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Pu, Tianjiao

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Computer Vision for Decoding Natural Processes: Wetland Dynamics Insights

By

Tianjiao Pu

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Engineering - Civil and Environmental Engineering

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Assistant Professor Cynthia Gerlein-Safdi, Chair

Associate Professor Laurel Larsen

Professor Mark Stacey

Summer 2024

Computer Vision for Decoding Natural Processes: Wetland Dynamics Insights

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Tianjiao Pu

Abstract

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Doctor of Philosophy in Engineering - Civil and Environmental Engineering

University of California, Berkeley

Assistant Professor Cynthia Gerlein-Safdi, Chair

Wetlands are essential for fulfilling global commitments on topics of climate, biodiversity, and sustainable development. However, due to climate change and human disturbances, there are growing concerns and significant attention being directed towards the degradation of wetlands, which is manifested through both a loss in area and a reduction in their functionalities. This thesis presents data-driven, training-free computer vision algorithms designed to address the challenges of monitoring and interpreting wetland dynamics. Through the development of these methodologies, we aim to answer key research questions regarding the temporal and spatial patterns of wetland refilling, the impact of climate variability on wetland dynamics, and the influence of anthropogenic activities, particularly the initiation of wildfires, on wetland ecosystems.

First, the superior penetrating capabilities of L-band microwaves from the Cyclone Global Navigation Satellite System (CYGNSS) are leveraged to detect water through dense vegetation and cloud cover prevalent in the tropics. We developed a segmentation algorithm, coupled with spatial analysis tailored to CYGNSS data, to differentiate land and water. This effort culminated in the creation of the UC Berkeley Random Walk Algorithm Water-Mask from CYGNSS (Berkeley-RWAWC) [rɔ:k], a quasi-global (37.4°N to 37.4°S), monthly waterbody map. This product significantly enhances the interpretation of seasonal and inter-annual variability in tropical hydrology, offering new perspectives for studies on these critical ecosystems. Building on this foundation, we advanced the algorithm towards operational hydrology by harnessing CYGNSS' near-real-time capabilities. The temporal resolution of the product was refined to capture daily water dynamics, addressing the critical need for timely monitoring and response to increasingly frequent and extreme hydroclimatic events. The enhanced product's performance was validated in the Sudd wetlands, an area characterized by complex natural and anthropogenic influences on flooding. The demonstration underscored the potential of integrating cutting-edge remote sensing technologies with robust algorithms to enhance disaster response and management. Finally, the study focus shifts to the Pan-

tanal, the world's largest tropical wetland, which has recently been affected by frequent mega wildfires. Multi-object tracking algorithms were developed and customized to label and track fire patterns, enabling an in-depth analysis of fire events in wetlands. The final chapter investigates trends in fire occurrences, examines the interplay between fire regimes and wetland refilling patterns, and explores the resilience of the Pantanal against extreme events.

To
my parents, Xijuan Gu and Jianguang Pu,
and my advisor, Cynthia Gerlein-Safdi.

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Chapter 1

Introduction

1.1 Hydrological Challenges Posed by Climate Change

In the realm of Earth's terrestrial hydrology, comprehensively capturing the spatial distribution and temporal dynamics of global inland water has been a long-standing scientific pursuit [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]. This pursuit is now more critical than ever due to climate change, driven by increased greenhouse gas emissions (GHG) [11], which is fundamentally reshaping the global distribution of water [12]. The shifts are happening now and at an ever-increasing pace [13], causing an upsurge in extreme events like floods and droughts across the globe [14, 15], in turn disrupting various natural ecosystems that have long been adapted to the ebb and flow of natural variability they experienced [16].

While the developed world bears substantial responsibility for the anthropogenic greenhouse gas emissions fueling climate change [17, 18], the disproportional impact is most keenly experienced by the tropical regions, where a significant portion of the developing world resides [19]. Developing regions, constrained by limited financial resources and governance capacity for effective adaptation and mitigation, are particularly vulnerable to climate-related shocks [20]. Understanding the dynamics of water distribution and its variations over time is vital for scientific, environmental, and humanistic applications. This knowledge is crucial for population preparedness in adapting to changing water availability while safeguarding natural ecosystems, their services, and the biodiversity they contain.

1.2 Wetlands: Ecological Significance and Climate Vulnerability

Among natural ecosystems, wetlands are among the most vulnerable to the hydrological shifts induced by climate change [21, 22, 23]. Definitions and descriptions of wetlands vary across the literature but to maintain consistency and align with a widely recognized standard, this work adopts the characterization from the Ramsar Convention, an international treaty focused on the conservation and sustainable use of wetlands [24]: Wetlands are collectively referred to as wetlands because they are permanently or seasonally inundated habitats, regardless of the differences in their geological features, hydrology dynamics, water chemistry, and other traits. Thus, the presence and movement of water are the primary factors regulating these ecosystems.

Wetlands are critical for maintaining ecological balance. A “healthy” wetland is described as one that can offer local services, such as retaining nutrients, sediments, and contaminants; carbon sequestration; supporting food webs and conserving biodiversity; mitigating droughts and floods; stabilizing shorelines, controlling erosion and protecting from storms; regulating local climatic conditions, especially rainfall and temperature and so on [24]. With 2,439 sites listed as wetlands of international importance, covering over 250 million hectares [25], wetlands are essential for fulfilling global commitments on topics of climate, biodiversity, and sustainable development. Unfortunately, not all the wetlands are in the “well-managed” conditions. Due to climate change and human disturbance, wetlands are degrading in terms of losing area and reduction in functionalities [26, 24]. Understanding and examining wetland dynamics remains challenging due to limited accurate data on the spatial and temporal variability of wetland extent. Capturing these dynamics through in-situ observations is particularly demanding and intricate, leading to significant gaps in our knowledge of wetland processes

1.3 Knowledge Gap on Tropical Wetlands

Remote sensing techniques have been instrumental in facilitating the observation of water, offering an unparalleled global perspective over the course of decades [27, 28, 29]. Various platforms are employed for water detection, ranging from optical sensors like Landsat [30] to near-infrared (NIR) instruments such as MODIS [31], and microwave missions like Sentinel-1 [32] and SMAP [33]. Landsat, renowned for its remarkable 30-meter spatial resolution, is one of the premier data sources for water body monitoring [8]. However, despite the extensive scope of remote sensing observations, knowledge gaps persist in hydrological monitoring in the tropics, particularly in terms of its seasonal and inter-seasonal patterns. Indeed, cloud cover and dense canopies are the two major challenges for obtaining valid optical and near-infrared observations. In tropical rainforests, the rainy season often entails extended periods of persistent cloud cover, sometimes lasting for multiple consecutive months [34].

Additionally, the presence of dense vegetation and canopies, particularly along the fringes of large water bodies, can sometimes fully conceal small water bodies, further limiting valid observations [8, 9]. This appears to be true even for Sentinel-1 SAR data, likely because the radar operates in C-band and is, therefore, more sensitive to the presence of vegetation [35].

As a consequence, most tropical water maps tend to underestimate the actual extent of these waterbodies, displaying a bias toward representing dry season conditions, which often represent only a fraction of the maximum extent during the peak of the rainy season [8]. This raises a pressing concern related to the quantification of the impact of inland waterbodies and wetlands in particular within the context of climate change. Wetlands represent Earth’s largest natural source of methane emissions, as well-documented [36], yet paradoxically, one of the most uncertain, due to limitations in the quality of wetland extent data [37]. Of particular importance are tropical wetlands, as they contribute substantially more methane compared to their high-latitude counterparts [38]. Meanwhile, within tropical regions, up to 80% of the uncertainty in wetland emissions of methane (CH_4) can be associated with the uncertainties in wetland extent [39]. Thus, it becomes crucial for accurately characterizing the spatial extent and temporal variations in inundation and aquatic habitats [40].

1.4 Filling the Gap with Spaceborne GNSS-R Technique

To overcome these constraints, recent studies have embraced microwave remote sensing tools, which provide superior cloud penetration capabilities and are less influenced by dense vegetation. Coarse spatial resolution radiometer datasets, with a resolution greater than 25 kilometers, provide a wealth of temporally rich observations. Notable inundation products include GIEMS-2 [10], which provides monthly data, and SWAMPSv3 [9], delivering daily information. On the other hand, high spatial resolution synthetic aperture radar (SAR) datasets, with resolutions of less than 100 meters, offer detailed observations but limited temporal coverage. For instance, Sentinel-1 SAR currently has a revisit frequency of 6–12 days, and the upcoming NASA-ISRO Synthetic Aperture Radar (NISAR) mission is expected to provide a similar revisit frequency [41].

Thus, existing microwave-based inundation products necessitate trade-offs between spatial and temporal resolution. The Global Navigation Satellite System Reflectometry (GNSS-R) technology emerged with great potential for filling the gap. GNSS is a collective term encompassing satellite constellations that offer global or regional positioning, navigation, and timing (PNT) services. Presently, these systems include the United States’ Global Positioning System (GPS), Russian Global’naya Navigatsionnaya Sputnikova Sistema (GLONASS), the European Galileo system, the Chinese BeiDou System (BDS), the Japanese Quasi-Zenith Satellite System (QZSS), and the Indian Regional Navigation Satellite System (IRNSS/NavIC). The basic principle of GNSS-R involves receiving signals transmitted from these navigation

satellites and measuring the changes in the signals' properties as they interact with the Earth's surface [42].

Launched in December 2016, the Cyclone Global Navigation Satellite System (CYGNSS) is the first space-based science GNSS-R constellation system that focuses on tropical cyclones and tropical convection. Originally conceived to address the urgent demand for better hurricane intensity forecasts, CYGNSS allows for high-resolution wind measurements under extreme conditions such as heavy rain and intense winds, and offers a high revisit frequency, as evidenced by statistical distributions indicating a median revisit time of 2.8 hours and a mean revisit time of 7.2 hours [43]. Furthermore, GNSS-R technique, being "receiver only", eliminates the need for a transmitter, substantially lowering sensor power requirements compared to traditional scatterometers [44], therefore significantly reducing the cost of these missions compared to active microwave satellites.

Beyond its primary mission, CYGNSS data has demonstrated remarkable sensitivity to inland water. GPS satellites, operating at 1.575 GHz in the L-band, can penetrate clouds, rain, and dense vegetation canopies, while also offering strong signals through coherent specular scattering when in contact with calm water surfaces, setting them apart from the diffuse scattering in the surroundings [45]. The bi-static radar geometry also appears to contribute to CYGNSS' high sensitivity to inland waters, allowing for better sensitivity to small waterways than SAR [35]. Distinguished by rapid data acquisition capabilities, high revisit frequency, cost-effectiveness, extensive coverage spanning approximately 38°S to 38°N, and enduring mission longevity, CYGNSS data has emerged as a transformative asset in the field of hydrological remote sensing.

1.5 Advancing Wetland Monitoring with Training-Free Computer Vision Algorithms

Given the advent of new but limited data, the complexity of diverse landscape features, and the lack of ground truth data, training-free computer vision algorithms have been selected for their capability to operate effectively in such context. Computer vision algorithms are computational methods designed to interpret and understand visual information. They perform tasks such as image classification, object detection, segmentation, and tracking, using techniques that range from basic statistical methods to advanced deep learning models [46]. Training-free computer vision algorithms, in particular, do not require a pre-training phase with labeled datasets. Unlike machine learning approaches that rely on large volumes of annotated data to learn patterns and make predictions, training-free algorithms operate based on predefined rules, mathematical models, or heuristics. Techniques such as edge detection, thresholding, and template matching fall under this category. The primary advantage of training-free algorithms is their ability to function effectively without extensive data preparation and labeling, making them particularly useful where labeled data is scarce or

unavailable. In this study, we demonstrate the adaptability and effectiveness of training-free computer vision algorithms in enhancing wetland ecosystem monitoring and investigation using remote sensing data. This innovative mapping effort illuminated the intricacies of wetland hydrodynamics.

In Chapter 2, the superior penetrating capabilities of L-band microwaves from the GNSS-R technique are leveraged to detect water beneath dense vegetation and persistent cloud cover. Using data from CYGNSS, we developed a land-water binary classification method that combines the random walk algorithm with spatial analysis. Additionally, a parameterization strategy based on dynamic thresholding was implemented to ensure consistent classification results, regardless of background moisture changes caused by vegetation growth and complex landscape features across different regions. This effort culminated in the creation of the UC Berkeley Random Walk Algorithm WaterMask from CYGNSS (Berkeley-RWAWC) [rok], a quasi-global (37.4°N to 37.4°S), monthly waterbody map. This product significantly enhances our understanding of seasonal and interannual variability in tropical hydrology, offering new perspectives on these critical ecosystems. This chapter was published in *Water Resources Research* in 2024 [47].

In Chapter 3, we further advanced the algorithm for operational hydrology by harnessing the near-real-time capabilities of CYGNSS. The temporal resolution of the product was significantly refined to capture daily water dynamics, thereby addressing the critical need for timely monitoring and response to increasingly frequent and extreme hydroclimatic events. The enhanced product underwent validation in the Sudd wetlands, a region characterized by complex natural and anthropogenic influences on flooding. This case study highlighted the effectiveness and reliability of our approach, underscoring the potential of integrating cutting-edge remote sensing technologies with robust training-free computer vision algorithms. Such integration is essential for improving disaster response and management, providing timely and accurate information to stakeholders, and enhancing the resilience of vulnerable wetland ecosystems against climate-induced disruptions.

Finally, the focus of the study shifts to the Pantanal, the world’s largest tropical wetland, which has recently been severely impacted by frequent mega wildfires. Density-Based Spatial Clustering of Applications with Noise (DBSCAN) was employed for spatial clustering, and Hungarian methods were utilized for multi-object tracking. Customized multi-object tracking algorithms were developed to label and track fire patterns. This chapter delves into the trends in fire occurrences over recent years, examining the intricate interplay between fire regimes and wetland refilling patterns. Additionally, it explores the resilience of the Pantanal against extreme events, shedding light on the adaptive capacities and vulnerabilities of this critical ecosystem. Through this investigation, the study aims to provide valuable insights into the factors driving fire dynamics and their implications for wetland health and sustainability, ultimately contributing to more effective management and conservation strategies for the Pantanal in the face of climate change and human activities.

Chapter 2

GNSS-R Data-Driven Inundation Mapping

2.1 Introduction

In this chapter, we present the UC Berkeley Random Walk Algorithm WaterMask from CYGNSS (Berkeley-RWAWC), a data product designed to address the challenges of monitoring inundation in regions with dense vegetation and persistent cloud cover. Our algorithm demonstrates the practical application of Global Navigation Satellite System Reflectometry (GNSS-R) technology for water mapping by leveraging data from the Cyclone Global Navigation Satellite System (CYGNSS). Berkeley-RWAWC provides monthly maps with a latency of one month, starting from August 2018, and covers a significant latitude range from 37.4°N to 37.4°S. These maps not only showcase our algorithm’s capability in detecting seasonal water variations but also fill crucial knowledge gaps in monitoring Earth’s inland waters. This contribution is particularly significant in light of the escalating impact of climate change in tropical regions. By illustrating the utility and effectiveness of GNSS-R in environmental monitoring, Berkeley-RWAWC represents a substantial advancement in our understanding of tropical wetland dynamics.

2.2 Background

2.2.1 Existing WaterMasks

In this study, we select existing watermasks that are publicly accessible, and utilize microwave-based remote sensing technology to observe surface water dynamics. These products offer comparable resolution and temporal coverage, facilitating a meaningful comparison to evaluate the applicability of our CYGNSS-derived water mask. By focusing on such microwave-based remote sensing products, we aim to streamline and systematically evaluate our pro-

posed approach within the context of existing water mapping methodologies.

2.2.1.1 SWAMPS

The Surface Water Microwave Product Series (SWAMPS) is a coarse-resolution (~ 25 km) global inundated area fraction dataset derived from both active and passive microwave remote sensing. This dataset incorporates brightness temperature data from passive sensors like the Special Sensor Microwave Imager (SSM/I) and Special Sensor Microwave Imager Sounder (SSMIS), as well as radar backscatter data from active sensors such as the European Remote Sensing Satellite (ERS) Scatterometer, Quick Scatterometer (QuikSCAT), and Advanced Scatterometer (ASCAT) [9], and exhibits wetlands, rivers, lakes, reservoirs, rice paddies, and areas that experience episodic inundation. SWAMPS stands out as one of the most extensive microwave remote sensing datasets available for download, offering daily data files that cover the period from 2000 to 2020.

2.2.1.2 WAD2M

The Monthly global dataset of Wetland Area and Dynamics for Methane Modeling (WAD2M) is a derivative of SWAMPS, incorporating additional active and passive microwave remote sensing products [48]. This dataset is specifically designed to capture the spatiotemporal dynamics of both inundated and non-inundated vegetated wetlands, removing lakes, ponds, rice paddies, and rivers. WAD2M offers a spatial resolution of 25km and covers the time frame from 2000 to 2020.

2.2.2 CYGNSS

There is an ever-growing interest in employing CYGNSS data to retrieve geophysical variables related to terrestrial hydrology. This burgeoning field has not only prompted extensive research but has also led to the development of additional GNSS-R missions by governmental agencies and private companies. Research investigations have been conducted to assess CYGNSS's capacity for mapping inland surface water with different approaches e.g., [49, 50, 51, 52, 53, 54, 55, 56, 57, 35]. Furthermore, a capacity for detecting near-surface soil moisture sensitivity was also recognized e.g., [58, 59, 60, 61, 62, 63, 64]. Presently, there exist several GNSS-R missions in development, undertaken by both governmental agencies (e.g., ESA's HydroGNSS mission, as detailed by [65]) and private companies (e.g., Spire and Muon Space), all with the shared goal of retrieving hydrological data.

2.2.2.1 Existing Products

Currently, the only CYGNSS-based, publicly available data product is the UCAR/CU CYGNSS inundation product, which is generated at a spatial resolution of 3×3 km with a temporal resolution of three days, covering CYGNSS's entire observational range (within $\pm 38^\circ$ latitude) as detailed in the study by [66]. The study introduced a retrieval algorithm

specifically tailored for mapping fractional inundation, utilizing CYGNSS data as the primary input to a parameterized reflectivity model. The product provides a wealth of insightful information. Nevertheless, it is worth noting the uncertainties associated with this approach are primarily rooted in the parameterization of soil moisture and water surface roughness, which tend to result in an underestimation of fractional inundation, especially in regions featuring extensive surface water coverage. Ongoing research initiatives will emphasize the refinement of these model parameterizations and the optimization of spatial interpolation techniques, with a particular focus on enhancing performance during extreme events.

2.2.2.2 CYGNSS Data

In this study, we use the Delay Doppler Map (DDM) signal-to-noise ratio (SNR) of the level 1, version 3.1 CYGNSS data, which is publicly accessible through the Physical Oceanography Distributed Active Archive Center (<https://podaac.jpl.nasa.gov/CYGNSS>) to produce a surface reflectivity (SR) signal based on the methodology in [50]. The SNR was corrected for receiving and transmitting antenna gains, transmitted power level, and propagation loss from transmitter to specular point and specular point to receiver, assuming coherent scattering as described in [49]:

$$\text{SR}^{\text{coherent}} = \text{SNR} - P_r^t - G^r - G^t + 20 \log_{10}(\lambda) + 20 \log_{10}(\text{TxSP} + \text{SPRx}) + 20 \log_{10}(4\pi) \quad (2.1)$$

where P_r^t represents the transmitted power (in dBW), G^r and G^t refer to the receiving and transmitter antenna gains (in dB), respectively, λ denotes the GPS wavelength, which is equal to 0.19 m, the distances between the transmitter and the specular point, and between the specular point and the receiver, are denoted by TxSP and SPRx, respectively (both in meters). To provide a comparable range of variation in SR data to the initial SNR range, we removed the average of the 5% lowest data, which is a method employed in previous studies [49, 50, 67].

The available CYGNSS data at the time of investigation, covering from August 2018 to September 2023, was processed in this study. It is noteworthy that the time coverage of level 1, version 3.1 CYGNSS data begins in August 2018, in contrast to the earlier level 1, version 2.1 data used in previous studies [50, 67], which starts from June 2017. Prior to August 1, 2018, the CYGNSS data was obtained using the GPS navigation receiver's automatic gain control (AGC) mode, which restricted the strength of direct signals received from GPS satellites to a narrow dynamic range before signal processing. The AGC mode was disabled to allow the use of direct signal strength to monitor GPS transmit power level and improve calibration [68], and resulted in a change in the time span for L1 and higher data products from the Sensor Data Record (SDR) version 3.0 onward.

2.3 Methodology

The methodology initially developed by Gerlein-Safdi et al. [50, 67] for generating water-masks leverages both the spatial and temporal information contained in the SR data, and applies the random walker algorithm from the Python scikit-image library (<https://scikit-image.org/>) [69] to segment water and land. This approach does not rely heavily on data aggregation and is particularly well-suited for studying hydrological processes that exhibit seasonal variations. Here we present an extension of this exploratory work, which involves the establishment of a robust parameter and threshold selection system that can be applied regardless of the domain, as well as the coupling of surface topography data with the computer vision algorithm to optimize image segmentation with spatial analysis. By utilizing this methodology, we successfully generated a CYGNSS-based monthly watermarks product with a grid size of $0.01^\circ \times 0.01^\circ$ ($\sim 1 \text{ km} \times 1 \text{ km}$) and covers a latitudinal range from 37.4°N to 37.4°S . This product represents a continuous timeline spanning from August 2018 to the present and is being hosted on the Physical Oceanography Distributed Active Archive Center Cloud (https://podaac.jpl.nasa.gov/dataset/CYGNSS_L3_UC_BERKELEY_WATERMASK_V3.1) as the UC Berkeley CYGNSS Level 3 Monthly RWAWC Watermask Version 3.1, with monthly updates and maintenance ensured. Data for a given month will be released one month later due to the reliance on following-month information in the algorithm.

2.3.1 Pre-Labeling

The random walk approach proposed by Grady in [70] performs multilabel, interactive image segmentation. The method requires a set of pre-labeled pixels (seed points), which we refer to as markers throughout this work. The algorithm functions by labeling unseeded pixels with the respective label of the seed point that a random walker, with a bias to avoid crossing object boundaries (i.e., intensity gradients), is expected to reach first when initiated from that pixel. The calculation can be performed analytically [70], leading to an efficient and precise image segmentation. In the prior investigation [67], markers were allocated based on both monthly SR and the number of standard deviations (STD) from the multi-year average, which was found to be efficient in studying domains that exhibit high seasonal variations. It is important to emphasize why we are using the STD as the input image here: studies have shown that factors such as topography, vegetation cover, and wind-induced surface roughness will lead to varying levels of signal attenuation and, therefore, to different SR values [71, 72, 66]. Using month-specific STD maps instead of SR maps enables the random walk algorithm to efficiently connect identified water pixels based on their distribution and SR values. Additionally, it allows the inclusion of unassigned pixels with low SR values yet discernible moisture, as evident from their elevated values in the STD space [67]. In order to ensure that water bodies with low seasonal variations are also being captured as we are extending the study towards the entire CYGNSS domain, we propose a combination of four parameters for pre-labeling pixels, further explained below: SR, denoting Surface Reflectivity; STD, representing the number of Standard Deviations from the multi-year

average; SW, for Static Water; and ACC, indicating the Flow Accumulation

2.3.1.1 Surface Reflectivity (SR) Map

For each month, the *SR Map* is generated by gridding monthly SR values into a $0.01^\circ \times 0.01^\circ$ grid. Each grid cell contains the entire distribution of CYGNSS overpasses that occurred within its bounds. In cases where a grid cell contains more than one SR data, the monthly SR pixel is assigned with the average of the SR values. We then use a nearest neighbor interpolation method (SciPy, <https://scipy.org/>) to populate missing data for any pixels.

2.3.1.2 Standard Deviations (STD) Map

The *STD Map* is produced by assessing the deviation of SR value for each individual pixel from its 5-year average, using the yearly average and STD values. The computed STD map shows the number of STDs from the yearly average, and as such, a negative value signifies drier-than-usual conditions for that month, while a positive value indicates wetter-than-usual conditions for the corresponding pixel.

2.3.1.3 Static Water (SW) Map

The static water *SW Map* is generated by extracting the 5th percentile value from the yearly SR distribution for each pixel. Static water bodies can be effectively discerned using this strategy, as their SR value distribution is typically highly concentrated at elevated levels, which are evident as the 5th percentile value. Figure 2.1 provides an illustrative example of the notable contrast between the surface reflectivity distributions for always dry and always wet pixels using a violin plot.

2.3.1.4 Flow Accumulation (ACC) Map

The *ACC Map* uses flow accumulation, which is a geospatial product that is obtained by processing a digital elevation model (DEM). The calculation involves assigning a value to each pixel that corresponds to the number of upstream pixels that flow into it. This value is referred to as the accumulated grid cell count. Hence, pixels exhibiting higher values are indicative of potential water accumulation sites in the presence of water. Conversely, pixels characterized by lower values are more inclined to function as surface runoff areas in the event of water presence. We adopted the HydroSHEDS ACC map from [6] and the map was re-scaled from a resolution of 15 arc-seconds to 0.01 degree to ensure its alignment with the grid settings in this study.

2.3.1.5 Marker Selection

The set of parameters governing the marker allocation process and their respective physical implications are explained in Table 2.1. If a pixel falls into any category, it will be assigned

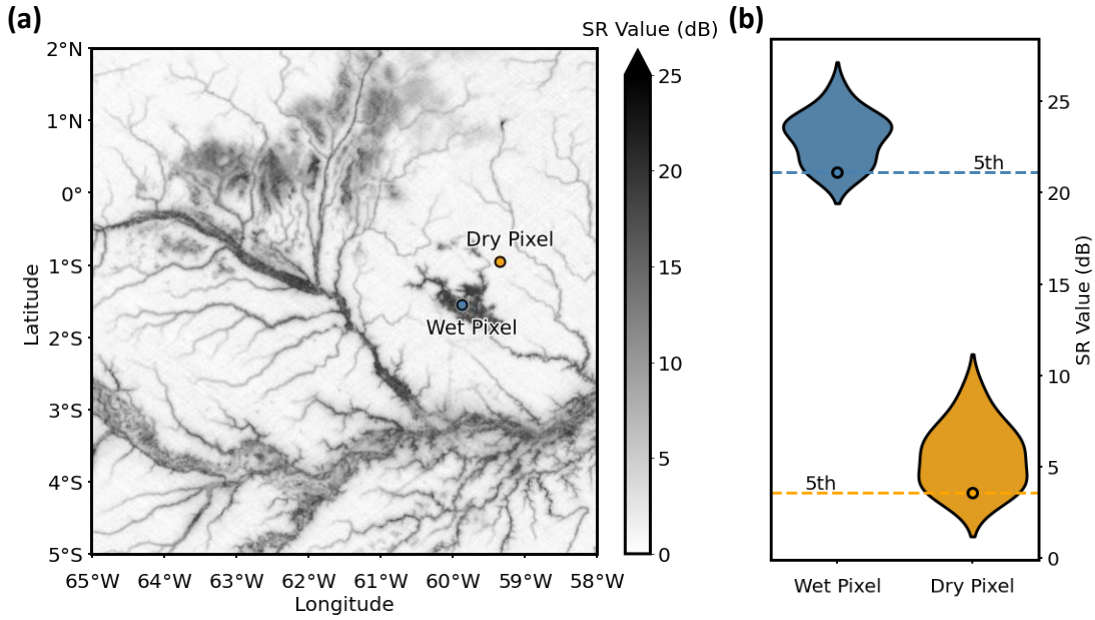


Figure 2.1: Illustration of Long-Term Dry and Wet Pixels.

(a) Long-term dry areas (in orange) and wet areas (in blue) are shown on the static water (SW) map, which consists of the 5th percentile value in the yearly SR distribution for each pixel. (b) The yearly SR value distribution for the two pixels respectively. Their 5th percentile values (SW) are marked with dash lines.

as a land/water marker. The breakdown of the categories described in Table 2.1 is as follows (using the upper bound indication as an example): (1) High values in both SR and STD suggest that the pixel has high moisture level and that the moisture level is notably higher than the pixel's yearly average, denoting a wet and wetter-than-usual condition. (2) High values in both SR and SW suggest that the pixel has high moisture level and the moisture level is always high for this pixel, denoting a wet and always wet condition. (3) High values in both SR and ACC suggest that the pixel has high moisture level with a tendency to accumulate water, denoting a wet and sink-if-water-exists condition. (4) High values in both STD and SW suggest that the moisture level is notably higher than the pixel's yearly average and that the moisture level is always high for this pixel, denoting a wetter-than-usual and always-wet condition. Utilizing part of the Amazon Basin in May 2021 as a representative case, Figure 2.2 elucidates the process of segmentation. The input image, assigned markers, and the resulting segmentation are showcased in Figure 2.2(a). Additionally, Figure 2.2(b) provides insights into each individual parameter, displaying their density distributions and exemplifying both upper and lower boundaries. For instance, for category (1) $SR \cap STD$, the upper bound indication would be an intersection graph of the upper bound figures of SR and STD in Figure 2.2(b). This highlights pixels showing high moisture levels and also elevated

moisture levels exceeding the yearly average, thus identifying them as water markers.

Table 2.1: Combining Parameters for Establishing Markers.

No.	Parameters	Lower Bound Indication	Upper Bound Indication
1	$SR^a \cap STD^{b,c}$	Dry $\cap$ Drier than Usual	Wet $\cap$ Wetter than Usual
2	$SR \cap SW^d$	Dry $\cap$ Always Dry	Wet $\cap$ Always Wet
3	$SR \cap ACC^e$	Dry $\cap$ Drain If Water Exists	Wet $\cap$ Sink If Water Exists
4	$STD \cap SW$	Drier than Usual $\cap$ Always Dry	Wetter than Usual $\cap$ Always Wet

^a Surface reflectivity (SR) indicates the moisture level of a pixel.

^b Standard deviation (STD) of SR values for the pixel this month, signifies moisture level variations.

^c $SR \cap STD$ indicates the intersection of the conditions defined by SR and STD.

^d Static Water (SW) is the 5th percentile SR value for the pixel, indicates its persistent moisture level.

^e Flow Accumulation (ACC) denotes a pixel's tendency to accumulate flow in water presence.

2.3.2 Random Walk with Spatial Analysis

Finally, within the framework of the random walk algorithm, we introduce a new variable termed the “Flow Accumulation Index” (F). It serves to interconnect spatial analysis with the random walk concept. Comprehensive insights into the algorithm’s fundamental components are illustrated in [70], regarding graph weight generation, equation establishment for problem-solving, and implementation details. In summary, a graph is defined as $G = (V, E)$, where V represents vertices and E represents edges. In a weighted graph, each edge is assigned a value (weight), denoted as w_{ij} , and the vertex degree d_i is given by $d_i = \sum w_{ij}$ for all incident edges e_{ij} . To interpret w_{ij} as a bias for a random walker choice, it’s necessary to set $w_{ij} > 0$. Additionally, an assumption is made for the graph to be connected and undirected (i.e., $w_{ij} = w_{ji}$). The weighting function for calculating edge weight was given by [70]:

$$w_{ij} = \exp [-\beta (g_i - g_j)^2] \quad (2.2)$$

where g_i denotes the image intensity at pixel i , and β is the only free parameter in this algorithm. As pointed out in [70], the weight function (2.2) has the potential to be adapted for use with consideration of features present within an image, such as texture information, filter coefficients, etc. For this study, we modified the weighting function by adding the Flow Accumulation Index (F): the updated weighting function then becomes:

$$w_{ij} = \exp [-\beta (g_i F_i - g_j F_j)^2] \quad (2.3)$$

where F is a re-weighted index based on the flow accumulation (ACC). The result provides adjustments to the segmentation results, where individual pools are linked if that is what

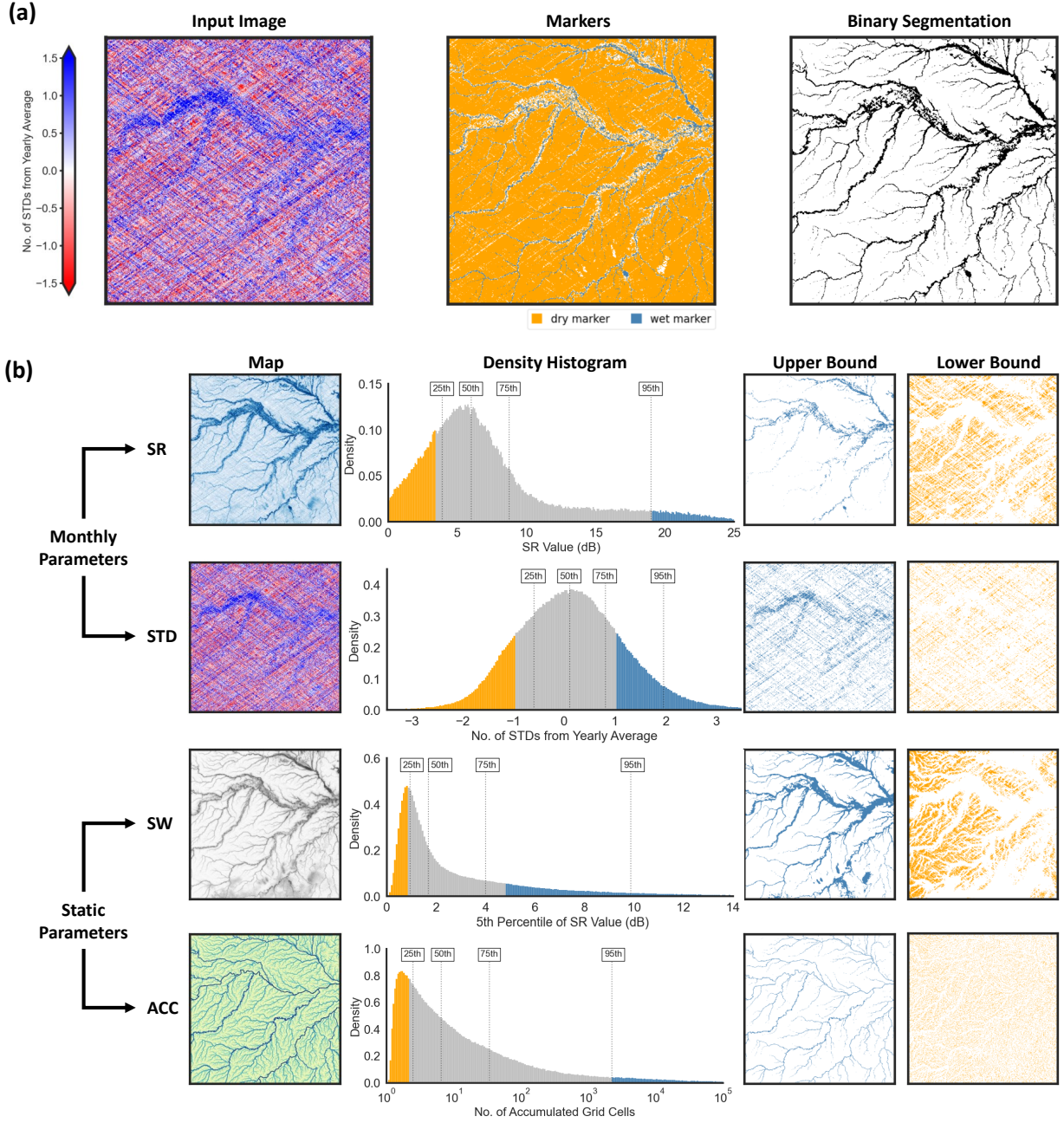


Figure 2.2: Illustration of the Image Segmentation Process.

(a) Left: Input image subjected to segmentation, known as the Monthly STD Map. Center: Allocated markers. Right: Resulting segmentation. (b) Individual parameters featuring their density distribution, along with instances of upper and lower bounds.

the topography favors, and vice versa as Figure 2.3(a) shows. Figure 2.3(b) provides corresponding references to the Digital Elevation Model (DEM) map and Flow Accumulation (ACC) map sourced from HydroSHEDS [6].

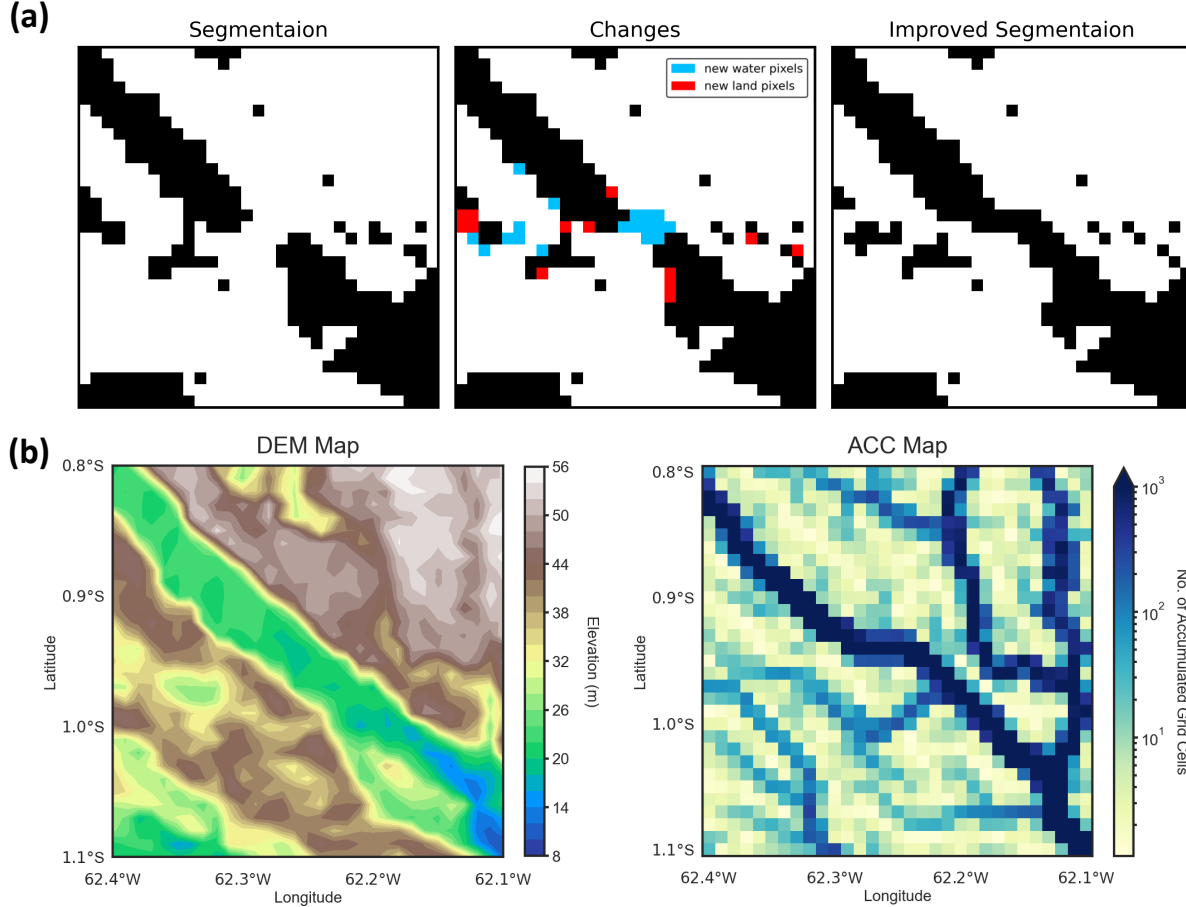


Figure 2.3: Segmentation Results with Spatial Analysis.

(a) Illustration of the adjustments made to improve segmentation results, where individual pools are connected or separated based on topographical features. (b) Corresponding Digital Elevation Model (DEM) map and Accumulated Flow Accumulation (ACC) map.

2.3.3 Mitigate False Positives and False Negatives

To improve the precision of the algorithm as it is scaled up to a broader spatial domain, we have meticulously addressed instances of both false negatives and false positives within the workflow. This strategic approach ensures a more accurate and reliable application of the algorithm across diverse scenarios.

To enhance dataset integrity, we implemented a filtering step to remove any pixel exhibiting anomalously high or low SR values compared to adjacent months, i.e. a deviation of more than 6.5 dB compared to adjacent months' values are flagged as anomalous SR values. Subsequently, they are excluded from the assigned marker pool. These pixels then undergo the random walk algorithm to determine whether they will be classified as water or land. This process effectively addresses outliers when assigning markers, thereby reducing segmentation artifacts such as stripings.

In addition, the Unsharp Mask (USM) technique, explained in [73], serves as an important tool during the marker assignment phase. The USM filter is applied to the SR map and while it does not explicitly detect edges, the filter enhances image contrast along object edges. This is achieved by identifying pixels with notable deviations from neighboring pixel values, thereby emphasizing fine details and subtle contrasts. By integrating the USM-filtered SR data into the marker assignment process, such as when a pixel demonstrates high SR and standard deviation (STD) alongside a notable USM-filtered SR value, we confidently designate it as a wet marker. This ensures the quality of the marker assignment in areas and in periods that are characterized by high moisture backgrounds. It significantly improves the accuracy of marker placement by highlighting subtle contrasts and details in moisture-rich environments.

Moreover, dry and flat regions, such as flat deserts, pose challenges as potential false positives due to their high SR values [74, 75]. We flagged out the dry and flat regions when assigning markers through cross-referencing the World Terrestrial Ecosystem (WTE) 2020 database [76] in conjunction with a slope map derived from the HydroSHEDS DEM [6]. Specifically, pixels were systematically excluded from the water marker category if they satisfied the upper bound criteria 2-4 in Table 2.1, while concurrently being classified in WTE as *Plains* or *Tablelands* in the Landform Class, *Dry* or *Desert* in the Moisture Class, and *Settlement*, *Shrubland*, or *Sparsely or Non-vegetated* in the Landcover Class and additionally exhibiting a slope of less than 0.05° in the DEM data.

Further, the presence of wind-induced surface roughness in large open water areas can lead to low SR values, resulting in portions of large open water domains being unaccounted for by the algorithm. This phenomenon is exemplified by Lake Victoria in Africa. To mitigate these uncertainties and effectively address the missing data in large water bodies, we apply a layer of data that identifies regions where water occurrence exceeds 95% based on the Global Surface Water Explorer (GSWE) [8] to the segmentation result.

Lastly, regions surpassing the DDM height limit of 4100 meters are recognized to have insufficient data availability. Pixels exceeding this altitude threshold are marked as null, reducing the likelihood of overlooking significant water bodies and therefore avoiding false negatives in high-altitude areas. This covers an area of approximately 2,292,988 km², with close to 85% situated in the Himalayas region and 15% in the Andes.

This workflow addresses various geographical and environmental factors and aids in refining the algorithm with diverse landscapes.

2.3.4 Tiling

The CYGNSS domain is partitioned into tiles of size $10^\circ \times 10^\circ$, and the algorithm is applied to each tile as Figure 2.4 shows. Notably, the algorithm exhibited robustness in that the parameters were established based on the distribution within each tile, and the markers could be assigned without impacting the resulting water mask. Besides, the dynamic threshold is a crucial component of the algorithm because it ensures consistent performance across various regions and different time frames. In different geographical areas, vegetation can undergo significant changes, making it essential for the algorithm to adapt and maintain its accuracy. By adjusting its thresholds dynamically, the algorithm can effectively address these variations and deliver reliable results regardless of the specific location or time period it is applied to. Figure 2.5 shows how the Amazon region becomes segmented into four tiles and serves as a demonstration of the algorithm’s robustness, as the markers are not assigned uniformly, yet the resulting water mask remains unaffected by the tile boundaries.

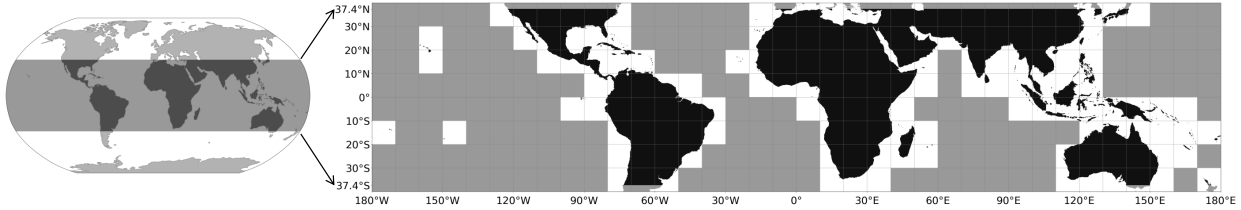


Figure 2.4: Global View of Berkeley-RWAWC Coverage Domain with Tiling.
Basemap generated using the Cartopy library in Python.

2.4 Results

Figure 2.6 presents May 2023 as an example of the watermask. Many large wetland and river basins are easily identifiable, even when zoomed out, including the Amazon Basin, the Pantanal, the Congo Basin, the Sudd, or the Yangtze River. Note the greyed areas over the Himalayas and the Andes, indicating areas of elevation higher than 4100 m over which the algorithm was not applied (see Section 2.3.3). An animation of the full timeseries from August 2018 to September 2023 is available as supplementary information (Movie S1, available online <https://rb.gy/7mm8lp>). Strong seasonality shows across the world, with various regions experiencing wet and dry seasons at various points in the year.

Additionally, Figure 2.7 presents zoomed-in views of four geographically diverse regions - namely the Amazon Basin, the Pantanal, the Sudd, and the Indo-Gangetic Plain - each

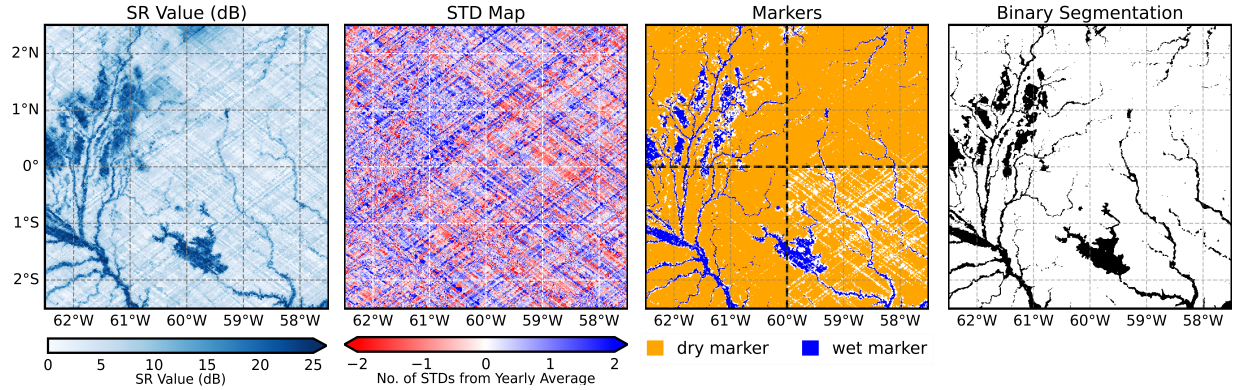


Figure 2.5: Illustration of the Algorithm's Robustness in Tiling

Far-left: SR Map. Center-left: STD Map. Center-right: non-uniform marker assignments aligned with the tiles, tiling is explicitly delineated with black dash lines. Far-right: the resulting water mask, which remains unaffected by non-uniform marker assignments.

representing distinct ecological and geographical contexts. Each map within Figure 2.7 depicts the surface water extent, representing the ratio of inundation occurrence monthly over a comprehensive 5-year period, spanning from August 2018 to July 2023. From the expansive river networks of the Amazon to the intricate wetlands of the Pantanal, and from the dynamic flood plains of the Indo-Gangetic region to the extensive water bodies in the Sudd, each figure offers a detailed insight into the spatial and temporal dynamics of inundation patterns. Figure 2.7 provides an alternative visual representation of the scale and behavior of water bodies that are being captured by Berkeley-RWAWC.

2.4.1 Comparison with SWAMPS and WAD2M

In Figure 2.8, we showcase regional comparisons that utilize the inundated area fraction (f_w) observed using the Berkeley-RWAWC, SWAMPS, and WAD2M data sources between August 2018, when Berkeley-RWAWC product begins, and December 2020, after which date WAD2M and SWAMPS are not available. Berkeley-RWAWC, originally gridded at a spatial resolution of 0.01° (approximately 1 kilometer at the equator), has been upscaled to a resolution of 0.25° for direct comparison. As previously introduced, we selected four regions of interest: the Amazon Basin, the Pantanal, the Sudd, and the Indo-Gangetic Plain, each illustrating unique ecological and geographical characteristics. Figure 2.8 indicates that the CYGNSS product exhibits a remarkable capacity to elucidate pronounced seasonal variations in surface water dynamics compared to the other two datasets. Furthermore, we present monthly maps for the year 2020 for these four distinct geographical regions as captured by the three datasets, showcased in Figure 2.9.

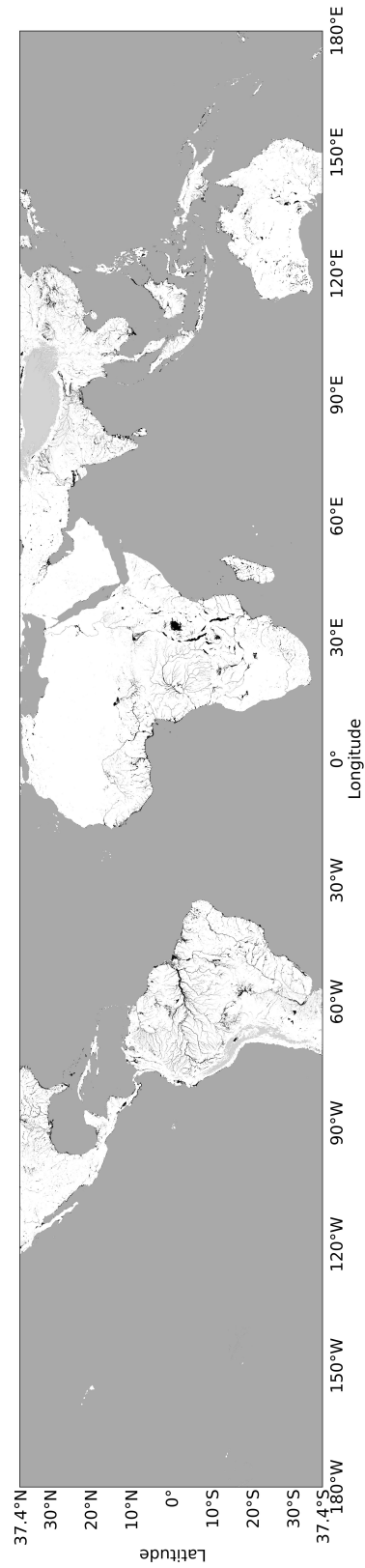


Figure 2.6: The Berkeley-RWAWC water extent map for May 2023. Inland water is shown in black, dry land in white, and grey areas depict either oceans or areas of high elevation where not enough data is available to produce accurate maps (e.g. the Himalayas and the Andes).

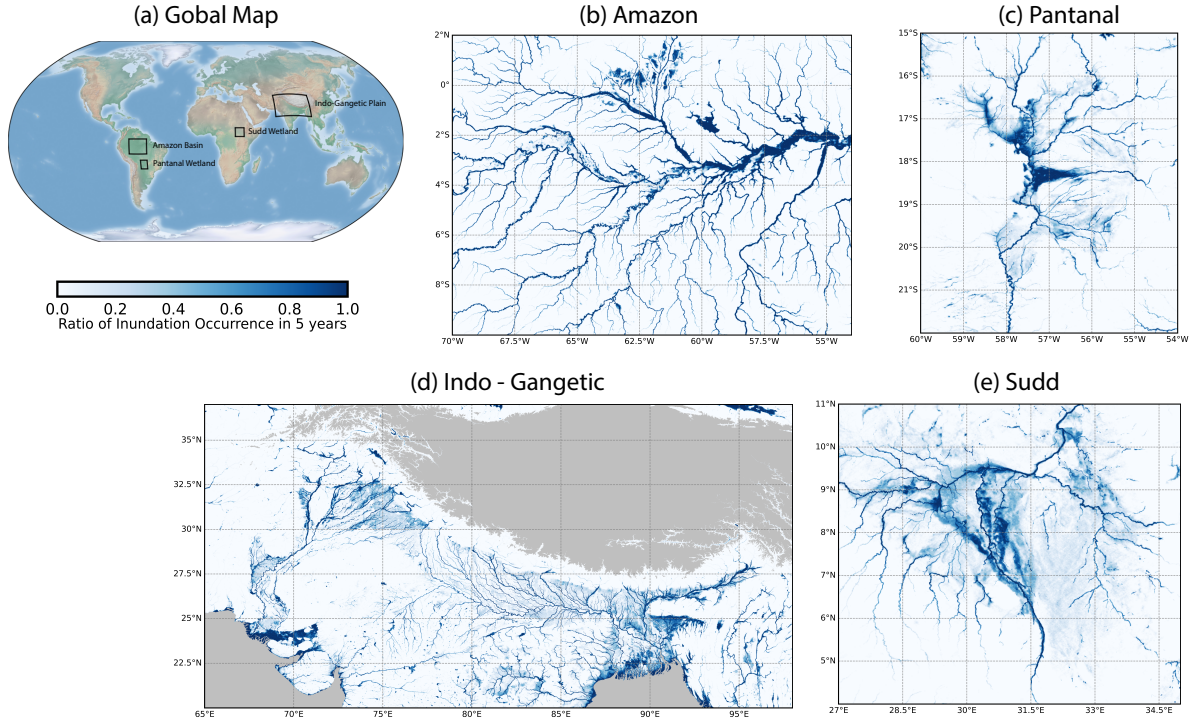


Figure 2.7: Five Year Inundation Ratios Across Key Global Wetlands.

(a) Global Map showing selected regions: the Amazon Basin, the Pantanal Wetland, the Indo-Gangetic Plain, and the Sudd Wetland. (b) the Amazon Basin. (c) The Pantanal Wetland. (d) The Indo-Gangetic Plain, ocean and the Himalayas are masked in grey. (e) The Sudd Wetland. Each map uses a color gradient (shown in the legend under the global map) to depict the ratio of inundation occurrence from 0.0 (no inundation) to 1.0 (constant inundation) over a five-year period.

It is interesting to note that WAD2M, which is supposed to be an improved version of the SWAMPS product, shows a greater extent than SWAMPS in three of the four locations, the Indo-Gangetic Plain being the exception. The Berkeley-RWAWC results for the Amazon and the Indo-Gangetic Plain exhibit similar seasonal patterns when compared to SWAMPS and WAD2M datasets. However, it is noteworthy that the mean average within the CYGNSS dataset is significantly higher than that observed in the other two datasets. For the Sudd, Berkeley-RWAWC data presents more pronounced and dramatic seasonal variations compared to SWAMPS and WAD2M datasets. In addition, we see an offset in the seasonality of the three products, with SWAMPS and the WAD2M peaking in late spring for just three months (e.g. April, May, and June of 2019) and staying stable otherwise, whereas Berkeley-RWAWC shows instead a pronounced seasonal pattern and reaches its maximal extent in late summer, with peaking evident in September and October. In the case of the Pantanal

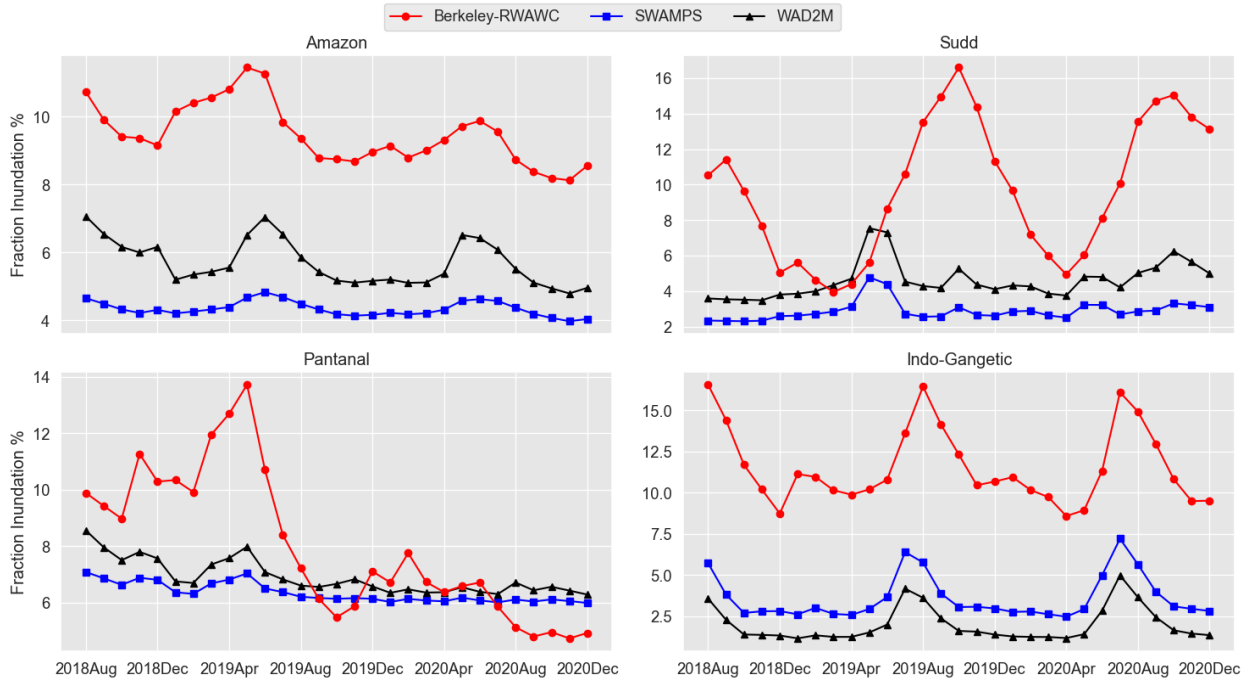


Figure 2.8: Regional comparisons of the timeseries of the inundated area fraction (f_w). Observed for Berkeley-RWAWC (red), SWAMPS (blue), and WAD2M (black) products between August 2018 and December 2020 over the Amazon Basin (upper left), the Sudd wetland (upper right), the Pantanal wetland (lower left), and the Indo-Gangetic Plain (lower right).

region, the Berkeley-RWAWC maps reveal a distinct high water extent peak in May 2019, a feature absent in the SWAMPS and WAD2M datasets. Figure 2.10 shows the inundation fraction in the Berkeley-RWAWC product over the Sudd and the Pantanal for an extended time window going until 2023 September. Broader trends emerge then: over the 5 years of data, the Sudd shows a regular seasonal range but exhibits a strong inter-annual upward trend. The Pantanal on the other hand shows a large interannual variability, with 2019 and 2023 showing large inundation extent, whereas 2020, 2021, and 2022 show much smaller peak wet season extent. No long-term trend is appearing in the Pantanal.

Finally, we compared all three products to optical data using the Modified Normalized Difference Water Index (MNDWI) computed from Landsat 8 data (<https://www.usgs.gov/landsat-missions/landsat-8>). The result for the Sudd wetland for the month of November 2020 is presented in Figure 2.11. Although gaps due to cloud cover and missing data are evident, Figure 2.11 provides a first-order comparison of MNDWI against the three discussed products. Notably, the Berkeley-RWAWC product demonstrates higher agreement with observed patterns, underscoring its reliability and accuracy. Note that this image was obtained by using all available Landsat 8 data from Nov. 2020, removing images with more

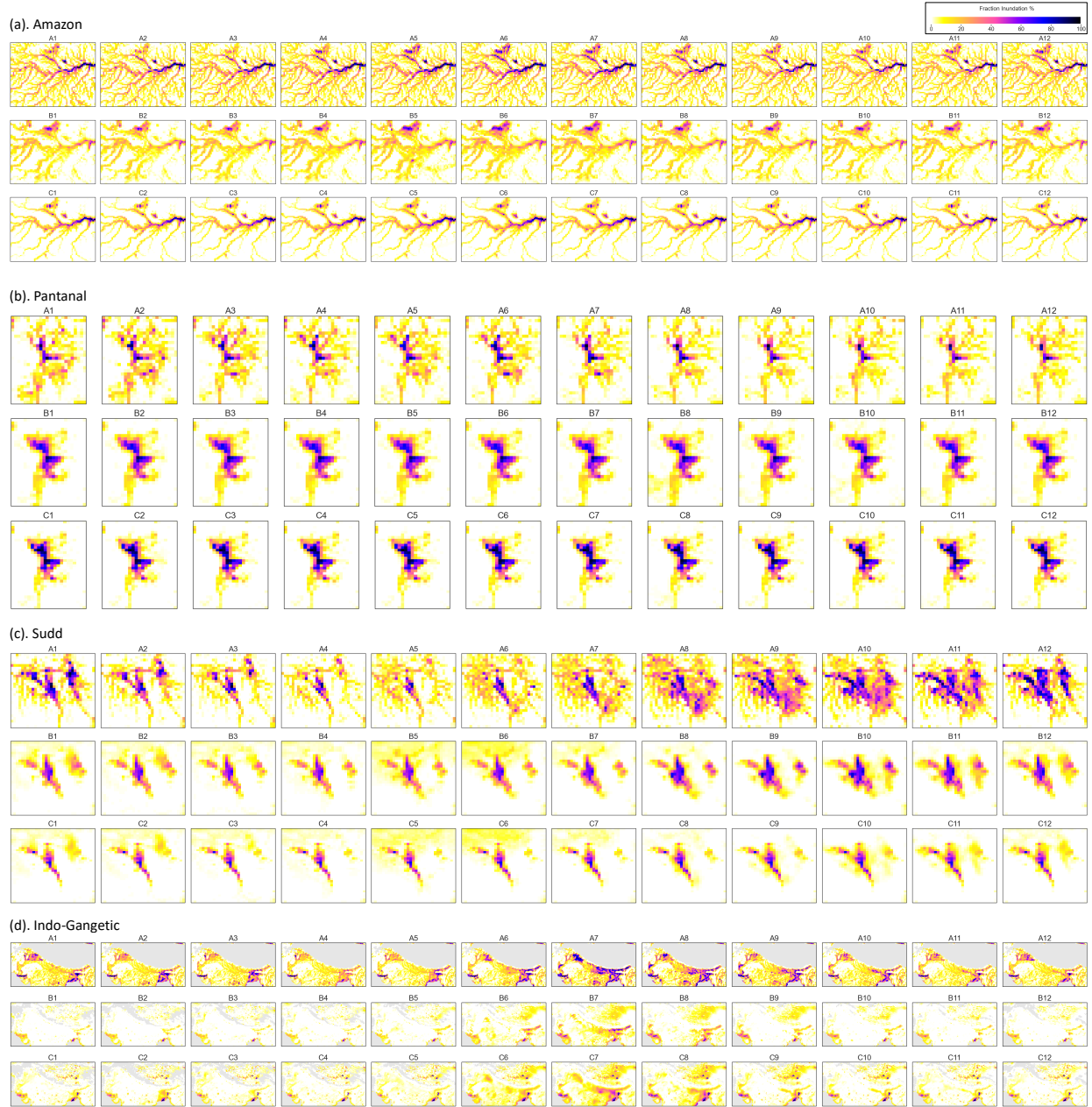


Figure 2.9: Inundation Fraction Comparison (2020).

(a) the Amazon Basin, (b), the Pantanal, (c) the Sudd, and (d) the Indo-Gangetic Plain for Berkeley-RWAWC (top), WAD2M (center), and SWAMPS (bottom). Berkeley-RWAWC, originally gridded in 0.01° , was upscaled into a resolution of 0.25° for direct comparison.

than 20% cloud cover, and taking the median of the images left (instead of the average, in order to attenuate the effect of cloud shadows on the ground).

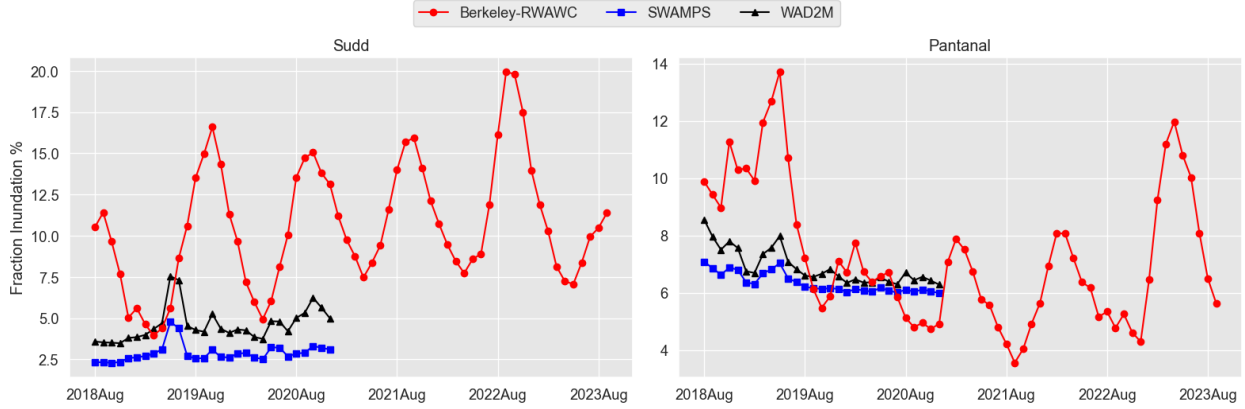


Figure 2.10: Regional comparisons of the inundated area fraction (f_w). Observed for Berkeley-RWAWC (red), SWAMPS (blue), and WAD2M (black) over the Sudd (left) and the Pantanal (right). Here, Berkeley RWAWC is shown until September 2023. WAD2M and SWAMPS end in December 2020 after which date the two datasets are not available.

2.5 Discussion

The new Berkeley-RWAWC product is a unique tool to understand the spatio-temporal dynamics of inland waterbodies in the Tropics and sub-Tropics. Being updated in near-real time, the product will allow for rapid estimation of seasonal patterns as they emerge. The product exhibits a much higher seasonal variability than WAD2M and SWAMPS, two products regularly used to capture inland waterbodies [77, 78, 79, 80, 81]. This heightened sensitivity to seasonal variability carries profound implications across an array of scientific disciplines. The capacity to discern more changes in surface water dynamics opens up a plethora of opportunities for the scientific community to advance our understanding of critical ecological processes and environmental management.

2.5.1 Potential Limitations

The proportion and distribution of standing water within pixels flagged as "wet" in the algorithm are not fully determined. [66] did extensive work to partition dry and wet areas within individual pixels, but this effort required additional datasets that brought new layers of uncertainty to the resulting partitioning. Because we do not expect saturated soils to produce a coherent reflection, we do not anticipate non-inundated pixels to be counted as "wet" but how small of a water body might generate a strong enough signal to be classified as "wet" is still an ongoing research topic for the field. This does have consequences for delineating the edges of waterbodies, particularly in close proximity to coastlines where the presence of calm coastal water might produce a strong coherent reflection, leading to over-estimating

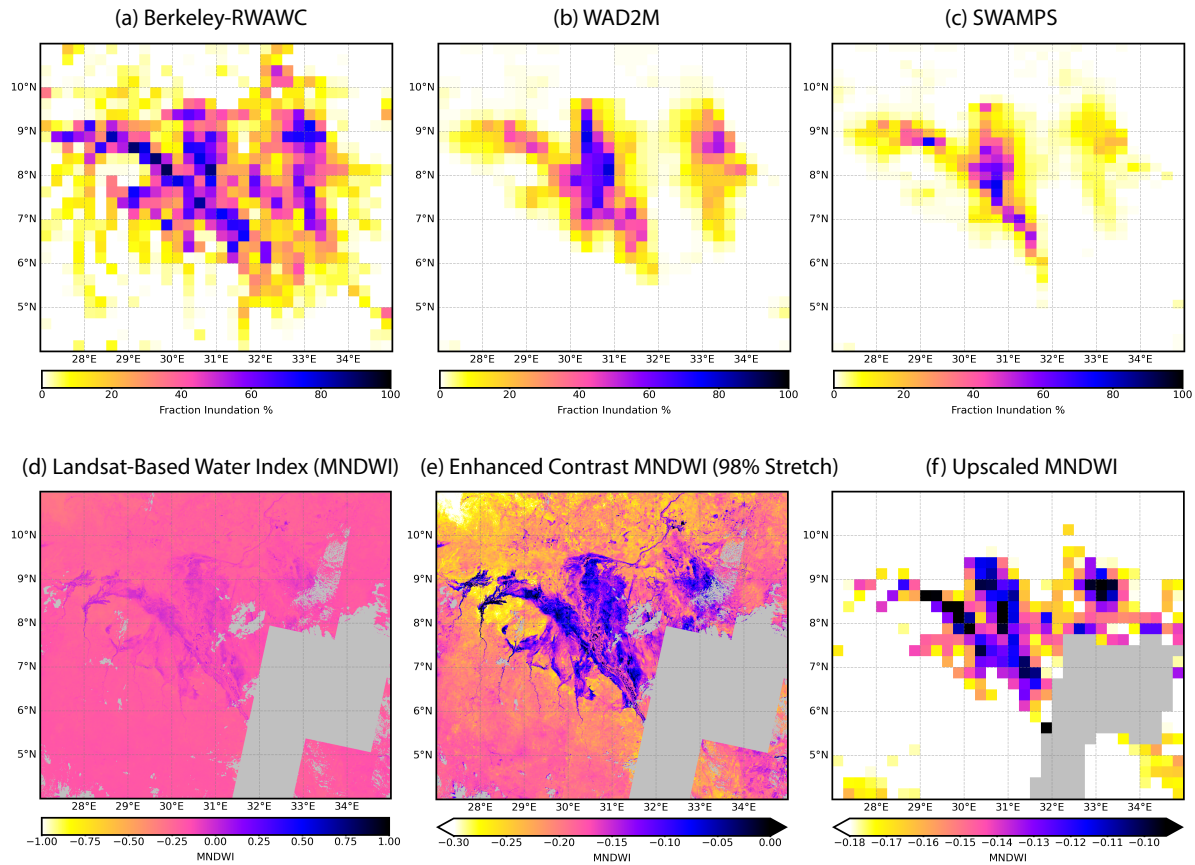


Figure 2.11: Case of the Sudd Wetland.

Monthly maps for November 2020 using (a) Berkeley-RWAWC upscaled from a resolution of 0.01° to 0.25° , (b) WAD2M, (c) SWAMPS, and (d) Modified Normalized Difference Water Index (MNDWI) computed from Landsat 8 data, data shown within the range of -1 (strong water presence) to 1 (non-water surfaces such as bare soil or urban areas), cloud cover and missing data are masked in grey, (e) the enhanced contrast MNDWI using a 98% stretch on the data range for visual clarity, and (f) MNDWI upscaled from a resolution of 30m to 0.25° for an effective first-order comparison with the other datasets.

the presence of inundated lands in coastal areas.

In terms of the algorithm’s robustness, we find it performs effectively with our tiling system. The only exception is in cases where a tile with relatively high moisture content borders a tile with very low moisture content. This is for example the case near the Sudd wetlands, where the boundary between the wet tile containing the Sudd borders the very dry Sahara. While the tiling does not affect the mapping of large rivers and main waterbodies, it appears to affect small tributaries at the tile edge.

Finally, there does not currently exist an appropriate dataset with which we could validate our data product: the inability of other satellite products to penetrate canopies and/or clouds makes them unsuitable validation tools. Airborne and in-situ stream flow data have recently been leveraged in [82], but this comparison can only attest that CYGNSS-based data is adequately capturing the seasonality of the water within a watershed and does not provide validation regarding the accuracy of the boundaries between dry and wet areas. The NASA-ISRO Synthetic Aperture Radar mission, whose launch has now been delayed several times, will likely offer the first appropriate dataset to validate our product. In the meantime, the Berkeley-RWAWC product (see Section 2.5.2) has been shown to greatly improve estimations of a multitude of different processes, attesting that the product is indeed producing improved maps of tropical wetlands.

2.5.2 Applications of the Berkeley-RWAWC product

The product’s advanced monitoring capabilities offer a valuable tool in the fight against climate change, helping to identify and manage one of the key sources of greenhouse gas emissions. Wetlands are known to be substantial sources of methane, a potent greenhouse gas, and understanding their dynamics is crucial for climate change mitigation efforts [39]. By providing detailed insights into the timing and duration of wetland inundation, the product enables researchers to pinpoint when and where methane emissions are most likely to occur. This information is essential for developing targeted strategies to better understand and predict methane release from wetlands in a changing climate. Additionally, the product’s ability to track changes in wetland conditions over time allows for the assessment of how different environmental factors, including human interventions, affect methane emission rates. This could be particularly beneficial in identifying areas where methane emissions are increasing and require urgent attention. The Berkeley-RWAWC product has already been leveraged for this purpose in multiple studies [67, 83], with more ongoing efforts leveraging the product currently in the work. For example, the implications of the increasing trend in inundation observed over the Sudd by the Berkeley-RWAWC might help explain the large, ever-growing methane emission signal being detected by methane monitoring satellites over the area [84, 85, 86].

Another pivotal application lies in unraveling the intricate interplay between fire regimes

and wetland refilling patterns [87, 88, 89]. The product can provide crucial insights into the timing and duration of inundation events, enabling researchers to assess how wetland refill rates may influence fire frequency, intensity, and ecological resilience, or the other way around. This knowledge is indispensable for fire management strategies and the conservation of vulnerable wetland ecosystems. Furthermore, the enhanced ability to monitor seasonal variations in wetlands has direct implications for wetland conservation efforts. For example, the high inundation wet season in 2018/2019 followed by low water years in 2019/2020 observed in the Pantanal might be associated with the catastrophic fire event that engulfed the Pantanal wetlands in both 2019 and 2020 [90]. The aftermath of this extensive fire outbreak raises concerns regarding the long-term ecological consequences, as initial indications suggest that the Pantanal’s unique biodiversity hotspot may face challenges in fully recovering from the unprecedented scale of these fires [91, 92].

Additionally, inland waterbodies serve as vital habitats for diverse flora and fauna, playing an essential role in maintaining biodiversity [93]. With this product, researchers can gain a new perspective on wetland dynamics, allowing for a more comprehensive evaluation of conservation strategies. This data can inform the identification of critical wetland areas, guide habitat restoration initiatives, and facilitate sustainable land use planning to safeguard these invaluable ecosystems. For example, in the realm of biodiversity conservation, this product offers an advantage in tracking the movements of wildlife that traverse multiple wetlands throughout the year. Many species, such as migration birds and amphibians, rely on wetlands as stopover points during their journeys [94, 95]. By providing a clearer view of wetland dynamics, the product aids in understanding the availability and accessibility of suitable habitats for these nomadic species. Researchers can use this information to devise effective conservation strategies that ensure the continuity of vital habitats, contributing to the preservation of biodiversity on a global scale.

Finally, this new product, with its high sensitivity to seasonal variations in inland waterbodies, not only wetlands but also rivers, might be a great tool to test theories related to river networks, their formations, and their sequential activation [96, 97, 98]. The tools being developed to better understand river networks are of crucial importance to understanding the hydrological response of river basins to extreme hydrological events, but data to appropriately test these theories have so far been very limited, both spatially and temporally.

In sum, the product’s capacity to illuminate seasonal variability in surface water dynamics holds transformative potential for a myriad of scientific applications. From fire ecology and wetland conservation to biodiversity preservation and to methane emission, the data generated by the product enriches our ability to comprehend and address complex environmental challenges, fostering a more informed and proactive approach to safeguarding our planet’s ecosystems and natural resources. While the product exhibits enhanced performance in capturing seasonal variations, it is crucial to acknowledge its inherent nature as a binary water mask. With a resolution of 0.01° in both latitude and longitude, each pixel stands

as a definitive sentinel, representing either a watery domain or dry land within a compact $\sim 1\text{km}$ by 1km frame. This singular feature underscores the need for users to embrace the binary essence of our data product, acknowledging its precision level and distinctiveness when harnessing it for diverse applications.

2.6 Conclusions

This chapter presented the Berkeley-RWAWC inundation product, addressing a critical research gap in global inland water dynamics. Historically, challenges like cloud cover, dense vegetation, and limited remote sensing revisit frequency hindered the characterization of seasonal inundation in tropical regions. Our study presents a significant advancement by adapting a computer vision algorithm for CYGNSS-based inundation mapping. Applied since August 2018, it enables monthly mapping at a 0.01° spatial resolution ($\sim 1\text{km}$). We detail our workflow and parameterization strategy. This methodology distinguishes itself by exclusively relying on static products combined with CYGNSS data for product development. This deliberate choice provides our results with a robust indication of CYGNSS data's unique contributions, setting our dataset apart from others in the field. Comparative analysis with SWAMPS and WAD2M in the Amazon, the Pantanal, the Sudd, and the Indo-Gangetic plain reveals higher seasonal variations in Berkeley-RWAWC. We discuss Berkeley-RWAWC's applications, emphasizing its role in advancing tropical hydrology. To enhance access, we introduce a data portal (https://podaac.jpl.nasa.gov/dataset/CYGNSS_L3_UC_BERKELEY_WATERMASK_V3.1) for the scientific community. This paper contributes to remote sensing and hydrology knowledge, improving insights into tropical wetland dynamics and their global hydrological significance.

Chapter 3

Operational Hydrology: GNSS-R Insights into Extreme Hydroclimatic Events

3.1 Introduction

In this chapter, we investigate the feasibility of developing daily updated surface water maps by expanding upon prior methodologies. Our objective is to leverage the near-real-time capabilities of CYGNSS data to their fullest potential, marking a significant advancement in operational hydrology by enabling the identification and analysis of daily variations in surface water dynamics. A case study focusing on the Sudd wetland during flooding seasons exemplifies our approach; daily mapping delineates fluctuations in water extents, with peak inundation levels closely mirroring the season’s maximum flooding reports. This correlation validates the accuracy and applicability of our GNSS-R data-driven approach.

The implications of our study extend beyond technical advancements in surface water mapping. Our findings strongly endorse the integration of GNSS-R data into broader environmental monitoring and management strategies, highlighting its capacity to enhance our understanding and stewardship of Earth’s vital wetland ecosystems. By laying the groundwork for consistent daily hydrological observations, we pave the way for a transformative shift in our comprehension of water dynamics to the global scale. This transition towards high-frequency hydrological data acquisition promises to refine our ability to predict flood events, guide sustainable water resource management practices, and contribute to the broader objectives of climate change mitigation and adaptation.

3.2 Background

3.2.1 Extreme Hydroclimatic Events

Studies based on advanced climate models, such as the Multi-Model Large Ensemble Archive (MMLEA) [99], and satellite observations of terrestrial water storage using the Gravity Recovery and Climate Experiment (GRACE) [100], both indicate that hydroclimatic extreme events are increasing in frequency, duration, and extent under warming conditions. Numerous efforts by researchers have demonstrated that rising temperatures are causing more erratic and extreme precipitation events worldwide [101, 102, 103, 104]. Furthermore, study has highlighted global trends in extreme precipitation, emphasizing that these events are not only becoming more frequent but also shifting in geographical distribution [105]. The intensification and geographical shift of hydroclimatic extremes have far-reaching implications, resulting in substantial economic losses, displacement of communities, and heightened food and water insecurity, particularly in regions already vulnerable due to socioeconomic factors. Specifically, in the context of floods and droughts, studies such as those by [106, 107, 108, 109] explore these societal impacts in detail, underscoring the urgent need for adaptive management strategies.

3.2.2 Anticipatory Action: The Case of South Sudan

Anticipatory Action Decision-Making Systems represent a proactive approach to disaster risk management, aiming to mitigate the impacts of extreme events before they occur. These systems enhance community resilience by integrating predictive models, early warning systems, and preemptive measures based on reliable forecasts and risk assessments [110]. This forward-thinking strategy in disaster preparedness has been driven by the efforts of both United Nations (UN) agencies and non-governmental organizations (NGOs) such as the Red Cross Red Crescent (RCRC), the World Food Programme (WFP), and the Start Network, with more than 50 countries engaged by 2023 [111].

The United Nations Office for the Coordination of Humanitarian Affairs (OCHA) began developing Anticipatory Action frameworks in 2019 (<https://www.unocha.org/anticipatory-action>). Since then, pilots have been established in several countries, including Somalia, Ethiopia, Bangladesh, Nepal, Niger, the Democratic Republic of the Congo, and South Sudan. In South Sudan, however, OCHA decided against developing a formal Anticipatory Action framework for floods due to a lack of validated flood forecasts and data scarcity. Despite this, data analysis was employed to initiate actions aimed at mitigating the impact of anticipated unprecedented flooding in the most at-risk areas ahead of rainy seasons.

Not only is South Sudan located in a tropical region that often experiences persistent cloud cover during the rainy season, but it also has complex hydrological features that further complicate flood warning efforts. A key factor contributing to South Sudan's flood risk is

the presence of the Sudd Wetland, a vast swamp ecosystem within the expansive Nile River Basin. Figure 3.1(a) illustrates the inundation frequency in South Sudan and its adjacent countries (including Central African Republic, Democratic Republic of the Congo, Ethiopia, Uganda, Kenya, and Tanzania) over recent years, based on the Berkeley-RWAWC water mask introduced in Chapter 2. The map aggregates monthly water presence from August 2018 to July 2023, normalized on a scale from 0 to 1, and plotted with darker colors indicating higher frequencies of water occurrence. Red dots mark the three major lakes downstream of which the Sudd Wetland lies: Lake Albert, Lake Kyoga, and Lake Victoria. Notably, Lake Victoria is the second-largest freshwater lake globally and the largest in Africa, spanning approximately 68,600 km² [112]. Figure 3.1(b) provides a broader view of Central and Eastern Africa with a digital elevation model (DEM) map emphasizing the same region as in Figure 3.1(a). The DEM map showcases the topographical gradient from the highlands, where the lakes reside, to the low-lying Sudd Wetland. This topographical gradient facilitates the natural flow of water from the upstream lakes into the White Nile, which traverses the region and ultimately feeds into the downstream Sudd Wetland. As a result, the Sudd Wetland encompasses a significant permanently inundated area, which undergoes considerable expansion when water is released from these upstream lakes, primarily regulated for hydropower demands. Additionally, inflows are further augmented by seasonal runoff, causing the Sudd to nearly double in size during the wet season [113].

One ongoing initiative, the Improved Anticipation of Floods on the White Nile (INFLOW) project (<https://clareprogramme.org/project/improved-anticipation-of-floods-on-the-white-nile-inflow>), seeks to enhance early warning capabilities in South Sudan. The project aims to bolster the capacity of humanitarian organizations to act on new information, addressing the inadequacies of hydrological forecast models. Recent efforts to monitor water extent in the project have employed thermal infrared (IR) imaging. This technique leverages the distinct thermal properties of water compared to land, as water bodies typically exhibit different thermal signatures, making them identifiable in thermal IR imagery.

Meanwhile, several issues are associated with using IR data. The surface water temperature, which is the primary measurement accessible to infrared (IR) sensors, can vary significantly due to factors such as depth, currents, and weather conditions. Atmospheric conditions such as humidity and temperature can affect thermal IR data, necessitating additional corrections. For instance, clouds pose a particular challenge to thermal IR imaging by absorbing and scattering infrared radiation, thereby restricting the sensor’s ability to accurately detect the Earth’s surface beneath them. This effect is especially pronounced in thick clouds composed of water droplets, which can severely obstruct thermal IR radiation [114]. Furthermore, the thermal properties of surfaces change between day and night, requiring different calibration and interpretation approaches. While thermal IR imaging can complement other remote sensing methods, addressing these challenges is essential for delivering water extent estimation.

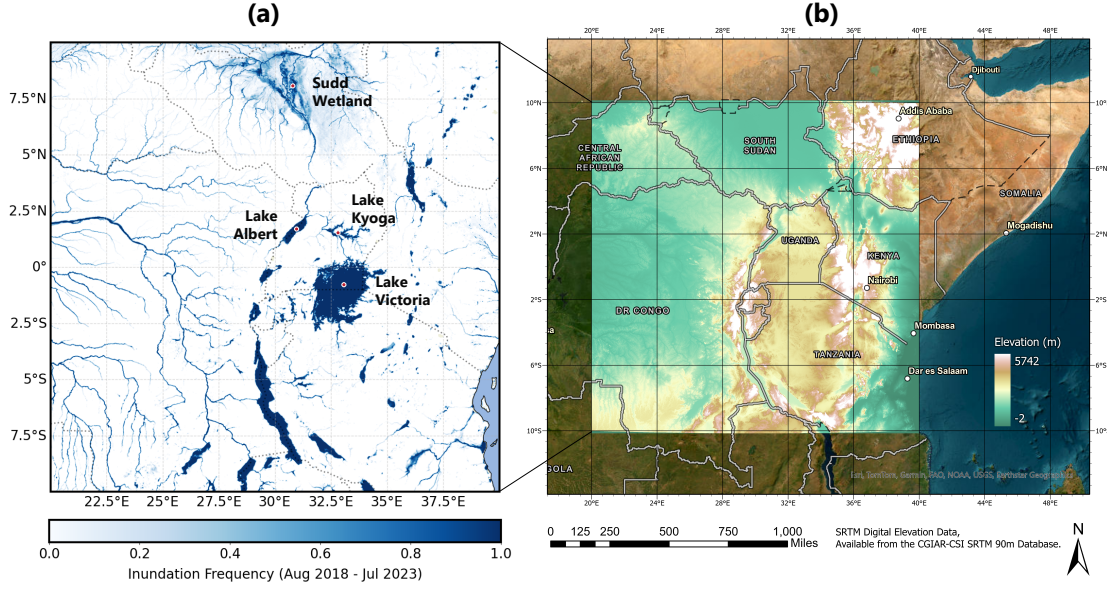


Figure 3.1: Inundation Frequency and Topographical Features in Central and Eastern Africa. (a) Inundation frequency based on the Monthly Berkeley-RWAWC water mask from August 2018 to July 2023. Key locations marked with red dots. (b) A zoomed-out view of Central and Eastern Africa, featuring a digital elevation model (DEM) to highlight the topographical variations.

3.3 Methodology

We adopted an alternative data assimilation approach where pixel values are updated with new daily information, prioritizing the most recent data instead of the average, as was the case of the monthly Berkeley-RWAWC algorithm (see Chapter 2). To determine the optimal data aggregation period, sensitivity tests were conducted to examine how different duration parameters affect the weight given to the most recent data. The results indicate that the choice of aggregation period is critical, as a longer period can significantly diminish the emphasis on the most recent data, thus failing to provide an up-to-date representation of water dynamics.

Let $P_{ij}(t)$ represent the pixel value at location (i, j) at time t in an $N \times N$ array. Each day, M data points (in the format of tracks) update the $N \times N$ array. In this context, tracks refer to the linear paths followed by the satellite as it captures data over a specific area. The tracks appear in a relatively random manner, meaning some pixels may get updated more frequently than others.

Therefore, the pixel value $P_{ij}(t)$ at location (i, j) is updated based on the availability of new data on day t . If new data $D_{ij}(t)$ is available, it replaces the previous data $D_{ij}(t - d)$ for the

same pixel, prioritizing the most recent data. Here d represents the day from the last time the pixel was updated. The expression $D_{ij}(t - d)$ can also be equivalent to $P_{ij}(t - 1)$:

$$P_{ij}(t) = \begin{cases} D_{ij}(t) & \text{if } D_{ij}(t) \text{ is available} \\ P_{ij}(t - 1) & \text{otherwise} \end{cases} \quad (3.1)$$

Due to the randomness of the CYGNSS overpass tracks, some pixels in the $N \times N$ array may remain empty after t days. To address this, spatial interpolation is applied to fill these empty pixels based on the values of nearby available pixels. This ensures that the array becomes non-NaN and maintains a coherent representation of the surface water dynamics. Thus, for a given pixel (i, j) , the interpolated value $\hat{P}_{ij}(t)$ is determined by considering the values of its neighboring pixels.

If we use a simple linear interpolation, the value at (i, j) can be expressed as:

$$\hat{P}_{ij}(t) = \frac{1}{k} \sum_{(m, n) \in \mathcal{N}(i, j)} P_{mn}(t) \quad (3.2)$$

where $\mathcal{N}(i, j)$ denotes the set of neighboring pixels of (i, j) , and k is the number of valid data points in this neighborhood used for interpolation.

In practice, after preprocessing, the NearestNDInterpolator from SciPy (<https://scipy.org/>) is utilized. While similar to linear interpolation, this method differs in that it assigns missing values based on the nearest available data point. This approach is particularly useful in scenarios where data points are sparse or irregularly distributed. The NearestNDInterpolator efficiently identifies the closest known data point for each missing value, thereby eliminating the need for triangulation and robustly filling gaps in the data.

Figure 3.2 presents an example using a section of the Sudd region, showcasing the interpolation results obtained with 1-month and 2-month data, respectively. In the second row of Figure 3.2(a), the known data points are overlaid on the interpolation results, offering a more intuitive view of data density and distribution. This visualization aids in understanding how data density affects the interpolation results. It is important to note that the amount of available data varies with latitude, making this figure a demonstration rather than a source of specific insights into general data aggregation formats. It illustrates the overall impact of data density and the choice of time periods on interpolation accuracy.

Figure 3.2(b) highlights the differences between the two interpolation results. While the overall differences remain noisy, the figure reveals that the Sudd (in the upper left corner) displays more blue, indicating a higher SNR in the 1-month data and suggesting wetter conditions compared to the 2-month data. Additionally, some water bodies emerge from

the noisy background, indicating observable changes in the SNR, such as Lake Turkana, located southeast of the Sudd near the middle bottom of the figure, and Lake Albert, which also appears prominently in the bottom left of the figure. This figure demonstrates that incorporating additional data points over a longer time diminishes the relative weight of the most recent data points. This indicates that while using a longer period (2 months) can smooth out some spatial features, it also reduces the prominence of recent changes captured by the 1-month data, thereby reducing the accuracy and timeliness of the water dynamics representation.

Building on insights from previous studies in chapter 2 and earlier in [50, 67], we learned that aggregating data over a one-month period enables the development of water mask products at a 1 km by 1 km scale. Consequently, we decided to use a 31-day moving window for data assimilation. This approach involves dropping the oldest day’s data and incorporating the latest day’s data, ensuring a continuous and timely update of surface water dynamics.

3.4 Results

3.4.1 2022 September Flooding: South Sudan

First, we assess whether our results can accurately capture historical flooding events. The United Nations Mission in South Sudan (UNMISS) reported that as of September 28, 2022, nearly 29,800 people had been displaced, with many relocated to higher ground and safer locations, primarily across Mundri West County (eastern Western Equatoria State). Further, heavy rainfall was forecasted over the next 24 hours in western South Sudan, including areas already affected by flooding [115]. We examined the rainfall patterns within the month using two different data sources: the Rainfall Estimates from Rain Gauge and Satellite Observations (CHIRPS) (<https://www.chc.ucsb.edu/data/chirps>) and the Global Precipitation Measurement IMERG Early Precipitation L3 (GPM) (<https://gpm.nasa.gov/data>). While there are some differences between the datasets, they generally exhibit similar patterns characterized by fluctuations rather than a consistent increase in precipitation, as shown in Figure 3.3. Meanwhile, our product demonstrates significant water accumulation, peaking in late September. This observation aligns with the flooding reports for that period, suggesting our methodology is capable for capturing water dynamics. While precipitation data might require further analysis to account for watershed dynamics and accurately estimate water accumulation in the Sudd, this approach offers a valuable near-realtime alternative to traditional precipitation products for assessing flooding. By providing a timely comparison, it serves as a useful sanity check for evaluating flooding risk. This test underscores the usefulness of our method, demonstrating its potential for enhancing flood prediction and management strategies.

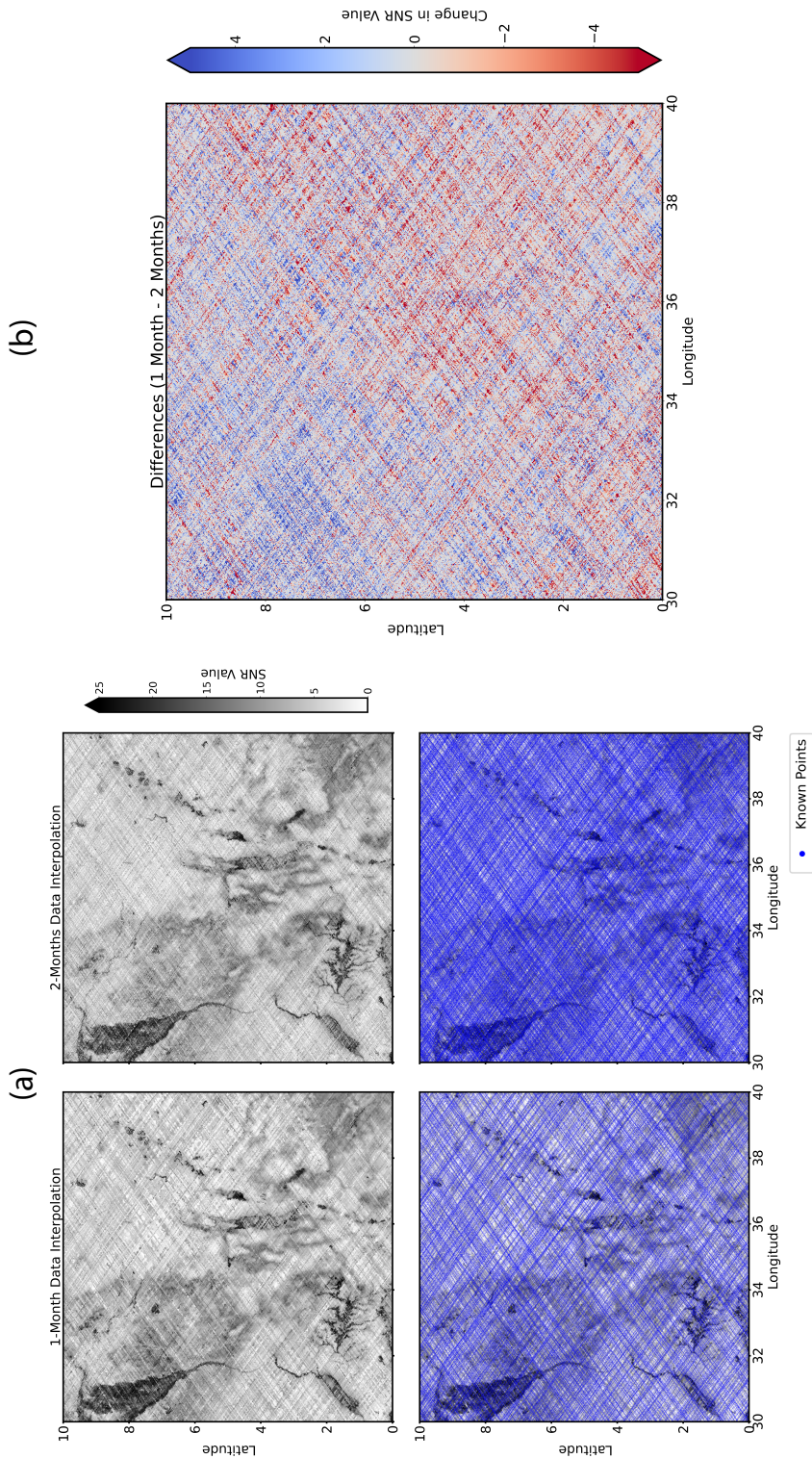


Figure 3.2: Comparison of Interpolation Results Over Different Time Periods. (a) Interpolation results (top) and the placement of known points overlaid on the interpolation results (bottom). (b) Differences between using 1-month and 2-month time periods for interpolation.

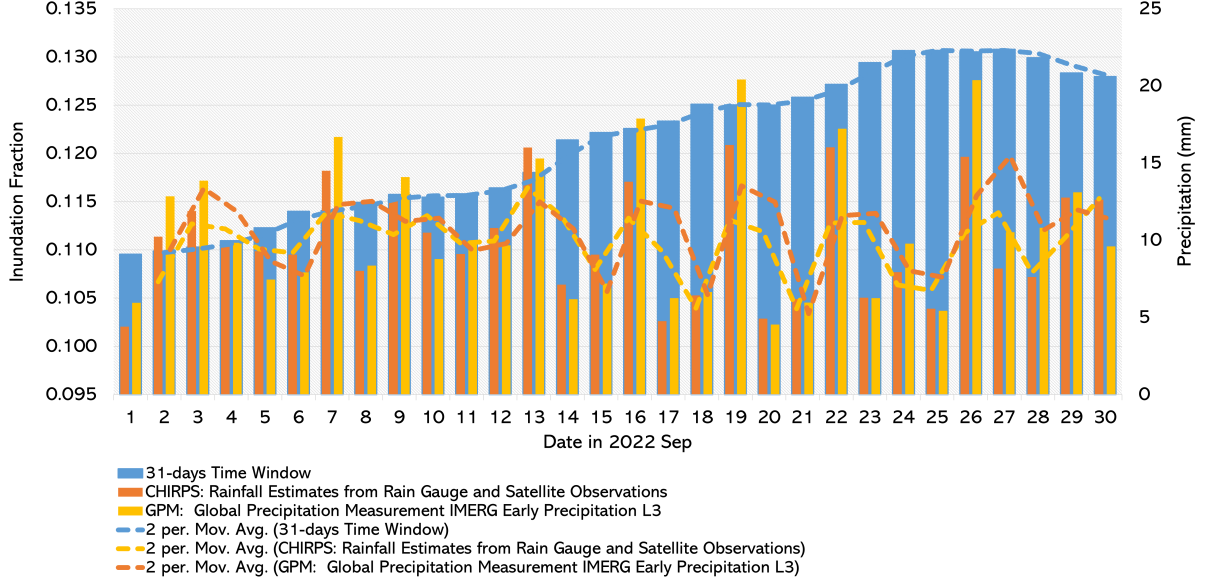


Figure 3.3: Inundation Fraction and Precipitation in South Sudan for September 2022
This figure illustrates the daily inundation fraction (blue bars) along with precipitation data from CHIRPS (orange bars) and GPM (yellow bars) for September 2022. The figure includes 2-period moving averages for both inundation and precipitation data (dashed lines), providing a smoothed representation of trends over the month.

3.4.2 2024 Early Summer Trends: South Sudan

OCHA has been alerted to the possibility of planned releases of water from upstream dams in Uganda, where significant portions of the three lakes—Lake Albert, Lake Kyoga, and Lake Victoria—are located. This release may impact the water dynamics downstream in South Sudan. Therefore, we have examined the latest daily dynamics of water from March 1st to June 25th, 2024 to understand how these operations might affect South Sudan.

To accommodate the varying scales of these water bodies when assessing the changes, we utilize the relative inundation ratio, which can be expressed as $\frac{N_i}{\bar{N}}$, where N_i represents the number of inundated pixels classified as water on day i , and $\bar{N}$ denotes the average number of inundated pixels over the entire study period, defined as $\bar{N} = \frac{1}{T} \sum_{i=1}^T N_i$ for a period of T days. A value greater than 1 indicates higher-than-average inundation, while a value less than 1 signifies lower-than-average inundation. If the ratio fluctuates around 1, it suggests a relatively stable surface water extent. Figure 3.4 illustrates the water dynamics for the four regions, with the relative inundation ratio. The primary y-axis presents the water dynamics of the three upstream lakes, while the secondary y-axis captures the changes in the Sudd Wetland, displayed on a different scale to reflect its variations. Lake Albert and Lake Victoria

exhibit small fluctuations. In contrast, Lake Kyoga shows a significant increase in surface water extent beginning on April 14th. This dramatic rise highlights an essential dynamic in this lake's hydrology during the study period. The Sudd Wetland exhibited a marked surge starting on May 7th, approximately three weeks after Lake Kyoga's water level began to rise noticeably. According to the precipitation record as Figure 3.5 shows, Lake Victoria and Lake Kyoga experienced elevated precipitation from March 23rd to May 9th, while noticeable precipitation in the Sudd Wetland commenced around May 12th. Meanwhile, the relative inundation ratio indicates a rise in the Sudd's surface water extent on May 7th, which is earlier. This upsurge in the Sudd is likely associated with the operational schedules of upstream dams in Uganda, suggesting a delay and a correlation with dam releases during that period.

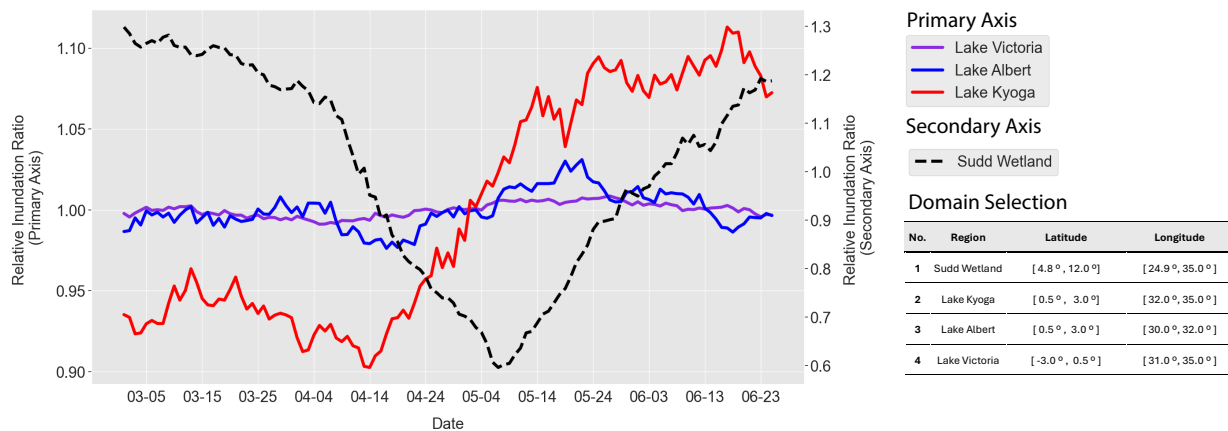


Figure 3.4: Hydrological Trends in Key Locations Relative to South Sudan Relative Inundation Ratio (Daily Inundation Counts / Average Inundation Counts) from March 1, 2024, to June 25, 2024. The primary y-axis shows the relative inundation ratios for Lake Victoria, Lake Albert, and Lake Kyoga. The secondary y-axis displays the relative inundation ratio for the Sudd Wetland. The table presents the latitudinal and longitudinal coordinates of the four selected domains.

3.5 Discussion

Our study has demonstrated the utility of daily updated surface water maps in capturing significant hydrological events, such as the flooding in South Sudan in September 2022 and the dynamic water changes observed in early summer 2024. Moving forward, we investigate its indication for early summer surface water dynamic in the entire tropical and subtropical domain. While our results are promising, it is crucial to address the potential limitations and the possibility of false positives and false negatives in our data.

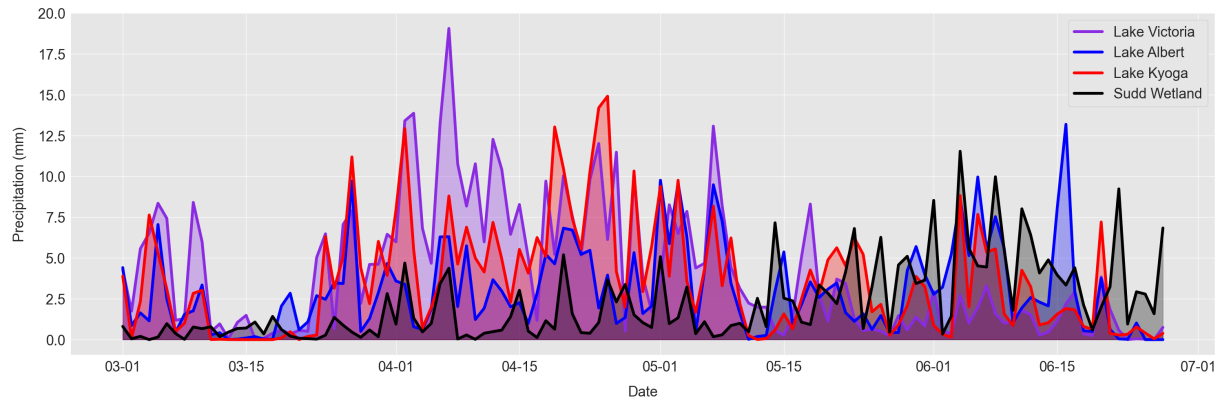


Figure 3.5: Precipitation Records (CHIRPS) for Key Locations Relative to South Sudan. Line plot with transparent fill areas representing precipitation trends for Lake Victoria, Lake Albert, Lake Kyoga and the Sudd Wetland respectively.

3.5.1 2024 Early Summer Trends: Tropical and Subtropical

Thanks to previous efforts in adapting the algorithm for the entire tropical and subtropical domain, we are now able to observe general trending patterns on a daily time scale. To effectively extract information from the daily dynamics, here we use the concept of Hot Spots and Hot Moments (HSHMs). Environmental HSHMs were originally defined by McClain et al. (2003) as rare locations or events that support or induce disproportionately high activity levels (e.g., chemical reaction rates) compared to surrounding areas or preceding times [116]. Applying this concept to our study, we identify HSHMs in the context of water dynamics, where specific pixels (hot spots) exhibit significantly higher or lower inundation levels, and particular days (hot moments) show maximum or minimum inundation activity. This approach allows us to pinpoint critical areas and times for focused analysis and resource allocation.

Figure 3.6 presents the latest hot spots as of June 25th. This figure illustrates how the inundation fraction in each region has changed compared to the mean inundation throughout early summer. The visualization reveals significant variations in surface water extent globally, highlighting areas with both substantial gains and losses in inundation. In South America, the Amazon Basin exhibits considerable increases in inundation, particularly in its northern and central regions. Similarly, parts of central Africa are showing significant inundation gains. Southeast Asia, including regions in and around Nepal, China, and Myanmar, also demonstrates increased inundation levels, matching the timeline that they are entering the monsoon season. Conversely, certain areas in Brazil and surrounding regions within South America experience decreased inundation, which is associated with emerging wildfires in the Pantanal starting in early June. In Africa, the southern parts witness noticeable decreases

in inundation. Northern Australia similarly shows significant areas with reduced inundation.

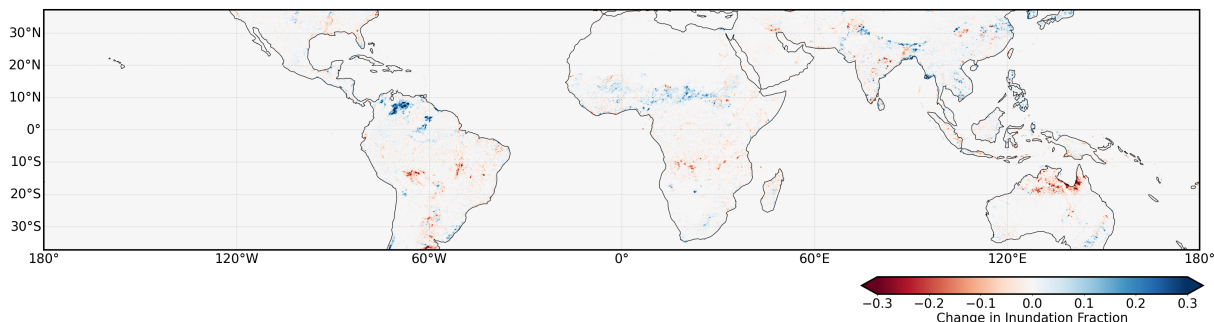


Figure 3.6: Hydrological Hot Spots (Early Summer 2024).
June 25th Inundation Fraction - Mean Inundation Fraction (March 1, 2024 - June 25, 2024).

3.5.2 Potential for False Positives and False Negatives

False positives occur when non-water areas are mistakenly identified as water, while false negatives happen when actual water bodies are missed. Several factors contribute to these errors, as mentioned in Chapter 2, Section 2.5.1 on Potential Limitations. Additionally, to enable the near-real-time capability of our methodology, we decided to drop the reference to adjacent results for removing striping features (see Section 2.3.3 in Chapter 2). This decision may lead to the presence of both false positive and false negative striping features on the map, as the lack of adjacent result comparison can sometimes fail to accurately identify continuous water bodies or misclassify land areas as water.

3.5.3 Limitations of the Study

While our methodology has shown robustness in capturing water dynamics, there are inherent limitations that need to be acknowledged. The spatial resolution of the CYGNSS data limits the granularity of the surface water maps. Finer details, especially in small or narrow water bodies, might be overlooked. Despite our efforts to provide daily updates, temporal gaps in data acquisition can occur due to satellite orbit constraints or data processing delays, which may affect the continuity of observations.

Furthermore, an essential aspect of our methodology involves the choice of the 31-day aggregation window, applied in our analysis of the Sudd and subsequently in the entire domain context. This decision was strategically made to balance the temporal resolution with the availability of CYGNSS data and to accommodate the inherent variability observed in wetland dynamics. This window size enables the rapid construction of water features within a

region without reliance on ancillary data, while also capturing short-term fluctuations essential for dynamic hydrological assessments. However, this approach necessitates a trade-off between the time window size and the spatial resolution of the output. Consistent with the methodology outlined in Chapter 2, which utilized monthly maps at a 0.01-degree resolution, we deemed this configuration optimal. This choice ensures methodological consistency, enhancing the comparability of our findings with previous studies, thereby reinforcing the reliability and relevance of our results in ongoing hydrological research, facilitating a comprehensive narrative on water dynamics over time.

3.5.4 Implications and Future Work

Despite these limitations, our approach offers valuable insights into global water dynamics. The ability to identify hot spots and hot moments in water inundation provides critical information for environmental monitoring and disaster management. Our findings suggest that this methodology can significantly enhance flood prediction and resource allocation, aiding humanitarian efforts in regions like South Sudan. Engagement with organizations such as OCHA will be pivotal in refining our model and ensuring its applicability in real-world scenarios. By incorporating feedback from field operations, we can improve the accuracy and reliability of our predictions.

Looking forward, this work lays the groundwork for integrating river routing using GNSS-R data, marking an initial step toward a more comprehensive hydrological modeling framework. Future river routing models could immensely benefit from the high temporal resolution and accurate surface water detection capabilities of GNSS-R. For instance, detecting a new water pixel at an upstream location would enable predictions of similar increases downstream shortly afterward. Similarly, identifying wet conditions at one site could indicate that linked upstream areas are already wet or will soon become wet. This enhanced understanding of water movement would facilitate improved flood forecasting, more precise river flow simulations, and better water resource management.

3.6 Conclusion

In this chapter, we introduced the steps for advancing the methodology established in Chapter 2 to transition from delivering monthly water masks to daily updates. We explained the updated parameter choices and examined their functionality within the context of anticipatory action. This new approach leverages the near-real-time capabilities of CYGNSS data, significantly enhancing our ability to monitor and analyze daily variations in surface water dynamics. Our case study on the Sudd wetland demonstrated the practical application of this methodology, where daily mapping delineates fluctuations in water extents and aligns closely with reported peak inundation levels. This correlation validates the robustness and accuracy of our GNSS-R data-driven approach. To further realize the potential of

this advanced product, engagement with the United Nations Office for the Coordination of Humanitarian Affairs (OCHA) is necessary. This collaboration will help us understand how our data can be integrated into real-world practices, particularly in disaster preparedness and response. Looking ahead, we believe that this daily updated surface water mapping product will be extremely useful. It promises to refine our ability to predict flood events, guide sustainable water resource management, and support climate change mitigation and adaptation efforts. By providing consistent daily hydrological observations, our work lays the groundwork for a transformative shift in global water dynamics comprehension, offering valuable insights for both scientific research and practical applications.

Chapter 4

Wildfires and Wetland Resilience

4.1 Introduction

The work in this final chapter aims to quantify the dynamic interaction between evolving fire behavior and the refilling patterns of wetlands in the Pantanal region, one of the world's most significant tropical wetland ecosystems. Spanning a five-year period from August 2018 to July 2023, our investigation integrates a diverse array of datasets encompassing fire incidences, precipitation patterns, land cover classifications, and inundation dynamics. By utilizing this extensive data collection, we seek to capture the temporal and spatial variations in both fire activity and wetland hydrology.

Central to our analysis is the development of a multi-object tracking algorithm for learning the fire patterns. This algorithm is capable of pinpointing the initial ignition locations of fires, and track their developments, enabling us to accurately distinguish between fires that are likely of anthropogenic origin, such as those caused by agricultural practices, and those that occur naturally, such as lightning-induced fires. Understanding the origins of these fires is crucial for determining the extent to which they are initiated by climate variability, such as extreme temperatures and drought conditions, or exacerbated by these factors. 'Initiated by climate variability' refers to fires whose ignition is primarily caused by climatic conditions, while 'exacerbated by these climatic factors' pertains to fires that, once ignited, are intensified and spread more rapidly due to unfavorable weather conditions.

The integration and analysis of these datasets allow us to explore the complex relationships and feedback mechanisms governing the interactions between fire behavior and wetland refilling. Specifically, we examine how precipitation patterns influence fire dynamics and how subsequent wetland inundation affects fire spread and intensity. This holistic approach captures the interplay between these environmental variables, providing a nuanced understanding of the ecological processes.

Ultimately, our study aims to contribute to the broader discourse on ecosystem resilience in wetland environments. By offering new insights into the factors driving fire behavior and wetland dynamics, we seek to enhance our understanding of these complex ecological interactions. This research underscores the importance of an integrated approach to environmental monitoring, highlighting the dynamic nature of ecological systems and the intricate relationships that sustain them. Additionally, it emphasizes the role of human behaviors in influencing these interactions, further illustrating the complex interplay between natural processes and anthropogenic activities.

4.2 Background

The Pantanal is one of the world's largest tropical wetland areas, spanning approximately 179,300 square kilometers, with about 80% of its expanse located in Brazil, and the remaining portions extending into Bolivia and Paraguay [117]. Situated in a vast floodplain in the center of the upper Paraguay River basin in South America, the Pantanal predominantly lies within the Brazilian states of Mato Grosso (MT; 35%) and Mato Grosso do Sul (MS; 65%) [118, 119].

The hydrological cycle of the Pantanal is intricately linked to the annual pulse of rainfall, which inundates the region from November to March in the north and from May to August in the south, transforming vast expanses of dry land into a network of interconnected waterways [120]. Figure 4.1 illustrates the delineation of the Pantanal using terrestrial eco-regions as defined by Dinerstein et al. [121]. Within this area of interest, the digital elevation model (DEM) data, along with the river network highlights, provides a detailed topographic perspective for overviewing the hydrological and ecological processes governing the Pantanal's wetland ecosystem. Most studies on the Pantanal have concentrated on the Brazilian portion, which is a complex of interconnected aquatic, terrestrial, and wetland ecosystems. The Brazilian Pantanal alone supports a rich diversity of species, including iconic jaguars, capybaras, giant otters, and a plethora of birdlife [122].

With its ecological richness, the Pantanal also faces numerous environmental pressures. Wildfires, exacerbated by climatic factors, land-use changes, and human activities, pose significant threats to its ecological integrity [123] and disrupt critical ecosystem processes, endangering the diverse flora and fauna of the region. In this study, we aim to provide a latest overview of the entire Pantanal region, investigating the interplay between fire dynamics and wetland refilling patterns. By analyzing data over a five-year period from August 2018 to July 2023, we seek to uncover the mechanisms driving these interactions and offer insights essential for the conservation and management of this vital ecosystem.

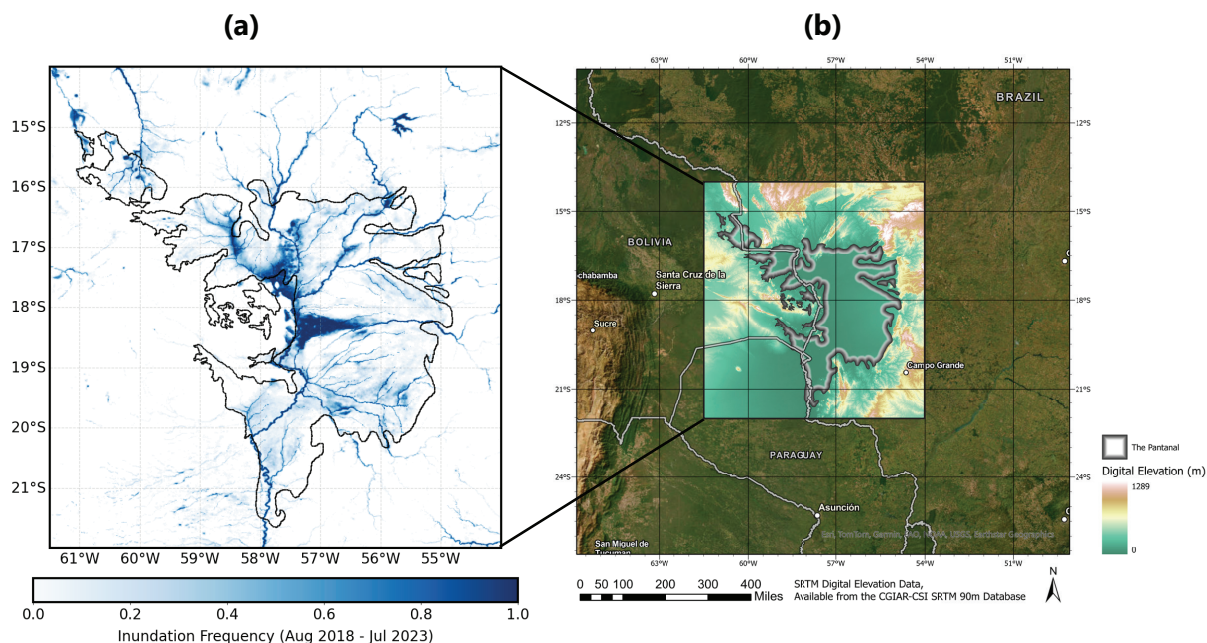


Figure 4.1: Inundation Frequency and Topographical Features in Pantanal. (a) Inundation frequency based on the Monthly Berkeley-RWAWC water mask from August 2018 to July 2023. (b) A zoomed-out view of the Pantanal, featuring a digital elevation model (DEM) to highlight the topographical variations.

4.3 Data Description and Exploratory Analysis

4.3.1 Fire - Burned Area

The fire dataset utilized in this study is sourced from the Terra and Aqua combined MCD64A1 Version 6 Burned Area data product (<https://lpdaac.usgs.gov/products/mcd64a1v061/>). This monthly, global dataset provides a gridded resolution of 500 meters, offering detailed per-pixel burned-area information along with quality assessments. The MCD64A1 methodology integrates 500-meter Moderate Resolution Imaging Spectroradiometer (MODIS) Surface Reflectance imagery with 1-kilometer MODIS active fire observations. Central to the algorithm is the use of a burn-sensitive Vegetation Index (VI), derived from MODIS shortwave infrared atmospherically corrected surface reflectance bands 5 and 7, supplemented with temporal texture measures. Dynamic thresholds generated from the VI are then applied to the composite data to identify burned areas [124].

An overview of the fire history. The temporal resolution of the data allows for an analysis of inter-annual variability, and the longitudinal span of over two decades provides insight into longer-term trends and potential shifts in fire seasonality. Figure 4.2 illustrates

the percentage of burned area within the Pantanal from November 2000 to January 2024. The data highlights a seasonal pattern, with the peak fire season typically occurring between August and October. Long-term trends from the dataset suggest that shifts in the timing and intensity of the fire season do occur. Such fluctuations can happen within a single year or over multiple years, indicating possible climatic or anthropogenic influences on fire regimes. More spatial details regarding the burned area patterns are presented in Figure 4.3. The figure presents a comprehensive analysis of fire activity in the Pantanal region over the span of 23 years. Each histogram depicts the monthly burned area fraction for a given year, with the three months exhibiting the highest burned extent highlighted in red to underscore the peak fire season. Beneath each histogram, the corresponding spatial distribution maps illustrate the geographic spread of burned areas during these peak months. These spatial maps provide a detailed view of the regions within the Pantanal most affected by fires, highlighting significant inter-annual variability in fire behavior and affected areas. Notably, the 2020 map reveals a markedly high density of burned areas, displaying distinct patterns compared to other years. This anomaly aligns with documented mega-fire events of 2020, suggesting a deviation in fire dynamics likely influenced by climatic or anthropogenic factors. It has also drawn our attention that there is a significant overlap between the fire seasons of 2019 and 2021. Specifically, 36% of the pixels burned during the 2019 fire season were burned again in the 2021 fire season as Figure 4.4 presents, characterized by significant forest areas outside of the Pantanal being affected.

As we examine the fire patterns within the Pantanal, it becomes critical to investigate the initial ignition sites and the subsequent progression of fire events in the region. By analyzing these spatio-temporal dynamics, our objective is to elucidate the underlying mechanisms driving wildfire initiation and spread. These insights are essential for developing an understanding of fire behavior within the Pantanal ecosystem. The methodology and detailed findings related to these dynamics will be elaborated in Section 4.4 Methodology.

4.3.2 Water - Rainfall

Rainfall data has served as a crucial reference for assessing both drought severity and the availability of fuel loads for potential wildfires. Extensive research underscores the indispensable utility of rainfall data in both analyzing historical fire events and predicting future occurrences within the region [125, 126, 127]. To assess rainfall patterns in our study, we first compared four different datasets: the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), the Global Precipitation Measurement mission (GPM), the fifth generation of European Centre for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalyses of the global climate (ERA5), and a reanalysis dataset specifically for land areas derived from ERA5 data (ERA5-Land).

The precipitation rates from these four data sources within the Pantanal region were extracted and plotted from August 2018 to August 2023, as shown in Figure 4.5. The patterns

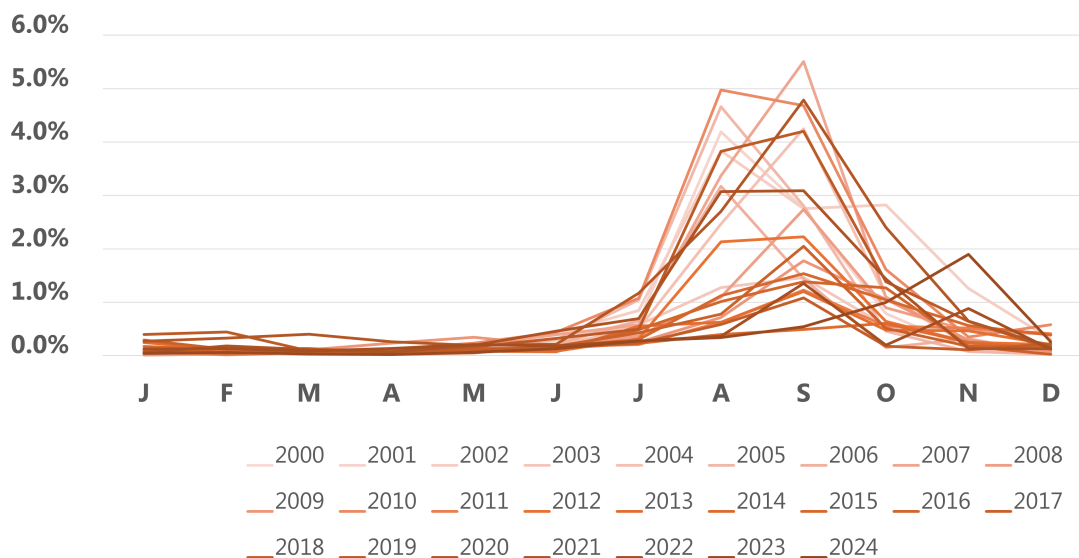


Figure 4.2: Time Series of Burned Area Fraction from MCD64A1 Data (November 2000 - January 2024).

across these sources are generally consistent, with peaks and troughs occurring at similar times, which suggests a clear seasonal cycle of rainfall: most rainfall occurs between November and March, while the dry season spans from June to October. Meanwhile, there are notable variances in the measurements from each source at the peaks. Starting from September 2022, ERA5-Land shows a markedly different pattern compared to the other sources, with a lower overall precipitation rate and less pronounced peaks. The discrepancy can be further identified from Figure 4.6, which presents the monthly variations in spatial pattern for the four datasets.

In Figure 4.6, each dataset is presented in a 4-row by 12-column structure, with each row representing the average monthly precipitation pattern over a year. For example, the first row of the CHIRPS dataset displays data from August 2018 to July 2019. Similar to Figure 4.5, the spatial patterns in all four datasets reveal an increase in precipitation rates across the entire domain from November to March each year. Notably, most of the major precipitation appears to occur around the Pantanal rather than centrally within it. Additionally, there is general agreement among the datasets regarding the primary locations of precipitation, which shifts annually.

For instance, the first row shows high precipitation rates in the northwest corner during

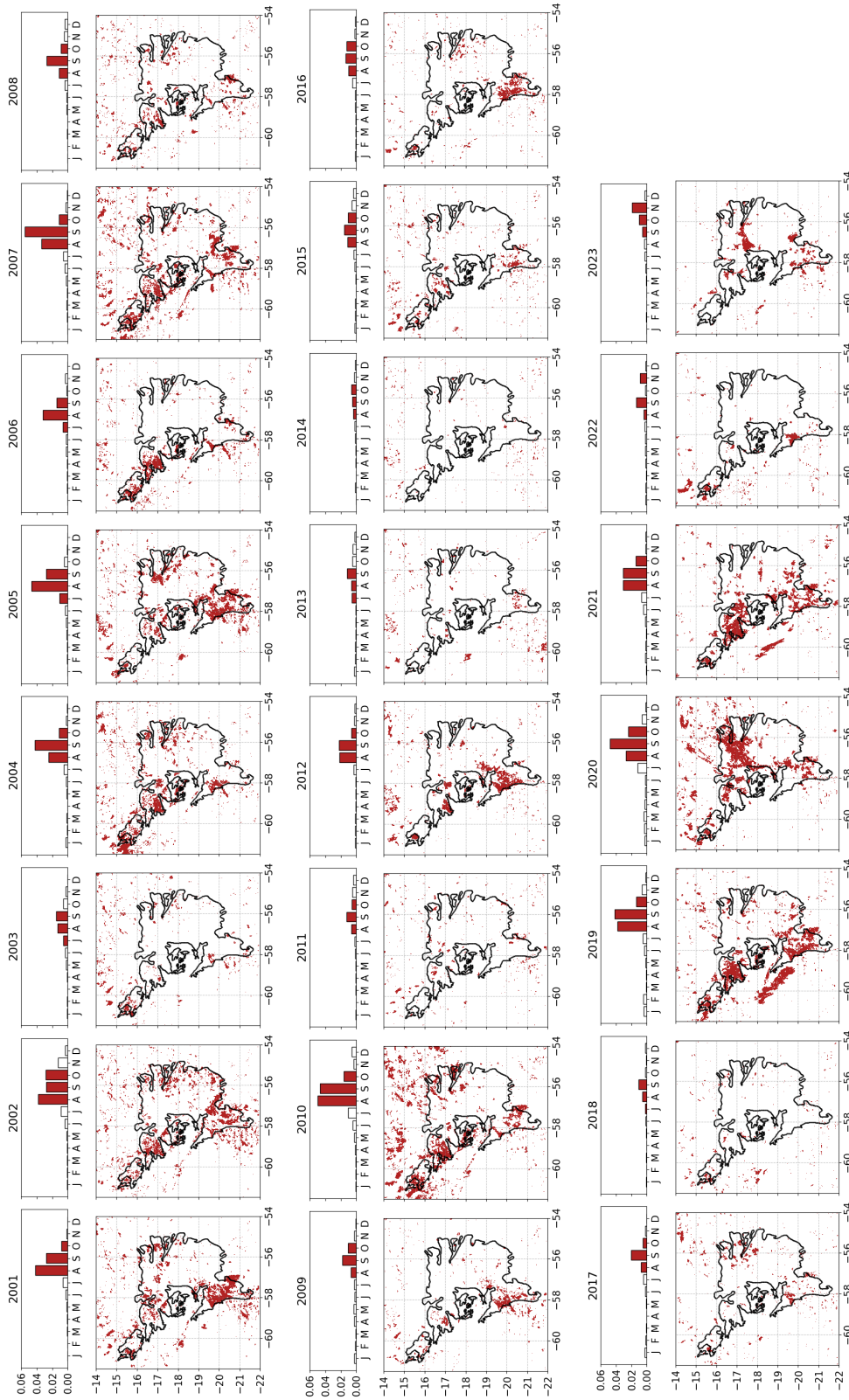


Figure 4.3: Overview of Fire Patterns (2001 - 2023).

Each histogram represents the burn extent throughout the year, showcasing the three months with the highest burned extent highlighted. Beneath each histogram, the corresponding spatial pattern of fires in the fire season is displayed. The boundaries of the Pantanal are outlined in black.

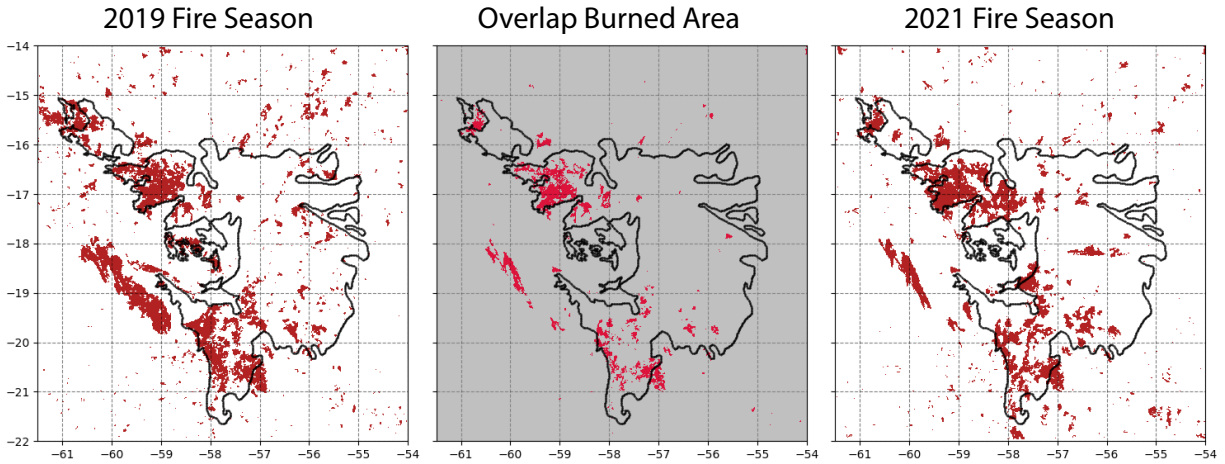


Figure 4.4: Comparison of Burned Area in the Fire Seasons of 2019 and 2021. The boundaries of the Pantanal are outlined in black.

the early rainy season (November 2018). In the second row, during the 2019 -2020 rainy season, the GPM, ERA5, and ERA5-Land datasets indicate continued high precipitation in the north and west, while the CHIRPS dataset shows a relatively lower amount but a similar pattern. In the third row for the year 2020 to 2021, more rainfall is observed from the south, while in the fourth row for year 2021 to 2022, it shifts to the north.

From the year 2022 to 2023, the datasets show increased rainfall from both the north, south, and west during its rainy season. In addition, the ERA-Land data source demonstrates a general attenuation in precipitation rates, differing from the other three data sources. This discrepancy suggests that the ERA5-Land dataset may underestimate precipitation during this period. Given these observations, we selected CHIRPS for the following analyses due to its highest spatial resolution.

4.3.3 Water - Inundation

In addition to the rainfall datasets, our study introduces a new dataset into this discourse: the UC Berkeley Random Walk Algorithm WaterMask from CYGNSS (Berkeley- RWAWC) (https://podaac.jpl.nasa.gov/dataset/CYGNSS_L3_UC_BERKELEY_WATERMASK_V3.1). As elaborated in Chapter 2, this is a watermask product designed to address the challenges of monitoring inundation in regions hindered by dense vegetation and cloud cover as is the case in most of the Tropics. Developed from the Cyclone Global Navigation Satellite System (CYGNSS) data, the Berkeley-RWAWC provides a refined water mask, unveiling previously unseen seasonal variations in inundation patterns. Berkeley-RWAWC spans from

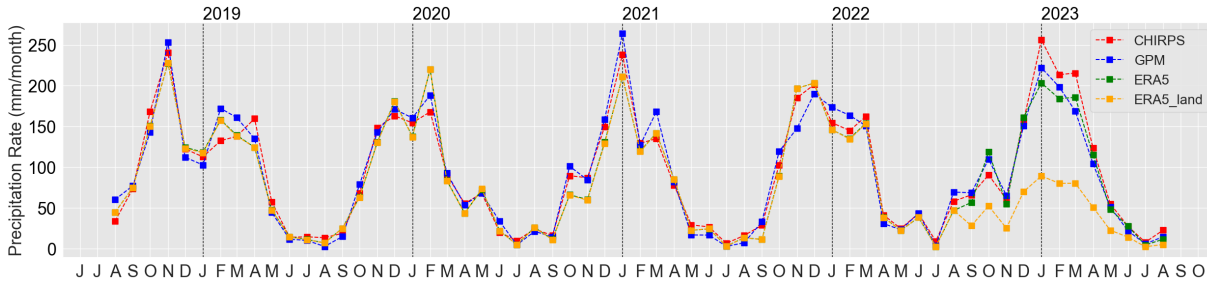


Figure 4.5: Time Series of Precipitation Rates from Various Data Source (August 2018 - August 2023).

(Red - CHIRPS): The Climate Hazards Group InfraRed Precipitation with Station data is a quasi-global rainfall dataset, covering latitudes from 50°S to 50°N, spanning from 1981 to near-present, with a spatial resolution of 0.05°, approximately 1 km. **(Blue - GPM):** The Global Precipitation Measurement mission, specifically the IMERG Final Run V07, provides research-quality gridded global multi-satellite precipitation estimates with quasi-Lagrangian time interpolation, gauge data, and climatological adjustment. It has a spatial resolution of 0.1°, approximately 9 km. **(Green - ERA5):** The fifth generation of European Centre for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalyses of the global climate, has a spatial resolution of 0.25°, approximately 27 km. **(Orange - ERA5 land):** A reanalysis dataset specifically for land areas derived from ERA5 data, offering an enhanced resolution of 0.1°, approximately 9 km, compared to ERA5.

37.4° North to 37.4° South and consists of monthly inundation maps at approximately 1 km by 1km resolution since August 2018.

The inundation product we utilize operates on a binary classification system, distinguishing between pixels that contain water and those that do not. When a pixel is labeled as water, it indicates that within this 1km by 1km area, there exists either a significant body of water or a smaller footprint with clear indications of water presence. This binary approach simplifies the interpretation, as it provides a clear distinction between areas with observable water features and those without. By identifying pixels as water, we infer the presence of either substantial water bodies, such as lakes or rivers, or smaller water features like ponds or wetlands. Figure 4.7 provides a detailed illustration of the spatial distribution of water during the wet season in the Pantanal from 2019 to 2023. The upper histograms display monthly water extent data, and the maps below illustrate the spatial distribution across the region during the wet season for each respective year. The inundation feature reveals notable variations across the years studied. Specifically, from 2020 to 2022, the wetland refilling appears markedly lower compared to the levels observed in 2019 and 2023. Furthermore, discernible trends emerge in specific regions over the study period: in 2022, there is clear evidence of increased inundation in the northern region, while in 2020 and 2021, a greater extent of inundation is observed in

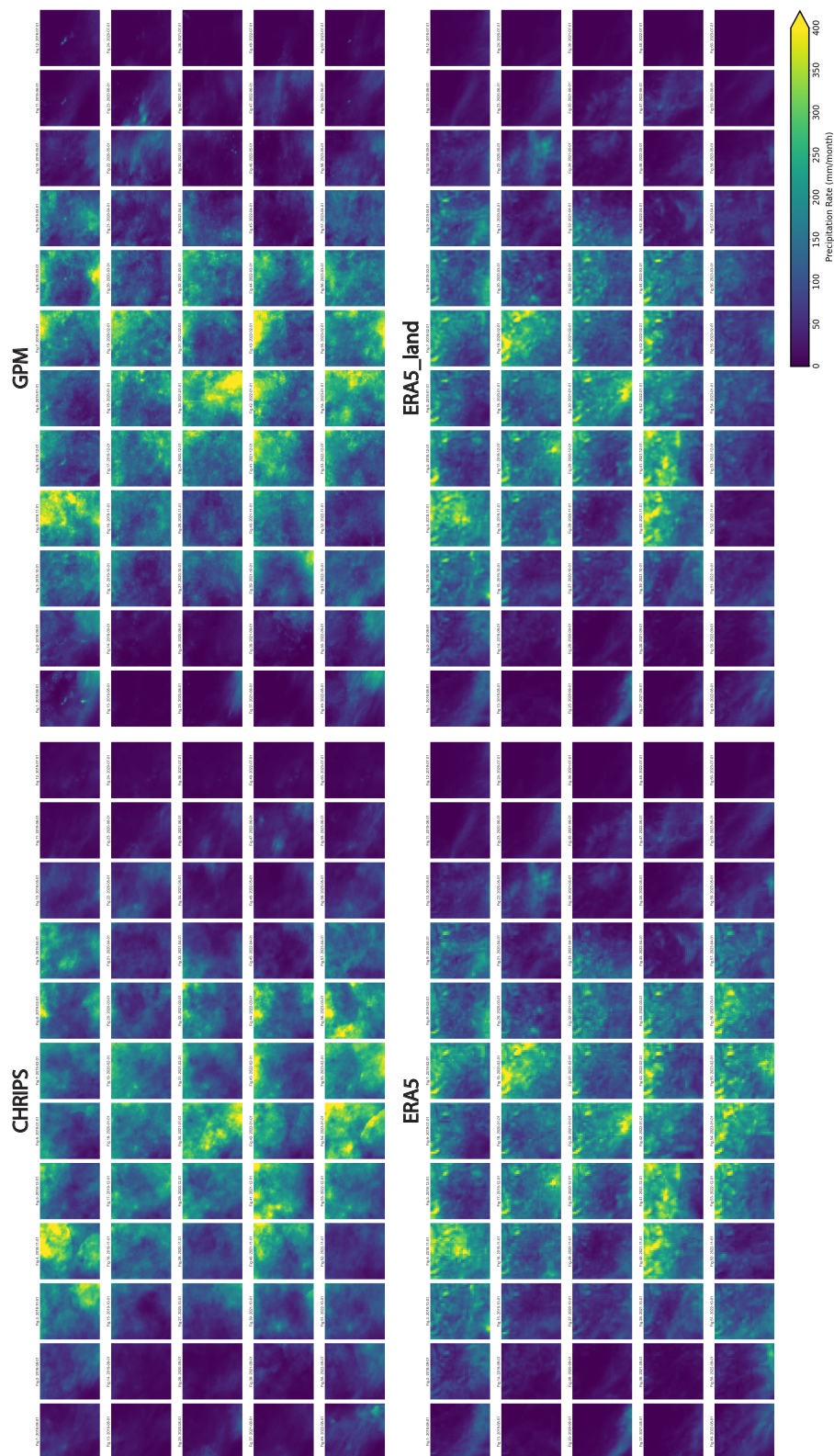


Figure 4.6: Spatial Pattern of Precipitation Rates from Various Data Sources (August 2018 - August 2023). Upper Left: CHIRPS, Upper Right: GPM, Bottom Left: ERA5, Bottom Right: ERA5-Land. Each dataset is displayed in a 4-row by 12-column structure, with each row representing the average monthly precipitation pattern over a year. For example, the first row of the CHIRPS dataset shows data from August 2018 to July 2019. This layout highlights seasonal precipitation trends and variations across different years for each dataset.

the southern region. The result is consistent with the spatial distribution of precipitation as discussed in the previous section.

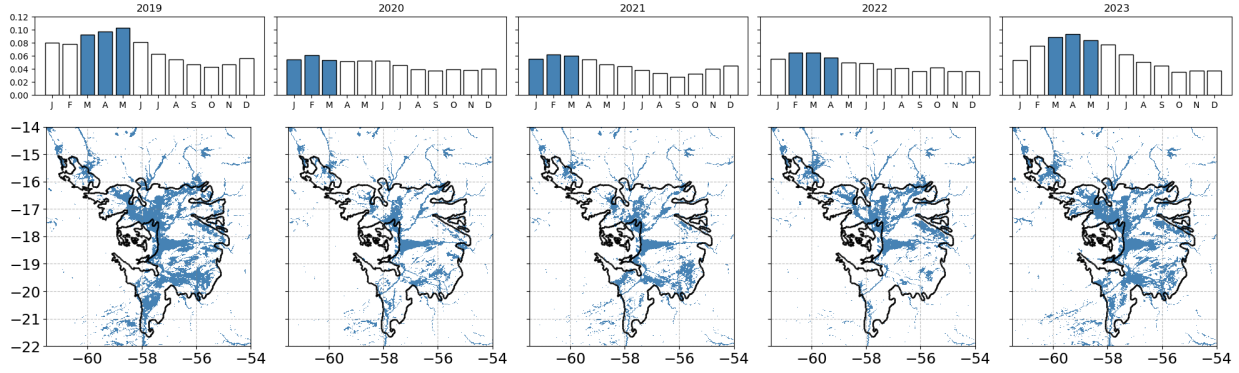


Figure 4.7: Wet Season Inundation Extent (2018 - 2023).

Upper Histograms: Monthly Inundation Fraction with the top three months highlighted in blue, indicating the wet season for each year. Bottom Spatial Plots: The wet season inundation extent based on Berkeley-RWAWC monthly data. Blue areas represent water, while white areas indicate non-water land. This representation is based on a binary classification.

4.3.4 Land Cover Land Type

To assess land changes, we collected Normalized Difference Vegetation Index (NDVI) data alongside land cover and land type classification data for the Pantanal region over the period from 2018 to 2023 based on MODIS. The Normalized Difference Vegetation Index (NDVI) is an essential remote sensing metric extensively utilized to assess vegetation health and density. NDVI is derived from satellite imagery and is computed using the difference between near-infrared (NIR) and red light reflectance, normalized by the sum of these two reflectance values. Mathematically, the index is expressed as:

$$\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} \quad (4.1)$$

This index leverages the distinct spectral characteristics of healthy vegetation, which absorbs most of the visible light (red) for photosynthesis and reflects a substantial portion of near-infrared light. Consequently, NDVI values range from -1 to +1, with higher values indicating dense, healthy vegetation, and lower values suggesting sparse or stressed vegetation, bare soil, or non-vegetated surfaces such as water bodies or urban areas. In Figure 4.8, we present the Normalized Difference Vegetation Index (NDVI) data obtained from the Terra Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Indices (MOD13Q1). The data is plotted in a daily format, showcasing temporal variations in the region. Notably, lower

NDVI values are observed during the fire-burning seasons over the years 2019, 2020, and 2021, indicating a reduction in vegetation health and density. Conversely, during the subsequent wet seasons, the vegetation regrowth is evident, with NDVI values returning to the same general levels observed prior to the fire events. This pattern seems to indicate the resilience of vegetation in the Pantanal region following seasonal disturbances, while one note is that cloud cover could impact the accuracy and quality of NDVI value.

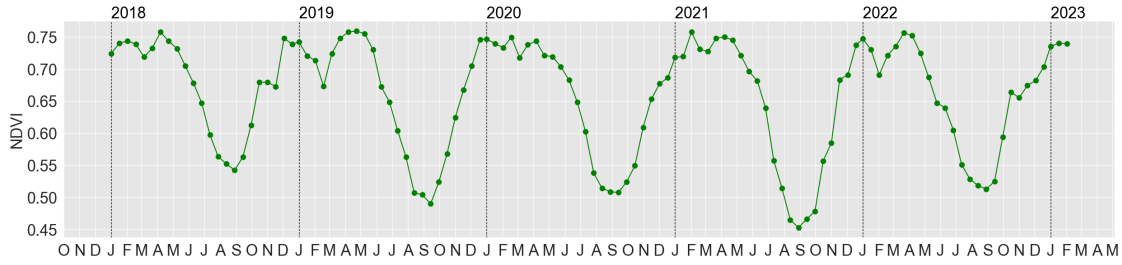


Figure 4.8: Time Series of NDVI (August 2018 - August 2023).

Daily mean NDVI values for the entire Pantanal region is shown. The data points reflect the available daily measurements, which may result in irregular time intervals due to data availability. This representation captures the vegetation dynamics across the whole region, highlighting variations and trends in NDVI over the study period.

Additionally, we incorporate the MODIS Terra and Aqua Land Cover Type dataset (<https://lpdaac.usgs.gov/products/mcd12q1v061/>), which provides yearly global land cover classifications at a spatial resolution of 500 meters. This dataset offers a characterization of land cover types, including vegetation, water bodies, urban areas, and agricultural land, among others [128]. This information can help in understanding the ecological context surrounding fire events, as different land cover types exhibit varying susceptibilities to fire and play distinct roles in fire propagation dynamics. Figure 4.9 provides an overview of Land Cover Land Type changes within the region over the last five years, utilizing the International Geosphere-Biosphere Programme (IGBP) legend and class descriptions. This figure illustrates the evolution of fire regime patterns based on land cover changes. Notably, a significant portion of forests burned in 2019 and 2021, are located outside the delineated Pantanal region, as shown in Figure 4.4, which highlights these burned areas. In contrast, a much higher portion of permanent wetlands were burned in 2020.

4.4 Methodology

Multi-object tracking (MOT) in computer vision is a sophisticated technique aimed at simultaneously identifying and monitoring the trajectories of multiple objects within a video sequence or a series of images. This process involves several critical steps, beginning with the detection of objects in each frame using algorithms such as convolutional neural net-

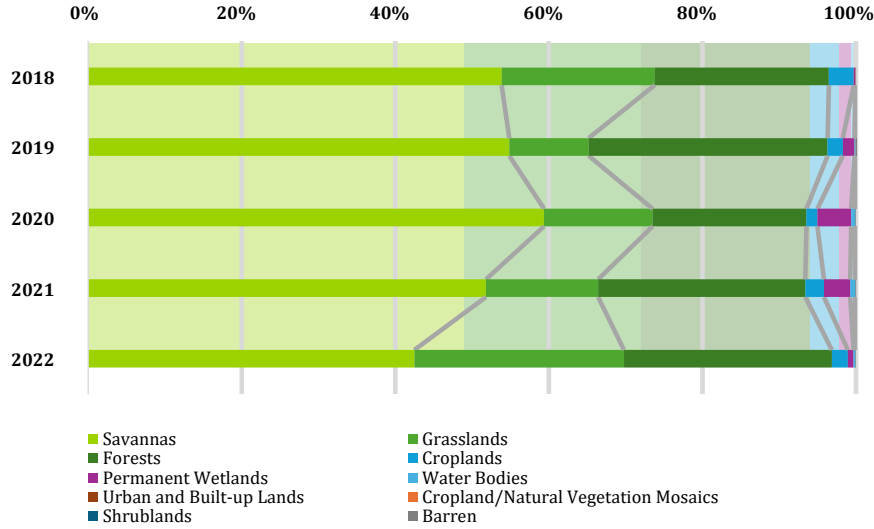


Figure 4.9: Fig. 7 Evolution of Fire Regime Patterns.

Background layer depicts the percentage coverage of each land class across the region. The bar plot for each year illustrates the proportion of land classes affected by fire.

works (CNNs) or other machine learning models designed for object recognition [129]. Once detected, these objects are then assigned unique identifiers to distinguish them from one another throughout the sequence. The challenge in MOT lies in maintaining the accuracy of these identifiers across frames, which requires robust association strategies to handle occlusions, appearance changes, and complex interactions among objects. Techniques such as the Hungarian algorithm, Kalman filtering, and various data association methods are commonly employed to predict the future positions of objects and update their tracks accordingly. Additionally, advancements in deep learning have led to the development of more sophisticated models that can learn appearance features and motion patterns, further enhancing tracking performance [130]. Effective multi-object tracking has significant implications across various fields, including autonomous driving, surveillance, sports analytics, and robotics, where understanding the dynamic behavior of multiple entities is crucial. The continuous evolution of MOT algorithms aims to achieve higher precision and robustness, addressing the inherent challenges posed by real-world scenarios.

In this context, as the input burned area data is binary, alternative approaches to CNNs can be more efficient. One such approach is the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm [131]. Unlike CNNs, which are typically used for feature extraction and classification in complex, high-dimensional data, DBSCAN is a clustering algorithm that excels in identifying dense regions of points and can effectively handle noise.

By using DBSCAN, it is possible to quickly extract group information from binary data, which is particularly useful when the primary task is to cluster and track objects based on spatial proximity rather than detailed image features. DBSCAN operates by grouping points that are closely packed together, marking points that lie alone in low-density regions as outliers. This characteristic makes it highly suitable for tasks where the distinction between objects and background noise is critical. Once clusters are formed, tracking these clusters over time becomes more straightforward, as the algorithm inherently handles varying densities and irregular shapes.

4.4.1 Daily Burned Area Map

Utilizing the 'Burn Date' and 'Last Day' attributes from the MCD64A1 burned-area dataset, we generate daily maps illustrating the spatial progression of burned areas. Figure 4.10, 4.11, and 4.12 presents the daily burned area spreading for years 2019, 2020 and 2021 during the fire seasons respectively. In both 2019 and 2021, forest fires exhibited similar patterns on a monthly scale, forming a long and narrow shape outside the Pantanal wetland delineation, as shown in Figure 4.4. According to the daily burned area maps, the burned area in 2019 developed over a longer period, from August 18 to October 23, whereas in 2021, they were observed from August 18 to September 24.

By examining the daily spread patterns of fires, we observed distinct differences between locations characterized by continuous, relatively small-scale burning and those experiencing rapid, extensive fire spread. The former tends to exhibit consistent, low-intensity fires, while the latter is marked by frequent, high-intensity events during the peak fire season. Thus, we consider it essential to develop a method capable of systematically characterizing and capturing these different features.

4.4.2 DBSCAN Algorithm for Event Labeling

To better characterize the burned extent from the daily map, we employ a DBSCAN algorithm. DBSCAN is a robust clustering method ideal for this task due to its ability to identify dense regions. It focuses on grouping closely packed points and labeling those in low-density regions as outliers. The algorithm operates by defining a neighborhood around each data point using a specified distance metric and clustering points that have a sufficient number of neighbors within this radius. The two parameters are: **Epsilon** (ϵ): the maximum distance between two samples to be considered neighbors and **MinPts**: the minimum number of samples within the ϵ radius to form a core point.

Given a dataset D , DBSCAN operates by first defining the neighborhood as

$$N_{\epsilon}(p) = \{q \in D \mid \text{distance}(p, q) \leq \epsilon\} \quad (4.2)$$

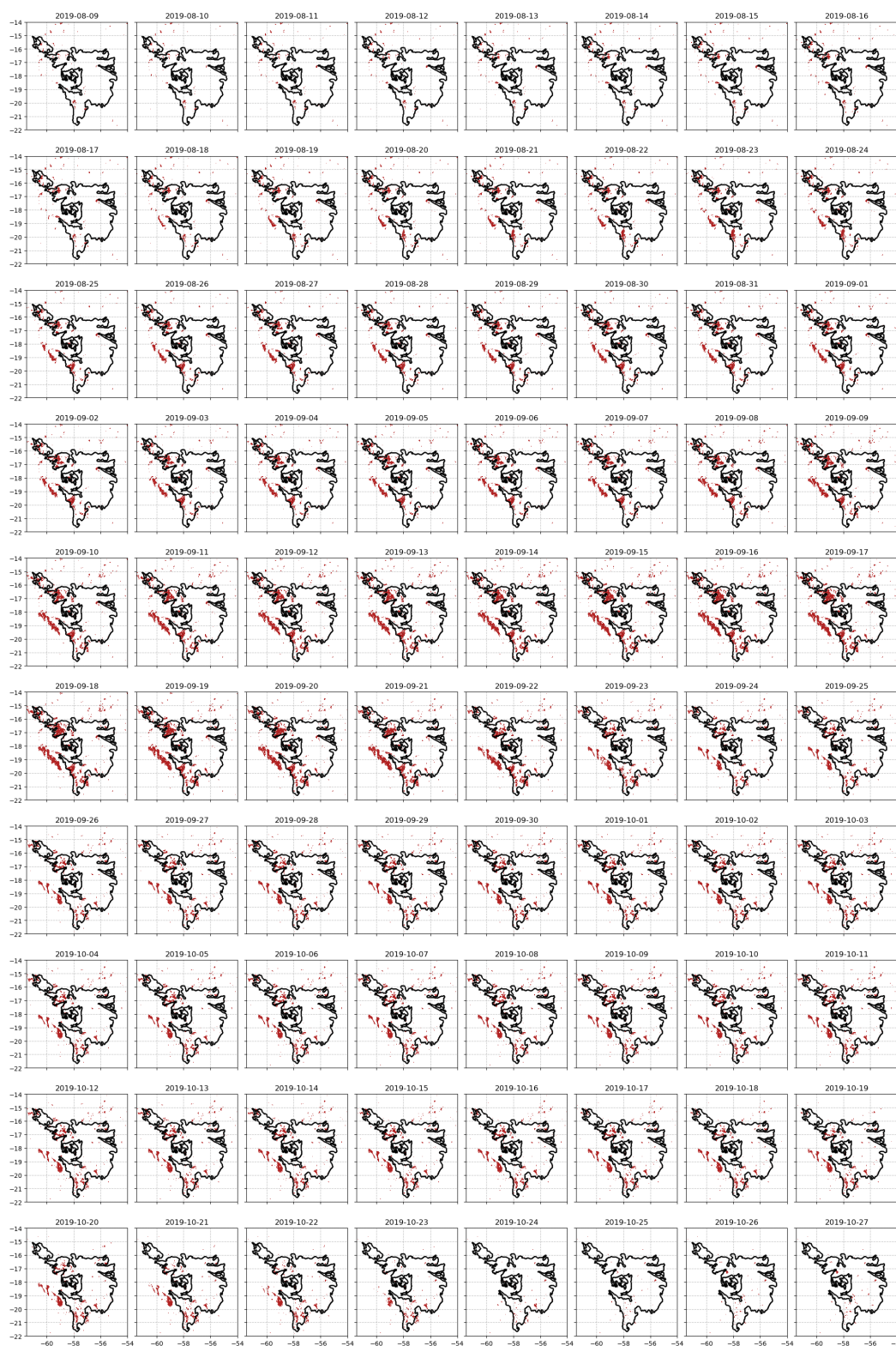


Figure 4.10: Daily Burned Area Spread Maps for the 2019 Fire Season.

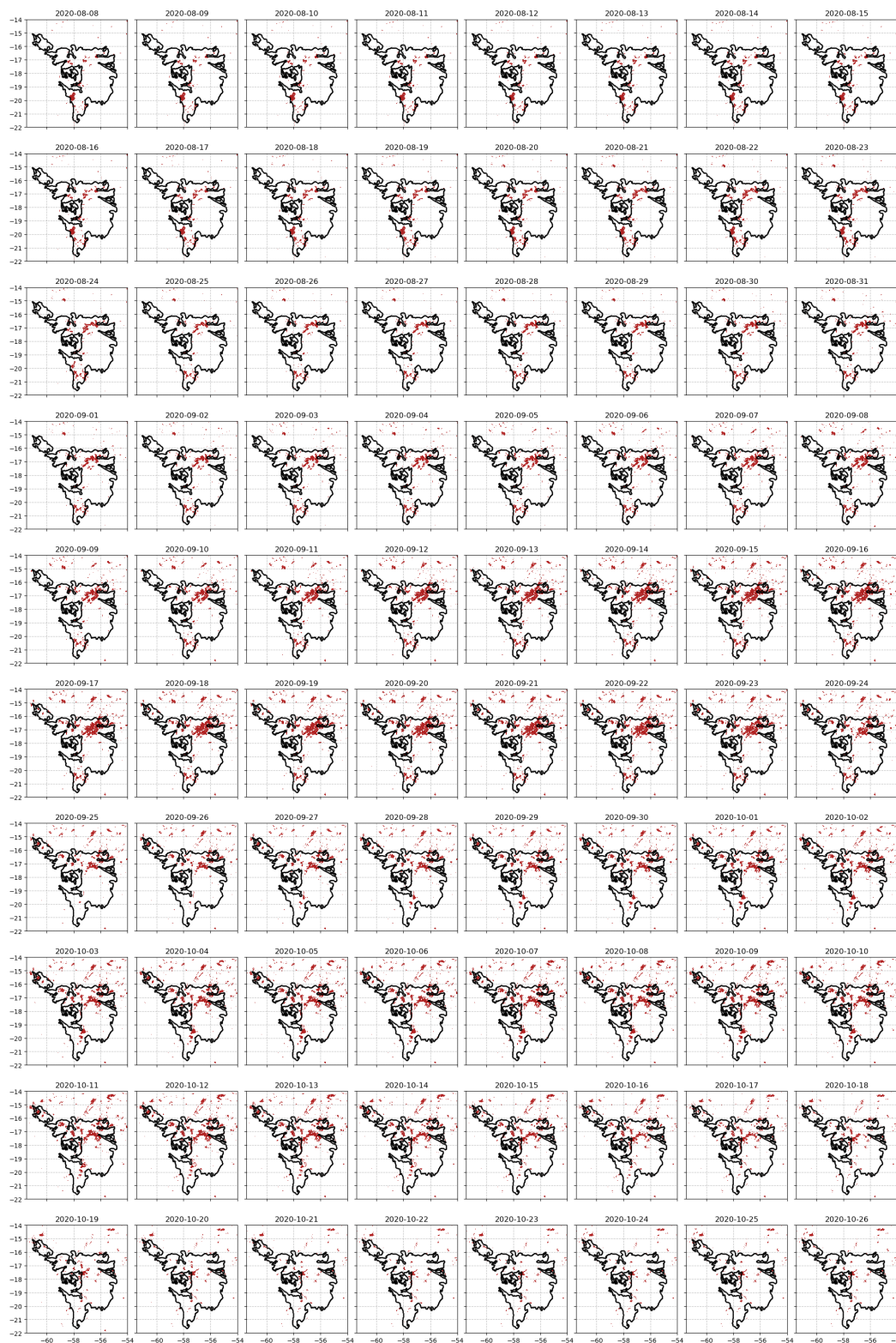


Figure 4.11: Daily Burned Area Maps for the 2020 Fire Season.



Figure 4.12: Daily Burned Area Maps for the 2021 Fire Season.

where $N_\epsilon(p)$ represents the neighborhood of point p with radius ϵ . Then the core points are classified by:

$$\text{Core}(p) = \begin{cases} \text{True} & \text{if } |N_\epsilon(p)| \geq \text{MinPts} \\ \text{False} & \text{otherwise} \end{cases} \quad (4.3)$$

Clusters are formed by core points and their density-reachable points. A point q is density-reachable from a point p if there is a sequence of points $p = p_1, p_2, \dots, p_n = q$ such that each $p_{i+1} \in N_\epsilon(p_i)$ and p_i is a core point. Points that do not meet the density criteria are classified as noise

This method is particularly advantageous for our study, as it can discover clusters of arbitrary shapes, providing a flexible and effective means of analyzing the spatial patterns of burned areas. We utilized parameters [$\epsilon = 3$, $\text{MinPts} = 3$] based on experimental results, to ensure optimal performance in detecting and classifying spatial clusters of interest. The parameter choice involves a trade-off between sensitivity and specificity. While these parameters optimize the detection and classification of mature fire events, they may overlook smaller or emerging fires. This trade-off is necessary to focus on burned areas that have developed significantly, which are more relevant for targeted intervention and ecological impact assessment.

4.4.3 Hungarian Method for Event Tracking

The Hungarian method, also known as the Kuhn-Munkres algorithm [132], is a combinatorial optimization algorithm designed to solve the assignment problem in polynomial time. This algorithm is particularly valuable in the context of event tracking, where the goal is to associate detected events or objects across consecutive frames or time points.

In event tracking, the Hungarian method is employed to minimize the overall cost of assignments, facilitating the matching of objects or events from one frame to the next based on a cost matrix C . Each element C_{ij} within this matrix represents the cost of assigning object i in frame t to object j in frame $t + 1$. These costs are typically calculated using metrics such as Euclidean distance, appearance similarity, or motion consistency, thereby reflecting the likelihood of correct associations. The assignment problem is mathematically formulated as finding a permutation σ of the columns (representing objects in frame $t + 1$) that minimizes the total cost, expressed as

$$\min_{\sigma} \sum_{i=1}^n C_{i,\sigma(i)} \quad (4.4)$$

where $\sigma(i)$ denotes the object in frame $t + 1$ assigned to object i in frame t , and n is the total number of objects.

The Hungarian method operates through a series of systematic steps. Initially, for each row in the cost matrix, the smallest entry is subtracted from all entries in that row, a procedure known as row reduction. This is followed by column reduction, where the smallest entry in each column is subtracted from all entries within the column. Subsequently, all zeros in the resulting matrix are covered using a minimum number of horizontal and vertical lines. If the minimum number of lines equals the number of rows (or columns), an optimal assignment among the zeros is attainable. In cases where not all zeros are covered, the matrix is adjusted by identifying the smallest uncovered value, subtracting it from all uncovered elements, and adding it to elements covered twice. This iterative process is repeated until an optimal assignment is determined, ensuring that each detected object or event in frame t is matched to its counterpart in frame $t + 1$ with the least total cost.

The algorithm’s ability to systematically explore all possible assignments and find the optimal one makes it robust against challenges such as occlusions, object entry, and exit. The efficiency and accuracy of the Hungarian method make it essential for multi-object tracking applications, ensuring consistent identity maintenance over time. This is crucial in fields such as surveillance, biological cell tracking, and autonomous vehicle navigation, where precise and reliable tracking is essential.

4.4.4 Enhanced Tracking Methodology and Data Management

In this study, we processed all daily burned area records using a multi-object tracking algorithm specifically tailored for detailed burned area analysis. This algorithmic adaptation involved optimizing the computational process to handle the complexity inherent in the Hungarian method, which is known for its cubic time complexity. To mitigate this, we employed techniques such as the utilization of sparse matrices and revised handling of edge cases, transitioning from a traditional one-to-one tracking approach to a more dynamic system.

In the object tracking implementation, we have integrated several additional features to ensure robustness and accuracy. The method handles object merging and splitting by assigning high penalties in the cost matrix for non-overlapping entities and enforcing a strict pixel overlap threshold, which requires objects to share pixels in successive frames to be considered the same, thereby minimizing false positives. The algorithm also disregards changes in object shape, simplifying the computational process while maintaining precision and adaptability, enabling efficient tracking even in rapidly changing environments.

Moreover, we enhanced the data management strategy by integrating a tree data structure for storing all detected objects. This structural choice allows hierarchical mapping of each incident, thereby facilitating the tracking of parent and child nodes within the burned area data. This method provides enhanced flexibility, allowing for a more granular examination of specific fire events and optimizing our ability to analyze and intervene in fire developments effectively, as demonstrated in Figure 4.13.

This enhanced methodology is particularly beneficial for labeling single fire "events" in cases where fires are spreading or shrinking and may be occluded by clouds. The application of these refined methods has yielded promising results, with intriguing figures and outcomes to be presented in Section 4.5.

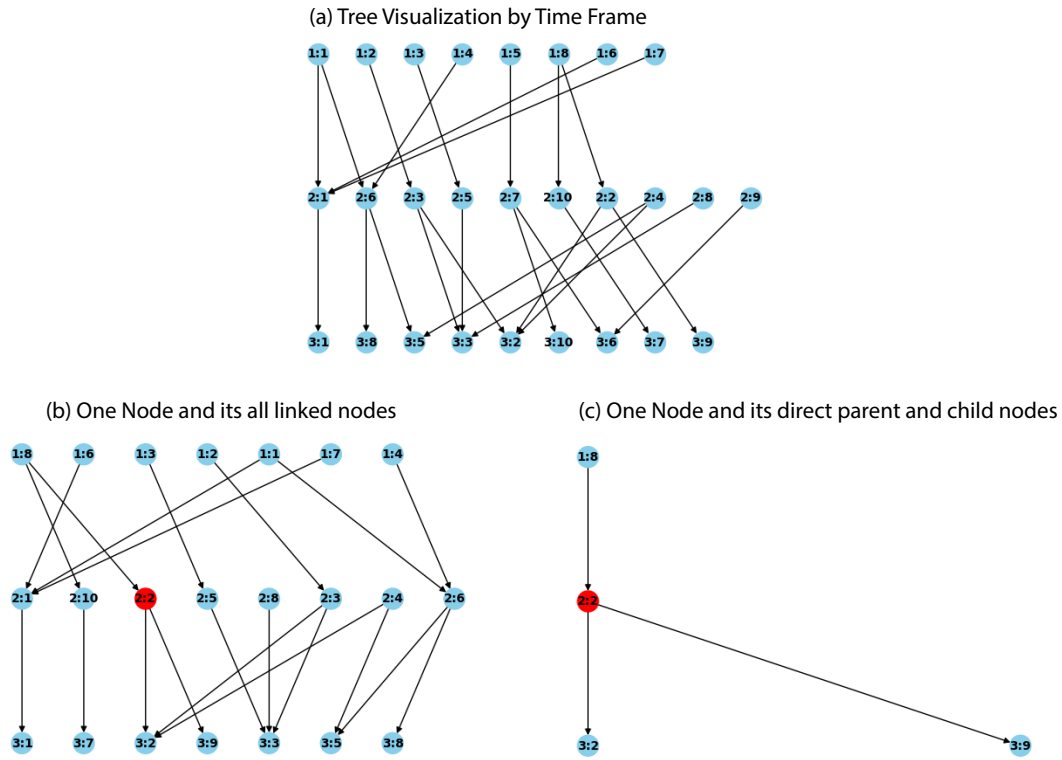


Figure 4.13: Node Search with Tree Structure.

(a) Full view of an example dataset, with each object labeled using the format "time frame: index" for each time frame. (b) Search results for one node and all its connected nodes. (c) Search results for one node, displaying its direct parent and child nodes.

4.5 Results

4.5.1 Correlation Analysis

First, we examine the interconnections among the precipitation rate, inundation extent, and burned area over the five-year period. Figure 4.14 presents a correlation matrix that has been optimized based on the best lag time between these variables. We use time series data of standardized anomalies, where each data point represents the average value over a three-month period. This averaging technique smooths out short-term variations to more clearly

reveal sustained trends across the datasets. Our findings indicate a strong alignment between the datasets. The analysis shows that the Burned Area has a correlation of -0.51 with the Inundation Area at a lag time of 1 month, a correlation of -0.66 with the Precipitation Rate at a lag time of 2 months, and the Inundation Area and Precipitation Rate exhibit a correlation of 0.65 at a lag time of 2 months.

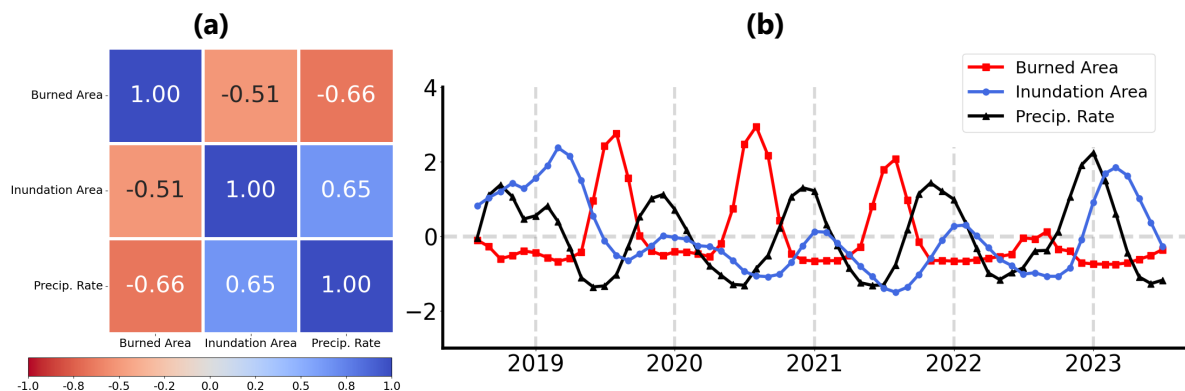


Figure 4.14: Standardized Anomalies of Burned Area, Inundation Area and Precipitation Rate over Fire Years (August 2018 - August 2023).

(a) Correlation matrix, computed based on the optimal lag times between variables, illustrating the relationships as follows: a -0.51 correlation between Burned Area and Inundation Area at a 1-month lag, a -0.66 correlation between Burned Area and Precipitation Rate at a 2-month lag, and a 0.65 correlation between Inundation Area and Precipitation Rate at a 2-month lag. (b) Time Series for the standardized anomalies. The data points for each variable represent three-month-averaged value, smoothing short-term variations to highlight more sustained trends.

It is noteworthy that despite the relatively stable precipitation rates observed from 2019 to 2022, with a slight increase in 2023, there was a clear decrease in Pantanal inundation extent during the wet seasons following the three major fire events as Figure 4.15 displayed. Figure 4.15 illustrates the seasonal inundation and fire patterns from 2018 to 2023, following a chronological timeline. The upper panel displays the wet season patterns, where light blue indicates pixels consistently labeled as wet across all five wet seasons, while dark blue represents other water pixels identified during each wet season. The bottom panel shows the fire season patterns, with red pixels marking the burned areas during each season. Both the wet and fire seasons are annotated with the corresponding months along the timeline in the middle. This trend suggests that while precipitation remained consistent, the ability of the Pantanal to retain water during its wet seasons was significantly compromised. The major fire events appear to have had a lasting impact on the region's hydrological dynamics, potentially altering the landscape in ways that reduced its water-holding capacity. Such alterations

could include changes in soil structure that might have led to a more hydrophobic surface, vegetation loss, and increased runoff, all of which contribute to diminished inundation. The interplay between stable precipitation and reduced inundation highlights the complexity of ecosystem responses to disturbances like wildfires.

In addition, a higher-level representation of how fire and water season patterns manifest in the Pantanal is provided in Figure 4.16. In this figure, red areas indicate regions dominated by fire events, while blue areas represent regions dominated by water-related events. This overlay offers a clear visual summary of the spatial dynamics between these two types of seasonal patterns. The spatial dynamics underscores the necessity of integrated management approaches that consider not only climatic factors but also the ecological aftermath of fire events. Understanding these interactions is critical for developing effective conservation strategies aimed at restoring and maintaining the hydrological and ecological balance of the Pantanal.

4.5.2 Fire Patterns

The performance of DBSCAN for burned area classification is presented in Figure 4.17 using a specific time frame (October 10, 2020). Each individual event is labeled with a red box, provides a depiction of how DBSCAN identifies distinct burned regions, showcasing the algorithm's capability to categorize spatial data. The labeled frame in Figure 4.17 provides insights into the extent and distribution of burned areas on a typical day during the fire season. It captures the temporal dynamics of fire-affected regions, revealing a combination of large and small burned areas.

Figure 4.18 and 4.19 illustrates how a large-scale burned area detected in the year 2020 evolves throughout the entire timeline, using the object tracking algorithm. An overview of the entire impacted region, searched and plotted all parent and child nodes linked to the largest burned area detected in the year, is presented in Figure 4.18. The burned area is color-coded from light red to dark red to reflect the duration of impact, showing the number of days affected. In Figure 4.19, each sub-figure is presented with the zoom-in view on the specific burned area to better visualize the tracking components. Individual burned areas are marked by red boxes. The figure demonstrates the algorithm's capability to follow the progression of the burned area over time, underscoring its effectiveness in dynamic and complex scenarios.

Leveraging our established object-tracking method, we also delve into the origins of the burning areas, providing a perspective on fire patterns from their initial development. The right-side subfigure in Figure 4.20 presents the temporal distribution of the origins of burned areas from 2018 to 2023, reveals distinctive temporal patterns in fire occurrences. During the years 2018, 2019, and 2020, a pronounced peak in fire activity is consistently observed around days 240 to 260, correlating with the late August to mid-September period. This recurrent

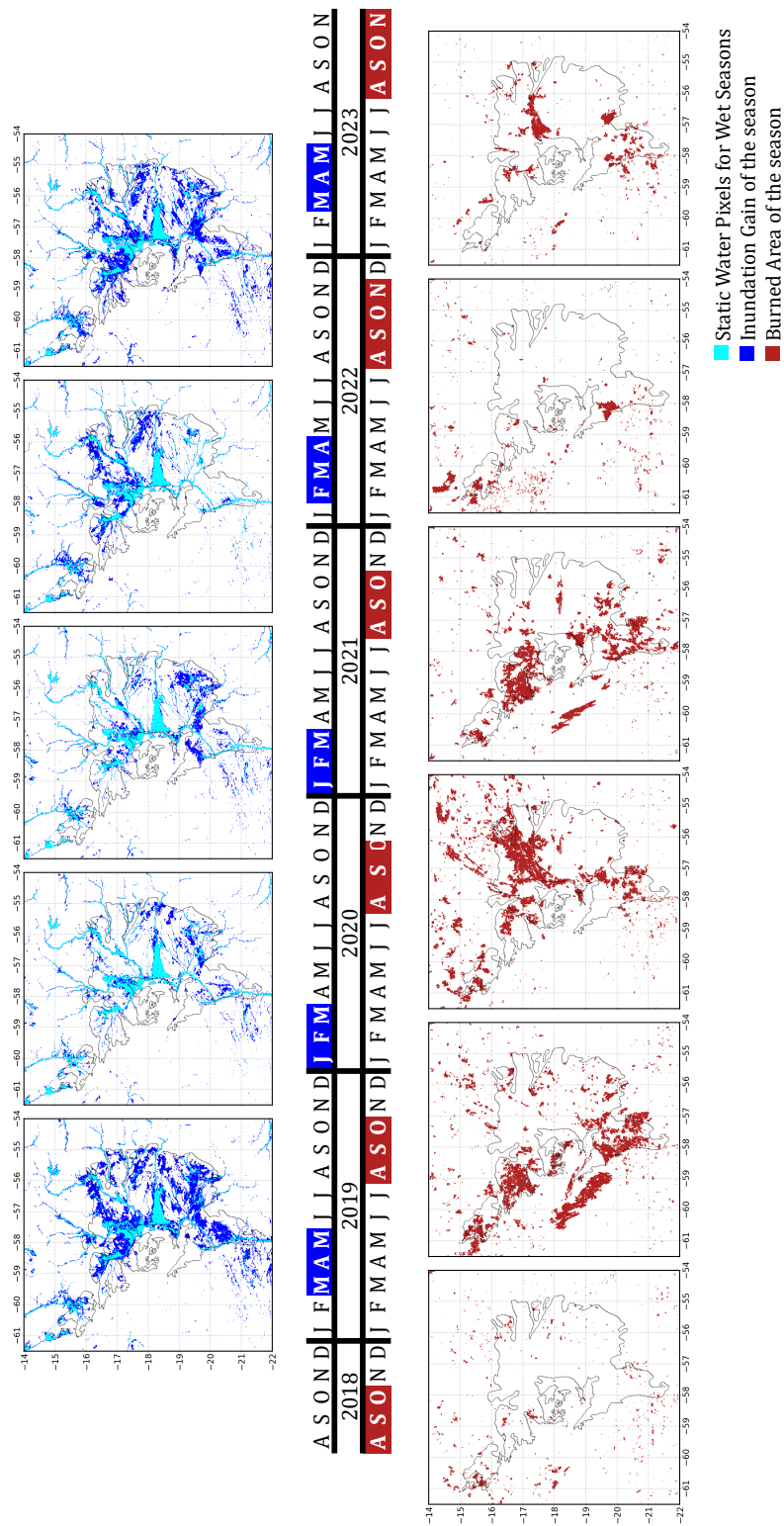


Figure 4.15: Seasonal Inundation and Fire Patterns From 2018 to 2023.

Upper panel: wet season patterns, with light blue indicating consistently wet pixels across all five seasons and dark blue showing other wet pixels. Bottom panel: fire season patterns, with red pixels marking burned areas. The timeline notes the months for both wet and fire seasons, highlighted in blue and red, respectively.

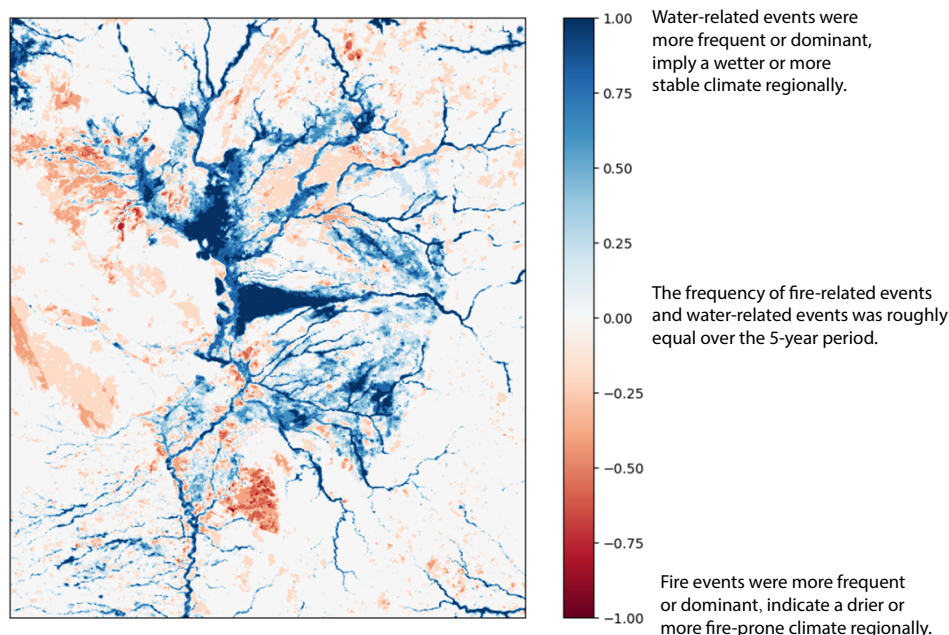


Figure 4.16: Overlay of Fire and Water Seasonal Patterns (August 2018 - August 2023). The colobar is a higher level representation of whether the region is dominated by water-related events or fire-related events..

pattern underscores a seasonal susceptibility to fire during these months. The year 2021 is characterized by a bimodal distribution, with notable peaks in early June (approximately day 160) and another during the historically peak fire period observed in prior years. In contrast, the years 2022 and 2023 demonstrate a temporal shift, with peak fire occurrences extending to post-day 300, around late October. These shifts in peak fire times may reflect underlying changes in climatic conditions, land-use patterns, signaling a potential evolution in fire dynamics in the region.

Figure 4.20(b) showcases an overlap matrix that quantifies the similarities in fire origin locations between each pair of years from 2018 to 2023. This matrix is color-coded to reflect the intensity of overlaps, with darker shades indicating a higher degree of spatial concordance in burned area origins. The data demonstrate notable continuity in fire locations between the years 2019 and 2020, and similarly between 2019 and 2021, suggesting persistent hotspots of fire activity. In contrast, the years 2018 and 2023 exhibit a marked low similarity in burned area origins, indicating a possible shift in fire-prone zones or alterations in environmental conditions influencing fire dynamics.

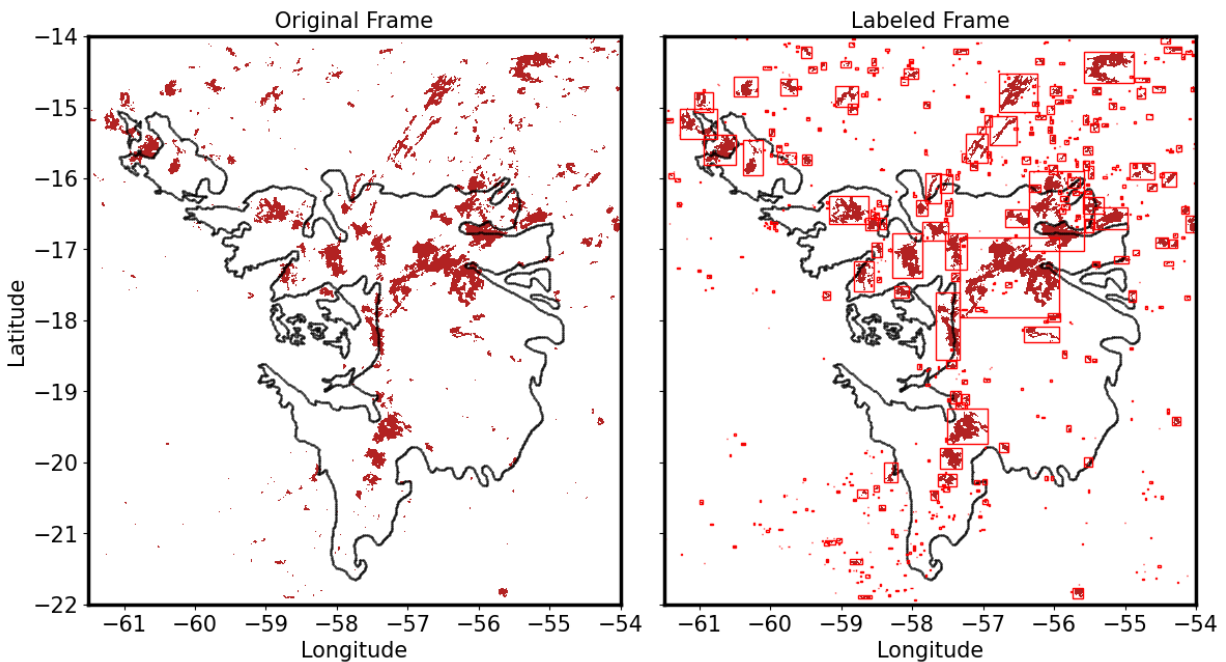


Figure 4.17: Burned Area Classification for Individual Time Frame.

Right: Burned area (red) for October 10, 2020. Left: After applying DBSCAN, individual events are labeled with red boxes to indicate their specific locations.

4.5.3 Hydrological Response to Fires: Long-term Dynamics

Additionally, we extend the investigation to evaluate the impact of fire occurrences in relation to the future inundation. Figure 4.21 presents an analysis of survival rates focusing on the duration between fire events and subsequent inundation across pixels with burning history. The survival curves show how long it takes for a pixel to experience inundation. The analysis is segmented into two scenarios: the first plot excludes pixels that also contain static water bodies, while the second incorporates them, providing insights into the hydrological impact of these static water bodies.

In the first plot (Figure 4.21 (a)), with the removal of static water bodies, the curve demonstrates a more rapid decline in survival rate for burned pixels compared to unburned ones, until the 20th month, where the two curves intersect. This indicates that regions recently affected by fire exhibit heightened vulnerability to faster inundation until approximately 1.6 years post-fire, likely attributable to changes in soil and vegetative characteristics impacting water absorption and runoff dynamics.

The second plot (Figure 4.21 (b)), which accounts for static water bodies, presents a slightly different view of hydrological dynamics. In this scenario, the curve for burned pixels shows

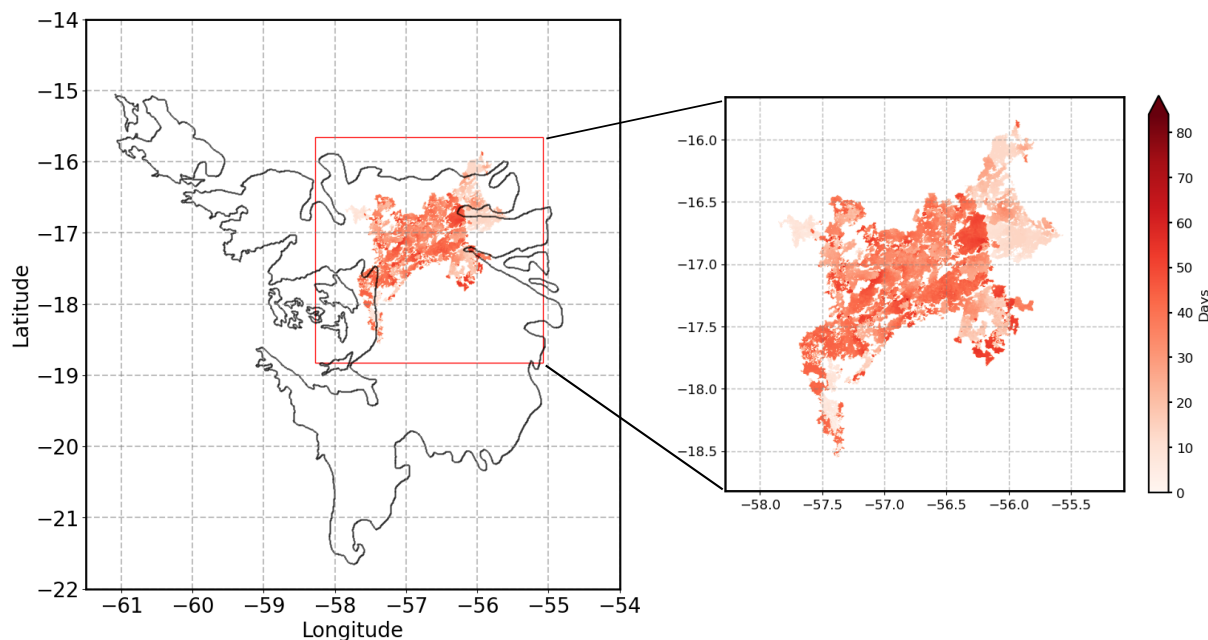


Figure 4.18: Burned Area Track for Individual Burned Event - Overview.

Tracking the evolution of a large-scale burned area detected in 2020 over time. The red box highlights and zooms in on the overall impacted region, with the burned area color-coded from light red to dark red to indicate the duration of impact, representing the number of days affected.

a pronounced and rapid decline until around the 30th month post-fire, suggesting that areas recently affected by fire are more vulnerable to quicker inundation for approximately 2.5 years, which is much longer than the first case. This observation underscores the role of static water bodies in modulating the hydrological response, highlighting their capacity to influence water absorption and retention in fire-impacted regions.

4.6 Discussion

The correlation analysis highlights the crucial role of precipitation and subsequent inundation in mitigating fire risks while illustrating how mega fires can impact the buffering capacity of wetlands during wet periods. The spatial distribution of precipitation rates and wetland refilling patterns aligns well, indicating a direct relationship between rainfall and wetland water extent. This finding is consistent with studies [133] showing that the Pantanal is a seasonal wetland where rainfall plays a significant role in the flood pulse, accounting for approximately 60% of the total variability in flooded areas. Furthermore, studies [134] suggest that although rainfall patterns are regionally synchronous, the hydrological responses

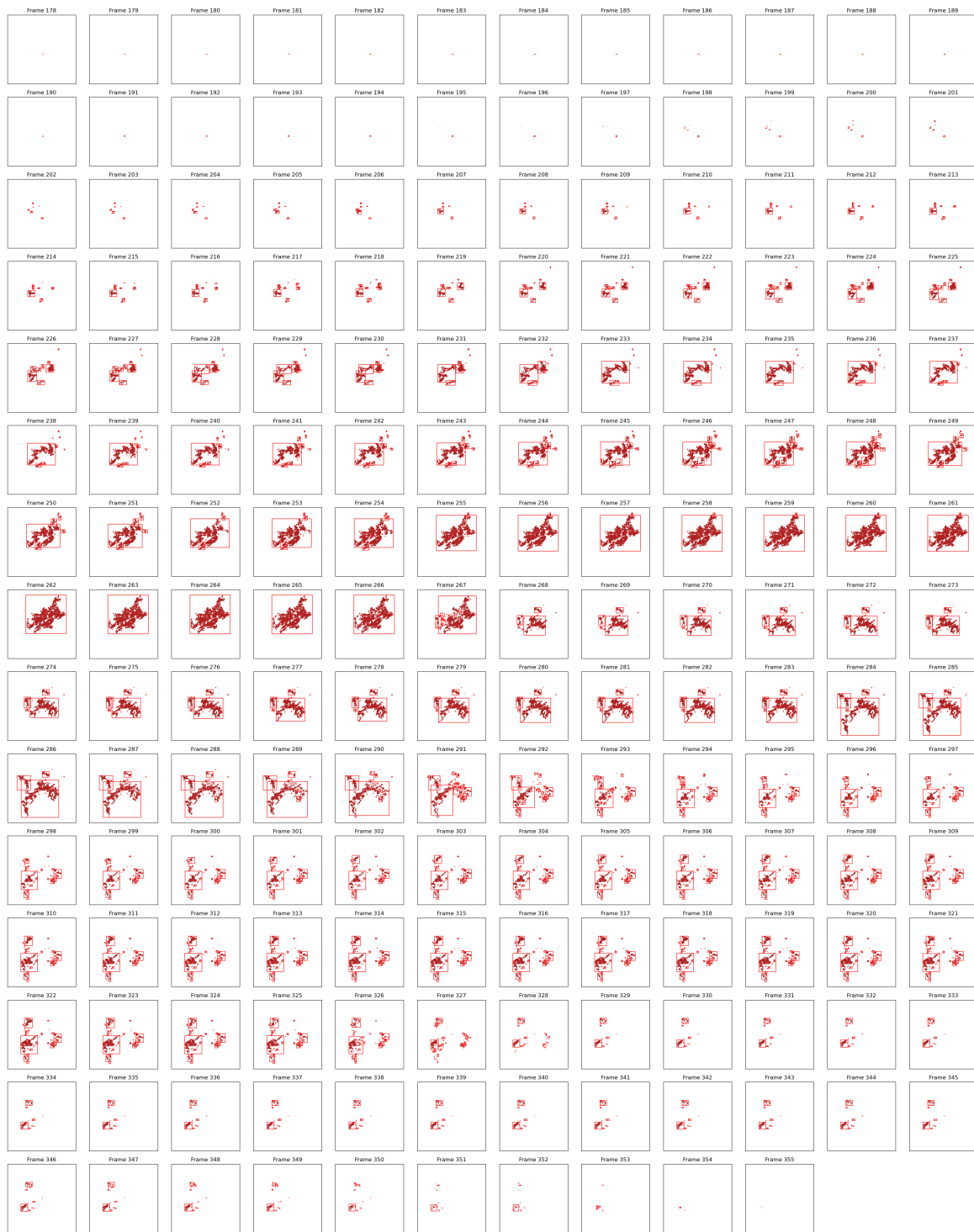


Figure 4.19: Burned Area Track for Individual Burned Event - Tracking Frames. Tracking the evolution of a large-scale burned area detected in 2020 over time. Each subfigure focuses on a specific time frame, and individual burned areas are labeled with red boxes to demonstrate the algorithm's effectiveness in following the dynamic progression of burned areas.

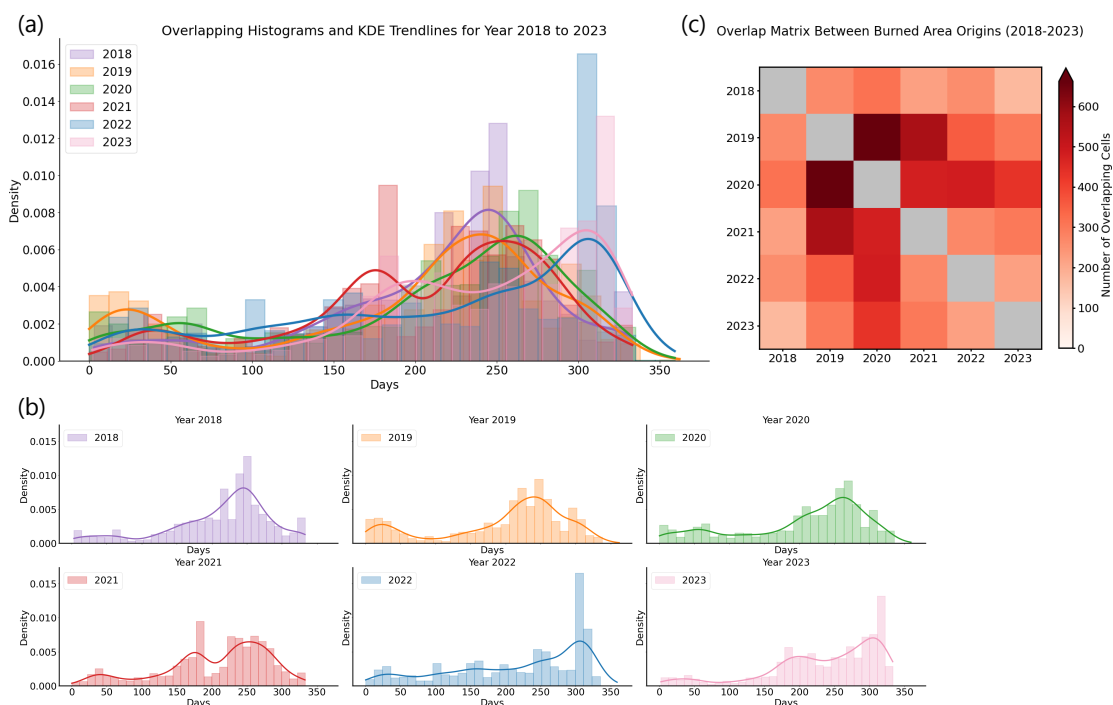


Figure 4.20: Temporal Dynamics and Spatial Overlap of Burned Area Origins from 2018 to 2023.

(a) Histograms displaying the origins of burned areas for each year. Overlaid on these histograms are Kernel Density Estimate (KDE) trendlines, which smooth the probability distribution of the data across the days of the year. (b) Individual density plots for each year, ranging from 2018 to 2023, to separately visualize the frequency of fire occurrences. (c) Matrix visualizes the overlap in burned area origins between each pair of years from 2018 to 2023. The intensity of the colors reflects the degree of overlap, with darker shades indicating a higher number of overlapping cells and thus greater similarity in the locations of fire origins.

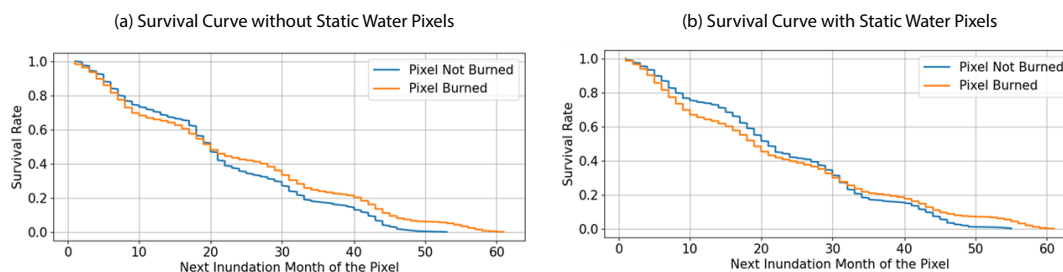


Figure 4.21: Hydrological Responses to Fire Events with Varied Inundation Categories. This figure explores survival rates post-fire, analyzing the time until inundation across different hydrological settings. (a) excludes static water bodies, showing a quicker decline in survival rates for burned pixels up to 20 months post-fire. (b) includes static water bodies, extending vulnerability to inundation to about 30 months.

in wetlands vary considerably depending on their proximity to inundated areas. Interannual variability in rainfall significantly affects vegetation dynamics near flooded regions, with local water storage leading to weaker and delayed vegetative responses. This literature also indicates the importance of flood pulse timing in determining vegetation productivity and suggests that local wetland conditions can be mediated by rainfall patterns in the Pantanal.

However, the observed decrease in wetland refilling after mega fires underscores the heightened vulnerability of wetlands during dry spells. This suggests that mega-fires not only deplete the immediate water reserves but also potentially alter the ecosystem's ability to recover and retain water in subsequent wet seasons. These changes could lead to a diminished capacity for wetlands to act as natural buffers against fires, thereby increasing the frequency and intensity of future fire events.

Our study goes further by applying DBSCAN clustering method and multi-object tracking algorithms to provide a detailed spatiotemporal analysis of fire events. This methodological advancement allows for more precise identification of fire ignition points and tracking of fire spread, offering new insights into fire dynamics in wetland ecosystems. In addition, we looked into the dynamics between fire events and water response in different hydrological settings. The inclusion or exclusion of static water bodies significantly alters the landscape's hydrological behavior post-fire, underscoring the importance of considering these elements in ecological and hydrological studies.

This study offers valuable insights into the interplay between precipitation, hydrology, and fire dynamics in wetland ecosystems. However, there are several areas where future research could expand upon these findings to address current limitations and explore new dimensions of this complex topic.

The current analysis is constrained by the monthly resolution of available datasets, which may obscure short-term hydrological phenomena such as flash floods. Future research could investigate high-resolution temporal data as chapter 3 presents, to capture more dynamic hydrological events, providing a richer understanding of water movement and its interaction with fire behavior in the Pantanal.

Refining the multi-object tracking algorithm to incorporate machine learning techniques could enhance the accuracy of fire spread categorization and extend its capabilities to make predictions. It is also worth studying more on the fire behavior characterization, to quantify the distinction between continuous low-intensity fires and rapid extensive fires. This involves examining the influence of both climatic conditions and anthropogenic factors on fire behavior. Moreover, analysis of land cover types within detected fire regimes can yield deeper insights into fire characteristics. Understanding whether fire events are confined to homogeneous land types or traverse multiple landscapes can help identify vulnerable areas and inform management practices.

The hydrological response to fires also offers an intriguing research direction, particularly in understanding the long-term dynamics of various inundation categories. By categorizing different types of inundation, such as static water bodies and rainfall-driven inundation, we can analyze how these factors interact with fire dynamics at the pixel level. This approach could help identify key ecological thresholds where changes in inundation lead to shifts in fire behavior, illuminating the role of hydrological conditions in shaping fire regimes.

4.7 Conclusion

In this study, our work sheds light on the complex interactions between fire dynamics, precipitation patterns, and wetland inundation in the Pantanal. By employing advanced tracking algorithms and comprehensive data analysis, we provide a detailed understanding of the factors driving fire behavior and wetland resilience. We have clear evidence of the relationship between precipitation and water-refilling spatial distribution. However, the consistent amount of precipitation does not correlate with the observed decrease in surface water inundation extent. This suggests that factors other than just precipitation are influencing wetland refilling. Notably, the occurrence of mega fires appears to significantly impact the hydrological dynamics of the Pantanal, reducing its capacity to retain water even when precipitation levels are stable. These findings highlight the importance of considering the compounded effects of fire and hydrological processes in the Pantanal. Mega fires likely alter the physical and biological properties of the soil, reducing its permeability and water retention capabilities. This, in turn, disrupts the natural refilling processes of wetlands, leading to prolonged dry spells and increased vulnerability of the ecosystem. In conclusion, our study emphasizes the necessity of considering both immediate and long-term impacts of fire events on wetland hydrology. The persistent decrease in water retention despite stable

precipitation rates points to significant alterations in the wetland's natural processes. Understanding these interactions is crucial for predicting future trends in wetland resilience and for developing strategies to mitigate the adverse effects of both natural and anthropogenic factors on these critical ecosystems. Our findings contribute to a more nuanced understanding of wetland dynamics, highlighting the intricate balance between climatic variables and ecological responses in shaping the health and sustainability of the Pantanal.

Chapter 5

Conclusion Remarks

This work leverages cutting-edge remote sensing technology and robust training-free computer vision algorithms to address significant challenges in analyzing wetland dynamics, with a particular focus on underrepresented tropical wetlands. It investigates the interplay between hydrological changes, climate variability, and anthropogenic influences, examining both flooding and wildfire impacts, and assesses wetland resilience.

The introduction of the UC Berkeley Random Walk Algorithm WaterMask from CYGNSS (Berkeley-RWAWC) marks a significant advancement in remote sensing-based inundation products, providing a quasi-global view of surface water dynamics beneath dense vegetation and persistent cloud cover. This work enhances our understanding of seasonal and interannual variability in tropical hydrology, offering new perspectives on these critical ecosystems. Furthermore, by refining the temporal resolution to capture daily water dynamics, this research addresses the urgent need for timely data to manage increasingly frequent and extreme hydroclimatic events.

The data-driven methodology developed in Chapters 2 and 3 intentionally minimizes the use of ancillary data, relying solely on GNSS-R-derived information to independently explore its capabilities. By focusing exclusively on GNSS-R data, we gain a clearer understanding of its characteristics and performance, which lays the groundwork for its integration with other datasets. This approach highlights the potential of GNSS-R as a powerful tool for monitoring water dynamics. As we advance, combining GNSS-R with other data sources promises to enhance our ability to monitor and analyze hydrological changes, offering significant opportunities for improving global water management in the face of climate change.

There are two major directions I find particularly interesting and worth further exploration. First, given that CYGNSS is an ongoing satellite mission with dynamic trajectory, fluctuations in the density and quality of data acquisition are expected as the mission progresses. These variations occur across different latitudes and longitudes, impacting data availability. It will be valuable to investigate data density further to optimize our capabilities in

using CYGNSS data, as well as data from other ongoing and upcoming GNSS-R missions. Understanding these patterns can inform strategies for maximizing data utility.

Secondly, integrating GNSS-R data with other complementary datasets could provide a more holistic understanding of hydrological processes. I envision this integration focusing on both deep learning and hydrological modeling aspects. On the deep learning front, using architectures such as Convolutional Neural Networks (CNNs), Transformers, and Long Short-Term Memory (LSTM) networks, GNSS-R data can be integrated with higher-resolution datasets like optical and SAR data to enhance water mapping. This approach can help identify areas likely to contain water that may not be visible due to the limitations of individual datasets. Deep learning algorithms can learn from GNSS-R information to detect subtle patterns, improving the accuracy of water detection and mapping. On the hydrological modeling side, leveraging GNSS-R data points alongside established river routing frameworks can provide a near-real-time view of inundation status. By integrating these data points into models, we can simulate and predict water movement more effectively. Techniques such as Monte Carlo simulations can be used to account for uncertainties and variations in hydrological processes, offering predictions of flooding and water distribution from a physical perspective.

In focusing on the Pantanal, the world's largest tropical wetland, Chapter 4 highlights the complex interactions between fire regimes and wetland refilling patterns, elucidating the impact of frequent mega wildfires on these ecosystems. The use of Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and multi-object tracking algorithms demonstrates the potential for advanced computational techniques to uncover patterns in fire dynamics.

There are many opportunities to build upon the current explorations. Further research could delve into the influence of varying climatic conditions on fire behavior and wetland recovery processes. As highlighted at the beginning of Chapter 4, exploring the extent to which fire events are initiated or exacerbated by climate variability, such as extreme temperatures and drought conditions, is crucial. This can be further examined by integrating observed fire patterns with additional environmental data, such as soil moisture, vegetation health indices, and drought indices.

A more detailed study of fire behavior characterization is also warranted, focusing on quantifying the differences between continuous low-intensity fires and rapid extensive fires. This involves analyzing the effects of both climatic conditions and human activities on fire dynamics. Additionally, examining land cover types within detected fire regimes can yield deeper insights into fire characteristics. Understanding whether fire events are confined to homogeneous land types or span multiple landscapes can help identify vulnerable areas and inform management practices.

The hydrological response to fires presents another intriguing research direction, particularly in understanding the dynamics of various inundation categories. By categorizing different types of inundation, such as static water bodies and rainfall-driven inundation, we can analyze how these factors interact with fire dynamics. This approach could help identify key ecological thresholds where changes in inundation lead to shifts in fire behavior, illuminating the role of hydrological conditions in shaping fire regimes. Moreover, the current analysis focuses primarily on long-term hydrological responses, whereas short-term responses could be better understood through high-resolution temporal data, as presented in Chapter 3, to capture more dynamic hydrological events.

Overall, this work contributes to the growing body of knowledge on wetland dynamics, emphasizing the need for innovative monitoring solutions that integrate remote sensing technologies with robust computer vision algorithms. By providing insights into hydrological and fire dynamics, this research supports the investigation of wetlands in the context of climate change and human activities.

Through this research journey, I have gained a deep appreciation for the complexity and resilience of wetland ecosystems. This work reflects my passion for advancing environmental science and underscores my commitment to developing practical solutions for some of the most pressing ecological challenges of our time. I am hopeful that these findings will inspire further research and action to preserve these vital ecosystems for future generations.

Bibliography

- [1] C. M. Finlayson and A. G. Spiers, eds. *Global review of wetland resources and priorities for wetland inventory*. en. Supervising scientist report 144. Canberra: Supervising Scientist, 1999. ISBN: 978-0-642-24347-8.
- [2] C. Prigent et al. “Remote sensing of global wetland dynamics with multiple satellite data sets”. en. In: *Geophysical Research Letters* 28.24 (2001), pp. 4631–4634. ISSN: 1944-8007. DOI: 10.1029/2001GL013263. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1029/2001GL013263>.
- [3] B. M. Fekete et al. “High-resolution fields of global runoff combining observed river discharge and simulated water balances”. en. In: *Global Biogeochemical Cycles* 16.3 (2002), pp. 15–1–15–10. ISSN: 1944-9224. DOI: 10.1029/1999GB001254. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1029/1999GB001254>.
- [4] B. Lehner and P. Döll. “Development and validation of a global database of lakes, reservoirs and wetlands”. en. In: *Journal of Hydrology* 296.1-4 (Aug. 2004), pp. 1–22. ISSN: 00221694. DOI: 10.1016/j.jhydrol.2004.03.028. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0022169404001404>.
- [5] C. Prigent et al. “Global inundation dynamics inferred from multiple satellite observations, 1993–2000”. en. In: *Journal of Geophysical Research: Atmospheres* 112.D12 (2007). ISSN: 2156-2202. DOI: 10.1029/2006JD007847. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1029/2006JD007847>.
- [6] B. Lehner et al. “New Global Hydrography Derived From Spaceborne Elevation Data”. In: *Eos, Transactions American Geophysical Union* 89.10 (2008), pp. 93–94. ISSN: 2324-9250. DOI: 10.1029/2008E0100001. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1029/2008E0100001>.
- [7] E. F. Wood et al. “Hyperresolution global land surface modeling: Meeting a grand challenge for monitoring Earth’s terrestrial water”. en. In: *Water Resources Research* 47.5 (2011). ISSN: 1944-7973. DOI: 10.1029/2010WR010090. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1029/2010WR010090>.
- [8] J.-F. Pekel et al. “High-resolution mapping of global surface water and its long-term changes”. en. In: *Nature* 540.7633 (Dec. 2016), pp. 418–422. ISSN: 1476-4687. DOI: 10.1038/nature20584. URL: <https://www.nature.com/articles/nature20584>.

- [9] K. Jensen and K. McDonald. “Surface Water Microwave Product Series Version 3: A Near-Real Time and 25-Year Historical Global Inundated Area Fraction Time Series From Active and Passive Microwave Remote Sensing”. en. In: *IEEE Geoscience and Remote Sensing Letters* 16.9 (Sept. 2019), pp. 1402–1406. ISSN: 1545-598X, 1558-0571. DOI: 10.1109/LGRS.2019.2898779. URL: <https://ieeexplore.ieee.org/document/8662682/>.
- [10] C. Prigent et al. “Satellite-Derived Global Surface Water Extent and Dynamics Over the Last 25 Years (GIEMS-2)”. en. In: *Journal of Geophysical Research: Atmospheres* 125.3 (2020), e2019JD030711. ISSN: 2169-8996. DOI: 10.1029/2019JD030711. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1029/2019JD030711>.
- [11] IPCC. *IPCC, 2023: Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]*. IPCC, Geneva, Switzerland. en. Tech. rep. Intergovernmental Panel on Climate Change (IPCC), July 2023. DOI: 10.59327/IPCC/AR6-9789291691647. URL: <https://www.ipcc.ch/report/ar6/syr/>.
- [12] G. Konapala et al. “Climate change will affect global water availability through compounding changes in seasonal precipitation and evaporation”. en. In: *Nature Communications* 11.1 (June 2020), p. 3044. ISSN: 2041-1723. DOI: 10.1038/s41467-020-16757-w. URL: <https://www.nature.com/articles/s41467-020-16757-w>.
- [13] W. Thiery et al. “Intergenerational inequities in exposure to climate extremes”. In: *Science* 374.6564 (Oct. 2021), pp. 158–160. DOI: 10.1126/science.abi7339. URL: <https://www.science.org/doi/10.1126/science.abi7339>.
- [14] R. A. Betts et al. “Changes in climate extremes, fresh water availability and vulnerability to food insecurity projected at 1.5°C and 2°C global warming with a higher-resolution global climate model”. In: *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 376.2119 (Apr. 2018), p. 20160452. DOI: 10.1098/rsta.2016.0452. URL: <https://royalsocietypublishing.org/doi/full/10.1098/rsta.2016.0452>.
- [15] S. Lange et al. “Projecting Exposure to Extreme Climate Impact Events Across Six Event Categories and Three Spatial Scales”. en. In: *Earth’s Future* 8.12 (2020), e2020EF001616. ISSN: 2328-4277. DOI: 10.1029/2020EF001616. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1029/2020EF001616>.
- [16] K. E. Trenberth et al. “Attribution of climate extreme events”. en. In: *Nature Climate Change* 5.8 (Aug. 2015), pp. 725–730. ISSN: 1758-6798. DOI: 10.1038/nclimate2657. URL: <https://www.nature.com/articles/nclimate2657>.

- [17] C. A. Mgbemene et al. “Industrialization and its backlash: focus on climate change and its consequences.” English. In: *Journal of Environmental Science and Technology* 9.4 (2016), pp. 301–316. ISSN: 1994-7887. URL: <https://www.cabdirect.org/cabdirect/abstract/20163290084>.
- [18] F. Dong et al. “The process of peak CO₂ emissions in developed economies: A perspective of industrialization and urbanization”. In: *Resources, Conservation and Recycling* 141 (Feb. 2019), pp. 61–75. ISSN: 0921-3449. DOI: 10.1016/j.resconrec.2018.10.010. URL: <https://www.sciencedirect.com/science/article/pii/S0921344918303756>.
- [19] UNESCO. *The United Nations World Water Development Report 2020 :: water and climate change*. en. UNESCO, 2020. ISBN: 978-92-3-100371-4. URL: <https://digitallibrary.un.org/record/3892703>.
- [20] M. Das Gupta. “Population, Poverty, and Climate Change”. In: *The World Bank Research Observer* 29.1 (Feb. 2014), pp. 83–108. ISSN: 0257-3032. DOI: 10.1093/wbro/1kt009. URL: <https://doi.org/10.1093/wbro/1kt009>.
- [21] K. L. Erwin. “Wetlands and global climate change: the role of wetland restoration in a changing world”. In: *Wetlands Ecology and Management* 17.1 (Feb. 1, 2009), pp. 71–84. ISSN: 1572-9834. DOI: 10.1007/s11273-008-9119-1. URL: <https://doi.org/10.1007/s11273-008-9119-1>.
- [22] W. J. Mitsch et al. “Wetlands, carbon, and climate change”. In: *Landscape Ecology* 28.4 (Apr. 1, 2013), pp. 583–597. ISSN: 1572-9761. DOI: 10.1007/s10980-012-9758-8. URL: <https://doi.org/10.1007/s10980-012-9758-8>.
- [23] S. Salimi et al. “Impact of climate change on wetland ecosystems: A critical review of experimental wetlands”. In: *Journal of Environmental Management* 286 (May 2021), p. 112160. ISSN: 0301-4797. DOI: 10.1016/j.jenvman.2021.112160. URL: <https://www.sciencedirect.com/science/article/pii/S030147972100222X>.
- [24] R. C. Secretariat. *An Introduction to the Convention on Wetlands (previously The Ramsar Convention Manual)*. Gland, Switzerland: Ramsar Convention Secretariat, 2016. URL: https://www.ramsar.org/sites/default/files/documents/library/handbook1_5ed_introductiontoconvention_e.pdf.
- [25] R. C. Secretariat. *The List of Wetlands of International Importance*. 2023. URL: <https://www.ramsar.org/sites/default/files/documents/library/sitelist.pdf>.
- [26] N. Davidson. “How much wetland has the world lost? Long-term and recent trends in global wetland area”. In: *Marine and Freshwater Research* 65 (Jan. 1, 2014), pp. 936–941. DOI: 10.1071/MF14173.
- [27] D. E. Alsdorf et al. “Measuring surface water from space”. en. In: *Reviews of Geophysics* 45.2 (2007). ISSN: 1944-9208. DOI: 10.1029/2006RG000197. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1029/2006RG000197>.

- [28] S. C. J. Palmer et al. “Remote sensing of inland waters: Challenges, progress and future directions”. In: *Remote Sensing of Environment*. Special Issue: Remote Sensing of Inland Waters 157 (Feb. 2015), pp. 1–8. ISSN: 0034-4257. DOI: 10.1016/j.rse.2014.09.021. URL: <https://www.sciencedirect.com/science/article/pii/S0034425714003666>.
- [29] S. N. Topp et al. “Research Trends in the Use of Remote Sensing for Inland Water Quality Science: Moving Towards Multidisciplinary Applications”. en. In: *Water* 12.1 (Jan. 2020), p. 169. ISSN: 2073-4441. DOI: 10.3390/w12010169. URL: <https://www.mdpi.com/2073-4441/12/1/169>.
- [30] J. G. Masek et al. “Landsat 9: Empowering open science and applications through continuity”. In: *Remote Sensing of Environment* 248 (Oct. 2020), p. 111968. ISSN: 0034-4257. DOI: 10.1016/j.rse.2020.111968. URL: <https://www.sciencedirect.com/science/article/pii/S0034425720303382>.
- [31] C. Justice et al. “An overview of MODIS Land data processing and product status”. en. In: *Remote Sensing of Environment* 83.1-2 (Nov. 2002), pp. 3–15. ISSN: 00344257. DOI: 10.1016/S0034-4257(02)00084-6. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0034425702000846>.
- [32] R. Torres et al. “GMES Sentinel-1 mission”. In: *Remote Sensing of Environment*. The Sentinel Missions - New Opportunities for Science 120 (May 15, 2012), pp. 9–24. ISSN: 0034-4257. DOI: 10.1016/j.rse.2011.05.028. URL: <https://www.sciencedirect.com/science/article/pii/S0034425712000600>.
- [33] D. Entekhabi et al. “The Soil Moisture Active Passive (SMAP) Mission”. en. In: *Proceedings of the IEEE* 98.5 (May 2010), pp. 704–716. ISSN: 0018-9219, 1558-2256. DOI: 10.1109/JPROC.2010.2043918. URL: <http://ieeexplore.ieee.org/document/5460980/>.
- [34] V. S. Martins et al. “Seasonal and interannual assessment of cloud cover and atmospheric constituents across the Amazon (2000–2015): Insights for remote sensing and climate analysis”. In: *ISPRS Journal of Photogrammetry and Remote Sensing*. SI: Latin America Issue 145 (Nov. 2018), pp. 309–327. ISSN: 0924-2716. DOI: 10.1016/j.isprsjprs.2018.05.013. URL: <https://www.sciencedirect.com/science/article/pii/S0924271618301461>.
- [35] B. Downs et al. “Assessing the Relative Performance of GNSS-R Flood Extent Observations: Case Study in South Sudan”. In: *IEEE Transactions on Geoscience and Remote Sensing* 61 (2023), pp. 1–13. ISSN: 1558-0644. DOI: 10.1109/TGRS.2023.3237461. URL: <https://ieeexplore.ieee.org/document/10018248>.
- [36] M. Saunio et al. “The Global Methane Budget 2000–2017”. English. In: *Earth System Science Data* 12.3 (July 2020), pp. 1561–1623. ISSN: 1866-3508. DOI: 10.5194/essd-12-1561-2020. URL: <https://essd.copernicus.org/articles/12/1561/2020/>.

- [37] R. J. Parker et al. “Evaluating year-to-year anomalies in tropical wetland methane emissions using satellite CH₄ observations”. In: *Remote Sensing of Environment* 211 (June 2018), pp. 261–275. ISSN: 0034-4257. DOI: 10.1016/j.rse.2018.02.011. URL: <https://www.sciencedirect.com/science/article/pii/S0034425718300178>.
- [38] Z. Zhang et al. “Emerging role of wetland methane emissions in driving 21st century climate change”. In: *Proceedings of the National Academy of Sciences* 114.36 (Sept. 2017), pp. 9647–9652. DOI: 10.1073/pnas.1618765114. URL: <https://www.pnas.org/doi/full/10.1073/pnas.1618765114>.
- [39] A. A. Bloom et al. “A global wetland methane emissions and uncertainty dataset for atmospheric chemical transport models (WetCHARTs version 1.0)”. English. In: *Geoscientific Model Development* 10.6 (June 2017), pp. 2141–2156. ISSN: 1991-959X. DOI: 10.5194/gmd-10-2141-2017. URL: <https://gmd.copernicus.org/articles/10/2141/2017/>.
- [40] J. M. Melack et al. “Challenges Regionalizing Methane Emissions Using Aquatic Environments in the Amazon Basin as Examples”. In: *Frontiers in Environmental Science* 10 (2022). ISSN: 2296-665X. URL: <https://www.frontiersin.org/article/s/10.3389/fenvs.2022.866082>.
- [41] K. Kellogg et al. “NASA-ISRO Synthetic Aperture Radar (NISAR) Mission”. In: *2020 IEEE Aerospace Conference*. Mar. 2020, pp. 1–21. DOI: 10.1109/AERO47225.2020.9172638. URL: <https://ieeexplore.ieee.org/abstract/document/9172638>.
- [42] S. Gleason et al. “Detection and Processing of bistatically reflected GPS signals from low Earth orbit for the purpose of ocean remote sensing”. en. In: *IEEE Transactions on Geoscience and Remote Sensing* 43.6 (June 2005), pp. 1229–1241. ISSN: 0196-2892. DOI: 10.1109/TGRS.2005.845643. URL: <http://ieeexplore.ieee.org/document/1433022/>.
- [43] C. S. Ruf. *CYGNSS Handbook*. en. Michigan Publishing Services, 2022. ISBN: 978-1-60785-787-7 978-1-60785-549-1. DOI: 10.3998/mpub.12741920. URL: <https://www.fulcrum.org/concern/monographs/g445cg50v?locale=en#toc>.
- [44] C. S. Ruf et al. “New Ocean Winds Satellite Mission to Probe Hurricanes and Tropical Convection”. EN. In: *Bulletin of the American Meteorological Society* 97.3 (Mar. 2016), pp. 385–395. ISSN: 0003-0007, 1520-0477. DOI: 10.1175/BAMS-D-14-00218.1. URL: <https://journals.ametsoc.org/view/journals/bams/97/3/bams-d-14-00218.1.xml>.
- [45] C. S. Ruf et al. “A New Paradigm in Earth Environmental Monitoring with the CYGNSS Small Satellite Constellation”. en. In: *Scientific Reports* 8.1 (June 2018), p. 8782. ISSN: 2045-2322. DOI: 10.1038/s41598-018-27127-4. URL: <https://www.nature.com/articles/s41598-018-27127-4>.
- [46] R. Szeliski. *Computer Vision: Algorithms and Applications*. Springer Nature, Jan. 3, 2022. 937 pp. ISBN: 978-3-030-34372-9.

- [47] T. Pu et al. “Berkeley-RWAWC: A New CYGNSS-Based Watermask Unveils Unique Observations of Seasonal Dynamics in the Tropics”. In: *Water Resources Research* 60.7 (2024), e2024WR037060. ISSN: 1944-7973. DOI: 10.1029/2024WR037060. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1029/2024WR037060>.
- [48] Z. Zhang et al. “Development of the global dataset of Wetland Area and Dynamics for Methane Modeling (WAD2M)”. English. In: *Earth System Science Data* 13.5 (May 2021), pp. 2001–2023. ISSN: 1866-3508. DOI: 10.5194/essd-13-2001-2021. URL: <https://essd.copernicus.org/articles/13/2001/2021/>.
- [49] C. Chew et al. “CYGNSS data map flood inundation during the 2017 Atlantic hurricane season”. In: *Scientific Reports* 8.1 (June 19, 2018), p. 9336. ISSN: 2045-2322. DOI: 10.1038/s41598-018-27673-x. URL: <https://www.nature.com/articles/s41598-018-27673-x>.
- [50] C. Gerlein-Safdi and C. S. Ruf. “A CYGNSS-Based Algorithm for the Detection of Inland Waterbodies”. en. In: *Geophysical Research Letters* 46.21 (2019), pp. 12065–12072. ISSN: 1944-8007. DOI: 10.1029/2019GL085134. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1029/2019GL085134>.
- [51] M. Morris et al. “A novel approach to monitoring wetland dynamics using CYGNSS: Everglades case study”. In: *Remote Sensing of Environment* 233 (Nov. 2019), p. 111417. ISSN: 0034-4257. DOI: 10.1016/j.rse.2019.111417. URL: <https://www.sciencedirect.com/science/article/pii/S0034425719304365>.
- [52] W. Wan et al. “Using CYGNSS Data to Monitor China’s Flood Inundation during Typhoon and Extreme Precipitation Events in 2017”. en. In: *Remote Sensing* 11.7 (Jan. 2019), p. 854. ISSN: 2072-4292. DOI: 10.3390/rs11070854. URL: <https://www.mdpi.com/2072-4292/11/7/854>.
- [53] M. M. Al-Khaldi et al. “Mapping the Dynamics of the South Asian Monsoon Using CYGNSS’s Level-1 Signal Coherency”. In: *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 14 (2021), pp. 1111–1119. ISSN: 2151-1535. DOI: 10.1109/JSTARS.2020.3042170. URL: <https://ieeexplore.ieee.org/document/9280328>.
- [54] W. Li et al. “First spaceborne demonstration of BeiDou-3 signals for GNSS reflectometry from CYGNSS constellation”. In: *Chinese Journal of Aeronautics* 34.9 (Sept. 2021), pp. 1–10. ISSN: 1000-9361. DOI: 10.1016/j.cja.2020.11.016. URL: <https://www.sciencedirect.com/science/article/pii/S100093612030580X>.
- [55] S. Zhang et al. “Using CYGNSS Data to Map Flood Inundation during the 2021 Extreme Precipitation in Henan Province, China”. en. In: *Remote Sensing* 13.24 (Jan. 2021), p. 5181. ISSN: 2072-4292. DOI: 10.3390/rs13245181. URL: <https://www.mdpi.com/2072-4292/13/24/5181>.

- [56] B. D. Chapman et al. “Comparison of SAR and CYGNSS Surface Water Extent Metrics”. In: *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 15 (2022), pp. 3235–3245. ISSN: 2151-1535. DOI: 10.1109/JSTARS.2022.3162764. URL: <https://ieeexplore.ieee.org/document/9745185>.
- [57] P. Zeiger et al. “Analysis of CYGNSS coherent reflectivity over land for the characterization of pan-tropical inundation dynamics”. In: *Remote Sensing of Environment* 282 (Dec. 2022), p. 113278. ISSN: 0034-4257. DOI: 10.1016/j.rse.2022.113278. URL: <https://www.sciencedirect.com/science/article/pii/S0034425722003844>.
- [58] C. C. Chew and E. E. Small. “Soil Moisture Sensing Using Spaceborne GNSS Reflections: Comparison of CYGNSS Reflectivity to SMAP Soil Moisture”. In: *Geophysical Research Letters* 45.9 (2018), pp. 4049–4057. ISSN: 1944-8007. DOI: 10.1029/2018GL077905. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1029/2018GL077905>.
- [59] H. Kim and V. Lakshmi. “Use of Cyclone Global Navigation Satellite System (CyGNSS) Observations for Estimation of Soil Moisture”. en. In: *Geophysical Research Letters* 45.16 (2018), pp. 8272–8282. ISSN: 1944-8007. DOI: 10.1029/2018GL078923. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1029/2018GL078923>.
- [60] M. M. Al-Khaldi et al. “Time-Series Retrieval of Soil Moisture Using CYGNSS”. In: *IEEE Transactions on Geoscience and Remote Sensing* 57.7 (July 2019), pp. 4322–4331. ISSN: 1558-0644. DOI: 10.1109/TGRS.2018.2890646. URL: <https://ieeexplore.ieee.org/document/8631126>.
- [61] M. P. Clarizia et al. “Analysis of CYGNSS Data for Soil Moisture Retrieval”. In: *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 12.7 (July 2019), pp. 2227–2235. ISSN: 2151-1535. DOI: 10.1109/JSTARS.2019.2895510. URL: <https://ieeexplore.ieee.org/document/8645800>.
- [62] O. Eroglu et al. “High Spatio-Temporal Resolution CYGNSS Soil Moisture Estimates Using Artificial Neural Networks”. en. In: *Remote Sensing* 11.19 (Jan. 2019), p. 2272. ISSN: 2072-4292. DOI: 10.3390/rs11192272. URL: <https://www.mdpi.com/2072-4292/11/19/2272>.
- [63] V. Senyurek et al. “Machine Learning-Based CYGNSS Soil Moisture Estimates over ISMN sites in CONUS”. en. In: *Remote Sensing* 12.7 (Jan. 2020), p. 1168. ISSN: 2072-4292. DOI: 10.3390/rs12071168. URL: <https://www.mdpi.com/2072-4292/12/7/1168>.
- [64] Q. Yan et al. “Pan-tropical soil moisture mapping based on a three-layer model from CYGNSS GNSS-R data”. In: *Remote Sensing of Environment* 247 (Sept. 2020), p. 111944. ISSN: 0034-4257. DOI: 10.1016/j.rse.2020.111944. URL: <https://www.sciencedirect.com/science/article/pii/S003442572030314X>.

- [65] M. J. Unwin et al. “An Introduction to the HydroGNSS GNSS Reflectometry Remote Sensing Mission”. In: *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 14 (2021), pp. 6987–6999. ISSN: 2151-1535. DOI: 10.1109/JSTARS.2021.3089550. URL: <https://ieeexplore.ieee.org/document/9456091>.
- [66] C. Chew et al. “Flooding and inundation maps using interpolated CYGNSS reflectivity observations”. In: *Remote Sensing of Environment* 293 (Aug. 2023), p. 113598. ISSN: 0034-4257. DOI: 10.1016/j.rse.2023.113598. URL: <https://www.sciencedirect.com/science/article/pii/S0034425723001499>.
- [67] C. Gerlein-Safdi et al. “Improving Representation of Tropical Wetland Methane Emissions With CYGNSS Inundation Maps”. In: *Global Biogeochemical Cycles* 35.12 (2021), e2020GB006890. ISSN: 1944-9224. DOI: 10.1029/2020GB006890. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1029/2020GB006890>.
- [68] C. Ruf. *CYGNSS Handbook 2022*. Nov. 2022. ISBN: 9781607857877. DOI: 10.3998/mpub.12741920.
- [69] S. van der Walt et al. “scikit-image: image processing in Python”. In: *PeerJ* 2 (2014), e453. ISSN: 2167-8359. DOI: 10.7717/peerj.453.
- [70] L. Grady. “Random Walks for Image Segmentation”. In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 28.11 (Nov. 2006), pp. 1768–1783. ISSN: 1939-3539. DOI: 10.1109/TPAMI.2006.233.
- [71] E. Loria et al. “Analysis of scattering characteristics from inland bodies of water observed by CYGNSS”. In: *Remote Sensing of Environment* 245 (Aug. 2020), p. 111825. ISSN: 00344257. DOI: 10.1016/j.rse.2020.111825. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0034425720301954>.
- [72] E. Loria et al. “Comparison of GNSS-R Coherent Reflection Detection Algorithms Using Simulated and Measured CYGNSS Data”. en. In: *IEEE Transactions on Geoscience and Remote Sensing* (2023), pp. 1–1. ISSN: 0196-2892, 1558-0644. DOI: 10.1109/TGRS.2023.3277411. URL: <https://ieeexplore.ieee.org/document/10128857/>.
- [73] R. C. Gonzalez and R. E. Woods. *Digital image processing*. en. New York, NY: Pearson, 2018. ISBN: 978-0-13-335672-4.
- [74] H. Carreno-Luengo et al. “First Evaluation of Topography on GNSS-R: An Empirical Study Based on a Digital Elevation Model”. en. In: *Remote Sensing* 11.21 (Jan. 2019), p. 2556. ISSN: 2072-4292. DOI: 10.3390/rs11212556. URL: <https://www.mdpi.com/2072-4292/11/21/2556>.
- [75] E. Hodges et al. “Using Lidar Digital Elevation Models for Reflectometry Land Applications”. In: *IEEE Transactions on Geoscience and Remote Sensing* 61 (2023), pp. 1–9. ISSN: 1558-0644. DOI: 10.1109/TGRS.2023.3256303. URL: <https://ieeexplore.ieee.org/abstract/document/10066308>.

- [76] R. Sayre. *World Terrestrial Ecosystems (WTE) 2020*. 2022. DOI: 10.5066/P9D061LP. URL: <https://www.sciencebase.gov/catalog/item/6296791ed34ec53d276bb293>.
- [77] X. Xi et al. “Methane Emissions From Land and Aquatic Ecosystems in Western Siberia: An Analysis With Methane Biogeochemistry Models”. In: *Journal of Geophysical Research: Biogeosciences* 128.7 (2023), e2023JG007466. DOI: <https://doi.org/10.1029/2023JG007466>. eprint: <https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2023JG007466>. URL: <https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2023JG007466>.
- [78] X. Liu and Q. Zhuang. “Methane emissions from Arctic landscapes during 2000–2015: an analysis with land and lake biogeochemistry models”. In: *Biogeosciences* 20.6 (2023), pp. 1181–1193. DOI: 10.5194/bg-20-1181-2023. URL: <https://bg.copernicus.org/articles/20/1181/2023/>.
- [79] Z. Deng et al. “Comparing national greenhouse gas budgets reported in UNFCCC inventories against atmospheric inversions”. In: *Earth System Science Data* 14.4 (2022), pp. 1639–1675. DOI: 10.5194/essd-14-1639-2022. URL: <https://essd.copernicus.org/articles/14/1639/2022/>.
- [80] R. B. Skeie et al. “Trends in atmospheric methane concentrations since 1990 were driven and modified by anthropogenic emissions”. In: *Communications Earth & Environment* 4.1 (2023), p. 317. DOI: 10.1038/s43247-023-00969-1. URL: <https://doi.org/10.1038/s43247-023-00969-1>.
- [81] Z. Zhang et al. “Recent intensification of wetland methane feedback”. In: *Nature Climate Change* 13.5 (2023), pp. 430–433. DOI: 10.1038/s41558-023-01629-0. URL: <https://doi.org/10.1038/s41558-023-01629-0>.
- [82] Q. Yan et al. “Mapping Surface Water Fraction Over the Pan-tropical Region Using CYGNSS Data”. In: *IEEE Transactions on Geoscience and Remote Sensing* (2024), pp. 1–1. DOI: 10.1109/TGRS.2024.3394744.
- [83] X. Lin et al. “Recent methane surges reveal heightened emissions from tropical inundated areas”. en. In: *EarthArXiv* (Sept. 2023). URL: <https://eartharxiv.org/repository/view/5895/>.
- [84] C. Frankenberg et al. “Global column-averaged methane mixing ratios from 2003 to 2009 as derived from SCIAMACHY: Trends and variability”. In: *Journal of Geophysical Research: Atmospheres* 116.D4 (Feb. 2011). DOI: <https://doi.org/10.1029/2010JD014849>. URL: <https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2010JD014849>.
- [85] H. Hu et al. “Toward Global Mapping of Methane With TROPOMI: First Results and Intersatellite Comparison to GOSAT”. en. In: *Geophysical Research Letters* 45.8 (Apr. 2018), pp. 3682–3689. ISSN: 0094-8276, 1944-8007. DOI: 10.1002/2018GL077259. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1002/2018GL077259>.

- [86] M. F. Lunt et al. “An increase in methane emissions from tropical Africa between 2010 and 2016 inferred from satellite data”. en. In: *Atmospheric Chemistry and Physics* 19.23 (Dec. 2019), pp. 14721–14740. ISSN: 1680-7324. DOI: 10.5194/acp-19-14721-2019. URL: <https://acp.copernicus.org/articles/19/14721/2019/>.
- [87] D. A. Martin. “At the nexus of fire, water and society”. In: *Philosophical Transactions of the Royal Society B: Biological Sciences* 371.1696 (June 2016), p. 20150172. DOI: 10.1098/rstb.2015.0172. URL: <https://royalsocietypublishing.org/doi/full/10.1098/rstb.2015.0172>.
- [88] G. M. Williams-Jara et al. “Fires in coastal wetlands: a review of research trends and management opportunities”. en. In: *Wetlands* 42.6 (July 2022), p. 56. ISSN: 1943-6246. DOI: 10.1007/s13157-022-01576-0. URL: <https://doi.org/10.1007/s13157-022-01576-0>.
- [89] J. S. Kominoski et al. “Fire Severity and Post-fire Hydrology Drive Nutrient Cycling and Plant Community Recovery in Intermittent Wetlands”. en. In: *Ecosystems* 25.2 (Mar. 2022), pp. 265–278. ISSN: 1435-0629. DOI: 10.1007/s10021-021-00653-5. URL: <https://doi.org/10.1007/s10021-021-00653-5>.
- [90] W. Leal Filho et al. “Fire in Paradise: Why the Pantanal is burning”. In: *Environmental Science & Policy* 123 (Sept. 2021), pp. 31–34. ISSN: 1462-9011. DOI: 10.1016/j.envsci.2021.05.005. URL: <https://www.sciencedirect.com/science/article/pii/S1462901121001258>.
- [91] J. F. Marques et al. “Fires dynamics in the Pantanal: Impacts of anthropogenic activities and climate change”. In: *Journal of Environmental Management* 299 (Dec. 2021), p. 113586. ISSN: 0301-4797. DOI: 10.1016/j.jenvman.2021.113586. URL: <https://www.sciencedirect.com/science/article/pii/S0301479721016480>.
- [92] D. B. Correa et al. “Increased burned area in the Pantanal over the past two decades”. In: *Science of The Total Environment* 835 (Aug. 2022), p. 155386. ISSN: 0048-9697. DOI: 10.1016/j.scitotenv.2022.155386. URL: <https://www.sciencedirect.com/science/article/pii/S0048969722024792>.
- [93] J. B. Zedler and S. Kercher. “WETLAND RESOURCES: Status, Trends, Ecosystem Services, and Restorability”. In: *Annual Review of Environment and Resources* 30.1 (2005), pp. 39–74. DOI: 10.1146/annurev.energy.30.050504.144248. URL: <https://doi.org/10.1146/annurev.energy.30.050504.144248>.
- [94] M. Somveille et al. “Mapping Global Diversity Patterns for Migratory Birds”. en. In: *PLOS ONE* 8.8 (Aug. 2013), e70907. ISSN: 1932-6203. DOI: 10.1371/journal.pone.0070907. URL: <https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0070907>.
- [95] C. A. Runge et al. “Protected areas and global conservation of migratory birds”. In: *Science* 350.6265 (Dec. 2015), pp. 1255–1258. DOI: 10.1126/science.aac9180. URL: <https://www.science.org/doi/full/10.1126/science.aac9180>.

- [96] A. Rinaldo et al. “Evolution and selection of river networks: Statics, dynamics, and complexity”. en. In: *Proceedings of the National Academy of Sciences* 111.7 (Feb. 2014), pp. 2417–2424. ISSN: 0027-8424, 1091-6490. DOI: 10.1073/pnas.1322700111. URL: <https://pnas.org/doi/full/10.1073/pnas.1322700111>.
- [97] L. E. Bertassello et al. “Eco-hydrological modelling of channel network dynamics—part 2: application to metapopulation dynamics”. en. In: *Royal Society Open Science* 9.11 (Nov. 2022), p. 220945. ISSN: 2054-5703. DOI: 10.1098/rsos.220945. URL: <https://royalsocietypublishing.org/doi/10.1098/rsos.220945>.
- [98] N. Durighetto et al. “Integrating spatially-and temporally-heterogeneous data on river network dynamics using graph theory”. In: *iScience* 26.8 (2023), p. 107417. ISSN: 2589-0042. DOI: <https://doi.org/10.1016/j.isci.2023.107417>. URL: <https://www.sciencedirect.com/science/article/pii/S2589004223014943>.
- [99] S. Stevenson et al. “Twenty-first century hydroclimate: A continually changing baseline, with more frequent extremes”. In: *Proceedings of the National Academy of Sciences* 119.12 (Mar. 22, 2022), e2108124119. DOI: 10.1073/pnas.2108124119. URL: <https://www.pnas.org/doi/abs/10.1073/pnas.2108124119>.
- [100] M. Rodell and B. Li. “Changing intensity of hydroclimatic extreme events revealed by GRACE and GRACE-FO”. In: *Nature Water* 1.3 (Mar. 2023), pp. 241–248. ISSN: 2731-6084. DOI: 10.1038/s44221-023-00040-5. URL: <https://www.nature.com/articles/s44221-023-00040-5>.
- [101] J.-H. Yoon et al. “Increasing water cycle extremes in California and in relation to ENSO cycle under global warming”. In: *Nature Communications* 6.1 (Oct. 21, 2015), p. 8657. ISSN: 2041-1723. DOI: 10.1038/ncomms9657. URL: <https://www.nature.com/articles/ncomms9657>.
- [102] D. A. Bishop et al. “Increased Fall Precipitation in the Southeastern United States Driven by Higher-Intensity, Frontal Precipitation”. In: *Geophysical Research Letters* 46.14 (2019), pp. 8300–8309. ISSN: 1944-8007. DOI: 10.1029/2019GL083177. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1029/2019GL083177>.
- [103] G. Blöschl et al. “Changing climate both increases and decreases European river floods”. In: *Nature* 573.7772 (Sept. 2019), pp. 108–111. ISSN: 1476-4687. DOI: 10.1038/s41586-019-1495-6. URL: <https://www.nature.com/articles/s41586-019-1495-6>.
- [104] H. Du et al. “Precipitation From Persistent Extremes is Increasing in Most Regions and Globally”. In: *Geophysical Research Letters* 46.11 (2019), pp. 6041–6049. ISSN: 1944-8007. DOI: 10.1029/2019GL081898. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1029/2019GL081898>.

- [105] S. M. Papalexiou and A. Montanari. “Global and Regional Increase of Precipitation Extremes Under Global Warming”. In: *Water Resources Research* 55.6 (2019), pp. 4901–4914. ISSN: 1944-7973. DOI: 10.1029/2018WR024067. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1029/2018WR024067>.
- [106] C. Brown et al. “Hydroclimate risk to economic growth in sub-Saharan Africa”. In: *Climatic Change* 106.4 (June 1, 2011), pp. 621–647. ISSN: 1573-1480. DOI: 10.1007/s10584-010-9956-9. URL: <https://doi.org/10.1007/s10584-010-9956-9>.
- [107] B. Güneralp et al. “Changing global patterns of urban exposure to flood and drought hazards”. In: *Global Environmental Change* 31 (Mar. 1, 2015), pp. 217–225. ISSN: 0959-3780. DOI: 10.1016/j.gloenvcha.2015.01.002. URL: <https://www.sciencedirect.com/science/article/pii/S0959378015000047>.
- [108] M. M. G. T. De Silva and A. Kawasaki. “Socioeconomic Vulnerability to Disaster Risk: A Case Study of Flood and Drought Impact in a Rural Sri Lankan Community”. In: *Ecological Economics* 152 (Oct. 1, 2018), pp. 131–140. ISSN: 0921-8009. DOI: 10.1016/j.ecolecon.2018.05.010. URL: <https://www.sciencedirect.com/science/article/pii/S092180091731604X>.
- [109] H. Tabari et al. “Amplified Drought and Flood Risk Under Future Socioeconomic and Climatic Change”. In: *Earth’s Future* 9.10 (2021), e2021EF002295. ISSN: 2328-4277. DOI: 10.1029/2021EF002295. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1029/2021EF002295>.
- [110] J. Chaves-Gonzalez et al. “Anticipatory action: Lessons for the future”. In: *Frontiers in Climate* 4 (Dec. 8, 2022). ISSN: 2624-9553. DOI: 10.3389/fclim.2022.932336. URL: <https://www.frontiersin.org/journals/climate/articles/10.3389/fclim.2022.932336/full>.
- [111] M. Wagner. *Early Action: The State of Play 2023*. Risk-informed Early Action Partnership, Geneva., 2024. URL: <https://www.early-action-reap.org/early-action-state-play-2023>.
- [112] S. Swenson and J. Wahr. “Monitoring the water balance of Lake Victoria, East Africa, from space”. In: *Journal of Hydrology* 370.1 (May 30, 2009), pp. 163–176. ISSN: 0022-1694. DOI: 10.1016/j.jhydrol.2009.03.008. URL: <https://www.sciencedirect.com/science/article/pii/S0022169409001516>.
- [113] C. A. Di Vittorio and A. P. Georgakakos. “Hydrologic Modeling of the Sudd Wetland using Satellite-based Data”. In: *Journal of Hydrology: Regional Studies* 37 (Oct. 1, 2021), p. 100922. ISSN: 2214-5818. DOI: 10.1016/j.ejrh.2021.100922. URL: <https://www.sciencedirect.com/science/article/pii/S2214581821001518>.
- [114] J. J. Hack. “Parameterization of moist convection in the National Center for Atmospheric Research community climate model (CCM2)”. In: *Journal of Geophysical Research: Atmospheres* 99 (D3 1994), pp. 5551–5568. ISSN: 2156-2202. DOI: 10.1029/93JD03478. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1029/93JD03478>.

- [115] OCHA. “South Sudan - Floods (UNMISS, Reliefweb, South Sudan Weather Service, media) (ECHO Daily Flash of 29 September 2022)”. In: (Sept. 29, 2022). URL: <http://reliefweb.int/report/south-sudan/south-sudan-floods-unmiss-reliefweb-south-sudan-weather-service-media-echo-daily-flash-29-september-2022>.
- [116] M. E. McClain et al. “Biogeochemical Hot Spots and Hot Moments at the Interface of Terrestrial and Aquatic Ecosystems”. In: *Ecosystems* 6.4 (June 1, 2003), pp. 301–312. ISSN: 1432-9840. DOI: 10.1007/s10021-003-0161-9. URL: <https://doi.org/10.1007/s10021-003-0161-9>.
- [117] W. J. Junk et al. “Biodiversity and its conservation in the Pantanal of Mato Grosso, Brazil”. In: *Aquatic Sciences* 68.3 (Oct. 1, 2006), pp. 278–309. ISSN: 1420-9055. DOI: 10.1007/s00027-006-0851-4. URL: <https://doi.org/10.1007/s00027-006-0851-4>.
- [118] A. Pott and V. J. Pott. “Features and conservation of the Brazilian Pantanal wetland”. In: *Wetlands Ecology and Management* 12.6 (Dec. 2004), pp. 547–552. ISSN: 0923-4861, 1572-9834. DOI: 10.1007/s11273-005-1754-1. URL: <http://link.springer.com/10.1007/s11273-005-1754-1>.
- [119] C. J. R. Alho and J. S. V. Silva. “Effects of Severe Floods and Droughts on Wildlife of the Pantanal Wetland (Brazil)—A Review”. In: *Animals* 2.4 (Dec. 2012), pp. 591–610. ISSN: 2076-2615. DOI: 10.3390/ani2040591. URL: <https://www.mdpi.com/2076-2615/2/4/591>.
- [120] S. Hamilton. “Hydrological controls of ecological structure and function in the Pantanal wetland (Brazil)”. In: *The Ecohydrology of South American Rivers and Wetlands* 6 (Jan. 1, 2002), pp. 133–158.
- [121] E. Dinerstein et al. “An Ecoregion-Based Approach to Protecting Half the Terrestrial Realm”. In: *BioScience* 67.6 (June 1, 2017), pp. 534–545. ISSN: 0006-3568. DOI: 10.1093/biosci/bix014. URL: <https://doi.org/10.1093/biosci/bix014>.
- [122] W. Tomas et al. “Mammals in the Pantanal wetland, Brazil”. In: Jan. 1, 2011, pp. 563–595. ISBN: 978-954-642-492-1.
- [123] P. S. Silva et al. “Heatwaves and fire in Pantanal: Historical and future perspectives from CORDEX-CORE”. In: *Journal of Environmental Management* 323 (Dec. 1, 2022), p. 116193. DOI: 10.1016/j.jenvman.2022.116193.
- [124] L. Giglio et al. *MODIS/Terra+Aqua Burned Area Monthly L3 Global 500m SIN Grid V061*. 2021. DOI: 10.5067/MODIS/MCD64A1.061. URL: <https://lpdaac.usgs.gov/products/mcd64a1v061/>.
- [125] L. Gudmundsson et al. “Predicting above normal wildfire activity in southern Europe as a function of meteorological drought”. In: *Environmental Research Letters* 9.8 (Aug. 2014), p. 084008. ISSN: 1748-9326. DOI: 10.1088/1748-9326/9/8/084008. URL: <https://dx.doi.org/10.1088/1748-9326/9/8/084008>.

- [126] E. M. Verhoeven et al. “Fire and rain are one: extreme rainfall events predict wildfire extent in an arid grassland”. In: *International Journal of Wildland Fire* 29.8 (May 12, 2020), pp. 702–711. ISSN: 1448-5516. DOI: 10.1071/WF19087. URL: <https://www.publish.csiro.au/wf/WF19087>.
- [127] D. Richardson et al. “Global increase in wildfire potential from compound fire weather and drought”. In: *npj Climate and Atmospheric Science* 5.1 (Mar. 25, 2022), pp. 1–12. ISSN: 2397-3722. DOI: 10.1038/s41612-022-00248-4. URL: <https://www.nature.com/articles/s41612-022-00248-4>.
- [128] M. Friedl and D. Sulla-Menashe. *MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500m SIN Grid V061*. 2022. DOI: 10.5067/MODIS/MCD12Q1.061. URL: <https://lpdaac.usgs.gov/products/mcd12q1v061/>.
- [129] R. Girshick et al. “Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation”. In: *2014 IEEE Conference on Computer Vision and Pattern Recognition*. 2014 IEEE Conference on Computer Vision and Pattern Recognition. June 2014, pp. 580–587. DOI: 10.1109/CVPR.2014.81. URL: <https://ieeexplore.ieee.org/document/6909475>.
- [130] J. Wang et al. “Deep High-Resolution Representation Learning for Visual Recognition”. In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 43.10 (Oct. 2021), pp. 3349–3364. ISSN: 1939-3539. DOI: 10.1109/TPAMI.2020.2983686. URL: https://ieeexplore.ieee.org/abstract/document/9052469?casa_token=u39X24RIdlwAAAAA:lp02n1V8iQYUEjnh5tx1Gs_iDHeEPL-3FXg55wH4Uej5UpNEJxRNx1uNw3M5-L2i15YKpIsR.
- [131] M. Ester et al. “A density-based algorithm for discovering clusters in large spatial databases with noise”. In: *Proceedings of the Second International Conference on Knowledge Discovery and Data Mining*. KDD’96. Portland, Oregon: AAAI Press, Aug. 2, 1996, pp. 226–231.
- [132] H. W. Kuhn. “The Hungarian method for the assignment problem”. In: *Naval Research Logistics Quarterly* 2.1 (1955), pp. 83–97. ISSN: 1931-9193. DOI: 10.1002/nav.3800020109. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1002/nav.3800020109>.
- [133] G. Pereira et al. “Rainfall patterns and geomorphological controls driving inundation frequency in tropical wetlands: How does the Pantanal flood?” In: *Progress in Physical Geography: Earth and Environment* 45.5 (Oct. 1, 2021), pp. 669–686. ISSN: 0309-1333. DOI: 10.1177/0309133320987719. URL: <https://doi.org/10.1177/0309133320987719>.
- [134] S. J. Ivory et al. “Vegetation, rainfall, and pulsing hydrology in the Pantanal, the world’s largest tropical wetland”. In: *Environmental Research Letters* 14.12 (Nov. 2019), p. 124017. ISSN: 1748-9326. DOI: 10.1088/1748-9326/ab4ffe. URL: <https://dx.doi.org/10.1088/1748-9326/ab4ffe>.