional and global level, contributing to the worsening of global environmental issues such as global warming.
List of publications

Peer reviewed journals


Other scientific publications


Sáez Gómez, P.; Camacho, C.; Palacios, S.; Molina, C.; Ruiz-Ramos, J. and Potti, J. Reclutamiento juvenil, dispersión natal e inicio de la reproducción en el Chotacabras Cuellirrojo (Caprimulgus ruficollis). In: XXII Congreso Español de Ornitología, 5-9 Dec 2014, Madrid (Spain).

Book chapter


Projects


Other


Planet Education and Research programme grant. Projects: “DETECT and SMART”. Access to a (5000sqkm/month) 4-band High-resolution optical Planet imagery for validating SAR-based environmental monitoring analysis.
JAXA – ALOS Mission Research programme. (Co-I). Project: "MoLaDy-PolSAR: Monitoring Land Dynamics using Polarimetric ALOS-4 SAR data". Access to 100 L-band ALOS programme images, 40 historical ALOS-2 and, 60 ALOS-4 acquisitions (new acquisitions) for SAR-based environmental change detection analysis (e.g. forest degradation, flooding) over the Forth Valley (Scotland).

**Invited review of journal manuscript**


Javier Ruiz Ramos was born in Écija, Spain, on September 7, 1990. He attended primary school at CEIP Blas Infante, and later completed secondary school in Science specialisation in 2008 at IES Luis Vélez de Guevara. During this period, Javier dedicated his spare time to sports, music and outdoor activities that helped him to balance his student life while developing a major interest for nature.

In 2009, Javier commenced a Bachelor of Engineering degree in Forestry at the Polytechnic University of Huelva. Over the course of his studies, he developed a strong interest in GIS and environmental conservation that led him to get involved in diverse biodiversity conservation research programmes in the neighbouring Doñana national park. Upon completing his degree in 2015, he moved to the United Kingdom where, after a transitional year, he started his Master of Science in Geographical Information Systems (GIS) and Science at Kingston University, London. It was during this period when he found his passion for the use of Remote Sensing technologies for environmental monitoring applications. Over the course of his masters, he expanded his knowledge in Earth Observation, developing his interest in remote sensing technologies for the continuous monitoring of natural ecosystems. In 2017, he completed his MSc with a thesis on the use of historical satellite imagery for investigating the impacts of Land Use/Land Cover changes on environmentally protected areas in southwestern Spain.

After his graduation, Javier began a PhD program in the area of Environment & Earth Observation at The Open University. His line of research focuses on highlighting the capabilities of Remote Sensing technologies, especially Synthetic Aperture Radar – SAR satellite sensors, for detecting landscape transformations associated with human socio-economic activities (e.g. deforestation, illegal mining, agriculture & urban expansion) or natural processes such as floods, windstorms or forest-fires. Alongside his PhD, Javier has worked on diverse conservation programmes and initiatives in Spain, Guyana, Sri-Lanka and the UK which have served him to gain experience in a wide range of tasks such as environmental monitoring and ground-truthing, biodiversity tracking or spatio-temporal analysis, among others.

Javier's current research interests are the development of new Remote-Sensing based environmental monitoring tools and their integration into decision-making schemes for the planning and conservation of natural ecosystems. He will continue his work as a Remote Sensing analyst at Permian Global, participating in the development of large-scale tropical forest protection and restoration projects that aim to reduce atmospheric carbon dioxide levels and protect natural habitats to safeguard biodiversity and support local communities. He is also highly interested in exploiting the power of capacity-building and collective participation approaches for designing and developing new ideas and solutions that support local communities. Hence, as an active member of the Cobra Collective Initiative, he will continue collaborating in diverse community-focused environmental projects, working towards the enhancement and application of the environmental monitoring tools developed in this thesis.