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LETTER

Assessing climate resilience in rice production: measuring the impact of the Millennium Challenge Corporation's IWRM scheme in the Senegal River Valley using remote sensing and machine learning

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Abstract

Satellite remote sensing (RS) and machine learning can be combined to develop methods for measuring the impacts of climate change on biomass and agricultural systems. From 2015 to 2023, we applied this approach in a critical earth observation-based evaluation of the Irrigation and Water Resources Management component of the Millennium Challenge Corporation's Senegal Compact. This project, funded by the United States Agency for International Development (USAID), was implemented in the Senegal River Valley from 2010 to 2015. Utilising these techniques, we successfully mapped rice cultivation areas, deciphered cropping practices, and analysed irrigation systems responses to different climatic conditions. A marked increase in cultivated rice area was found particularly in regions targeted by the project intervention. This is despite prolonged drought conditions which underscores a significant climate adaptation benefit from these irrigation works. We observed a notable dip in rice cultivation area in 2020, possibly due to the COVID-19 pandemic, followed by a recovery to pre-pandemic levels in 2023, likely aided by previously funded USAID's socio-economic resilience programmes in the region. Economic analysis of increased rice yields in the region translates to approximately US$ 61.2 million in market value since 2015, highlighting the economic returns from the project investment. Both the RS data and ground audits identify issues regarding post-project deterioration of irrigation infrastructure, emphasising the need for long-term maintenance of irrigation infrastructure to support climate adaptation benefits arising from irrigation. With a focus on crop irrigation, our findings stress the critical role of climate adaptation interventions for maintaining agricultural productivity in the face of adverse climate shocks. It further highlights the necessity of continuous investment and maintenance for ensuring climate resilient agrifood systems.

1. Introduction

The United Nations 2030 Agenda for Sustainable Development emphasises sustainable agriculture as key to eradicating hunger and ensuring food security—SDG2 (UN General Assembly 2015). Climate change poses a major threat to the productivity of agriculture and food systems from global to local levels. Hence, there are significant efforts and investments underway to transition to more climate resilient agrifood systems that are future-proofed against climate change stresses. Our definition of resilience encompasses the inherent ability of social, ecological, and economic systems to effectively manage and adapt to climate-related hazards, disturbances, or trends, while simultaneously preserving their potential for adaptation, learning, and transformation (Pörtner *et al* 2022). However, despite significant financial investments in climate adaptation measures, assessing the effectiveness and long-term impact of climate adaptation interventions and expenditures remains challenging. Traditional approaches often rely on expensive on-site surveys (with sparse site sampling) which is limited in scope and subject to bias. Satellite remote sensing (RS), with its frequent and extensive data collection, can provide a more objective and efficient alternative for measuring effectiveness of climate adaptation efforts in agricultural and food systems.

Located in the subtropical Sahel on the southern fringes of the Sahara Desert, the Senegal River Valley (SRV) is vulnerable to climate change-induced southward creep of the seasonal pulse of desertification replacing the semi-arid climate (Harris *et al* 2020, UNFCCC 2022, World Bank 2023). The SRV is part of the West Africa Senegal River Basin (SRB), which spans Senegal, Guinea, Mauritania, and Mali. Dam construction and associated waterflow management programmes have been the dominant intervention strategy to build resilience to water stresses in this region of the western Sahel (figure 1), as the wider region is being impacted by increased frequency and intensity of temperature, drought, and flooding stresses arising from climate change.

The SRB's 25 transboundary watercourses are managed by the river basin development authority, 'Organisation pour la Mise en Valeur du Fleuve Senegal' (OMVS; Senegal River Basin Development Authority), which is governed by Guinea, Mali, Mauritania, and Senegal. This organisation promotes 'coordinated water and energy development' (Okidi 2011) and manages the risk associated with large-scale water projects, including the construction of multipurpose dams facilitating year-round irrigated agriculture. Currently, OMVS is shifting towards irrigated rice production for domestic consumption to ease current severe foreign exchange deficits. However, evaluations indicate that the traditional rain-fed rice system is unsustainable, with irrigation schemes often abandoned unless renewed investment is available (Comas *et al* 2012). The OMVS has also faced criticism for its limited public engagement in decision-making (Sène *et al* 2007). Irrigation schemes across sub-Saharan Africa have a long history of under delivering on promised infrastructure, with many showing no noticeable impact over 60 years (Higginbottom *et al* 2021). Redicker *et al* (2022) further highlight the ineffectiveness of irrigation schemes (as high as 83% of schemes) across west Africa for many reasons, including not including the livelihood goals of smallholder farmers. Higginbottom *et al* (2023) note sub-Saharan Africa's modest gains in agricultural productivity despite numerous irrigation schemes, criticizing the historical laissez-faire agricultural policy.

From 2010 to 2015, the United States Agency for International Development (USAID)-funded Millennium Challenge Corporation (MCC) intervention project, in collaboration with the Government of Senegal, invested approximately US$ 540 million in the Senegal Compact targeted to the SRV delta region. Notably, the US$ 170 million Irrigation and Water Resources Management (IWRM) project under the Compact aimed to enhance agricultural productivity by upgrading the irrigation system in key locations across the SRV (Millenium Challenge Corporation 2009). Given the reliance of high productivity rice cultivation on effective irrigation systems (Styles and Marino 2002, Okada *et al* 2008, García-Bolaños *et al* 2011), the MCC IWRM investment focused on repairing and refurbishing existing irrigation canals, and building new ones where strategically needed, with the goal to enable cultivation of more than one rice crop per year.

After the project's completion in 2015, Mathematica (a research and data analytics company) were contracted to conduct follow-up audits, completing their final evaluation of the project's effectiveness in 2021 Harris *et al* (2021). Their project assessment combined questionnaires, local authority engagement, and a RS analysis from 2018 to 2020. The Mathematica audit report indicated that while the planned annual crop yield targets were not met (i.e. achieving 30 000 ha of rice cultivation in the dry season), the intervention generally succeeded in increasing overall rice production and yields in the targeted region (Coen *et al* 2019, Harris *et al* 2021). However, their audit report also notes that these improvements were not fully sustained after the project intervention, where establishing accurate and reliable quantitative metrics to determine net rice productivity changes over time proved challenging, particularly for measuring cultivation area and crop yield per unit area. The Mathematica audit team acknowledged the lack of precise actionable metrics to accurately measure change against baselines and therefore the overall impact and cost-effectiveness of the project intervention (Harris *et al* 2021).

In this study, we take a novel approach to provide a new analysis of the productivity and extent of rice cultivation in the IWRM intervention and wider region. We particularly focused on the successful cultivation of rice in the local dry season as this would correspond to successful irrigation and crop practices supporting increased annual yield in the intervention area. We expand upon Mathematica's RS analysis by including additional data sources and adopt more sophisticated methodologies incorporating decision tree classifiers and timeseries-to-image algorithms. To more accurately measure rice growing systems

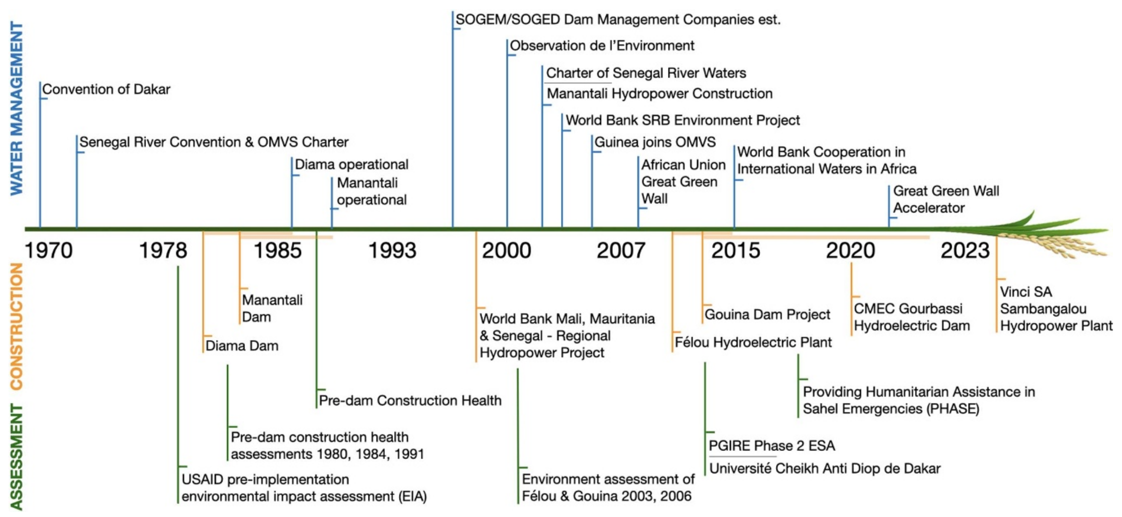

Figure 1. Key milestones for water management in the Africa Senegal River Basin (SRB) from 1970 to 2023. Construction to commencement is highlighted with translucent orange lines.

we make use of optical, infrared, and radar data to analyse rice paddies on the ground, beginning in 2015 at the end of the project and ending in 2023. We provide a more rigorous, cost-effective and independent assessment of the Senegal Compact project's efficacy using freely available earth observation (EO) data up until and beyond that covered by the final Mathematica published audit.

1.1. Region of interest

The MCC intervention focused on two key areas in the SRV. The primary area, the SRV delta, spans 788.63 km^2, extending from Saint–Louis to Rosso on the Mauritania border. The secondary area, Ngalenka, covering 400 ha, is located near Podor. However, Ngalenka was excluded from this study's results due to its small size and the cessation of rice cultivation post-2018, suggesting a long-term failure of the dry-season rice intervention. Harris *et al* (2021) notes that 'In the Podor Activity area, maintenance of the canals and pumps is generally good, according to co-operative leaders and SAED, but a structural problem limits the use of the perimeter to the rainy season only'.

In the SRV, rice is the predominant crop, supported by an extensive irrigation canal network (see figure 2). Our primary region of interest was those areas previously identified by the MCC as being directly impacted by the planned IWRN works between 2010–2015, which are delineated in figure 2. Additional comparative regions were identified as described in section 3.2.

2. Data

2.1. Satellite data

We combined optical and infrared data from the Landsat-8 mission and SAR data from Sentinel-1A to analyse rice production. Data was retrieved from Google Earth Engine (GEE; Gorelick *et al* 2017). Cloud pixel thresholds were set at 20% for Landsat-8 data (`LANDSAT/LC08/C02/T1_L2`). Seasonal composites were created using median values from March to June (Omar Ndaw *et al* 2020) and various vegetative and water indices were calculated, as listed in table 1.

Sentinel-1A data provided VH and VV polarisation composites. To analyse crop cultivation and cropping patterns, MODIS EVI, Landsat NDYI, and Sentinel-1A VH data were extracted from from USGS MOD13Q1 V6.1 (`MODIS/061/MOD13Q1`), USGS Landsat 8 Level 2, Collection 2, Tier 1 (`LANDSAT/LC08/C02/T1_L2`) and VH from Sentinel-1A (`COPERNICUS/S1_GRD`) respectively. Time series data for each pixel were extracted based on the cultivated mask defined in section 3.4.

2.2. Meteorological data

Meteorological data, crucial for analysing climatic stress (see section 4.4), included precipitation, air temperature, and evapotranspiration. Precipitation data was sourced from CHIRPS (Funk *et al* 2015), air temperature from Copernicus Climate Change Service ERA5 Daily Aggregates, and evapotranspiration from FLDAS (McNally 2018), all accessed through GEE. Given the large pixel size of this data, we averaged over the entire delta to get a single value per parameter per timestep.

2.3. Training data

Training data for the SRV delta region was chosen from the highest available resolution imagery which is Sentinel-2 at 10 m, and is classified into four categories: rice, bare soil, water, and wetlands. Rice crops were manually labelled with context from Sylla *et al* (2023a, 2023b). This was possible due to the

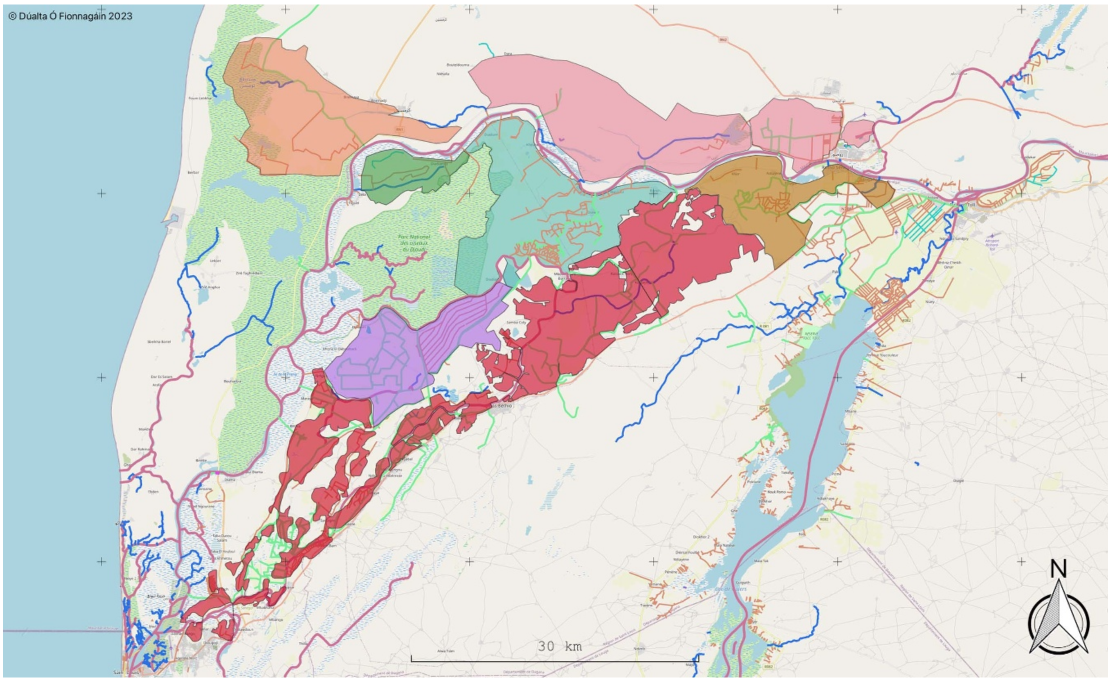

Figure 2. Map showing regions of interest described in section 3.2. ■: Intervention Delta, ■: Middle Delta, ■: Northeast Delta, ■: North Delta, ■: Northwest Delta, ■: East Mauritania, ■: West Mauritania. Irrigation networks from OpenStreetMaps are highlighted in various colours across the map (rivers—magenta; streams—blue; canals—green; drainage—orange; ditches—cyan).

Table 1. Vegetation and water indices that are used in the analyses. SWI is described in more depth in Tian *et al* (2017), Bauer-Marschallinger *et al* (2018).

Index	Formula
NDVI	(NIR − Red) / (NIR + Red)
MNDWI	(Green − SWIR1) / (Green + SWIR1)
LSWI	(NIR − SWIR1) / (NIR + SWIR1)
MSAVI	$(2\times\mathrm{NIR}+1-\sqrt{(2\times\mathrm{NIR}+1)^2-8(\mathrm{NIR}-\mathrm{Red})})/2$
EVI	$2.5(\mathrm{NIR}-\mathrm{RED})/(\mathrm{NIR}+6\times\mathrm{RED}-7.5\times\mathrm{BLUE}+1)$
NDYI	(Green—BLUE) / (Green + BLUE)
SWI	$\mathrm{SWI}_T\,(t_n)=\frac{\sum_i^n \mathrm{SSM}(t_i)\,\mathrm{e}^{-\frac{t_n-t_i}{T}}}{\sum_i^n \mathrm{e}^{-\frac{t_n-t_i}{T}}}$

widespread growing of rice in the region. A total of 292 polygons (78 553 pixels) were identified for 2020, with a 14.6% rice constituency. To address class imbalance, random sampling and class weighting were applied during model training.

For training and testing the convolutional neural network (CNN), 8000 time-series were hand labelled to be either no crop (fallow), double cropped (two peaks), dry cropped (early peak) or rainy crop (late peak) from the rice cultivation masks output from the previous step in the model (see section 3.5).

3. Methods

Machine learning (ML) is pivotal in RS data analysis, automating feature extraction and improving land cover classification and environmental variable prediction (Maponya *et al* 2020, Talukdar *et al* 2020, Wang *et al* 2022). ML techniques, including deep learning with time series images, have enhanced accuracy in cropland classification (Dong *et al* 2015, Tariq *et al* 2023).

These methods, described below, involve compositing satellite data, developing an ensemble boosted trees model, and employing a hidden Markov model (HMM) for post-processing. The full schematic of data processing is outlined in figure 3.

3.1. Compositing

Using GEE, we composited median full-resolution Landsat-8 optical and infrared data and Sentinel-1A VH and VV backscatter data during the dry season (1 March to 30 June annually from 2015 to 2023), a critical period for rice growth in the region (Omar Ndaw *et al* 2020). For SAR data, sensitive to water and vegetation changes, we included minimum, median, and maximum VH and VV composites for classification.

3.2. Control regions

To contextualise the SRV intervention's impact, six regions outside the Intervention Delta were identified as control areas. These include various SRV regions as well as areas in Mauritania, which were selected to provide a comprehensive comparison and understand regional variations in agricultural practices (García-Bolaños *et al* 2011). Figure 2 outlines these regions.

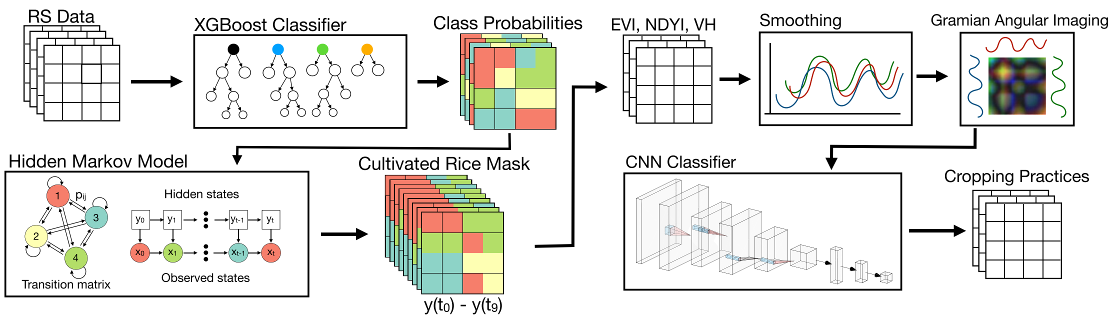

Figure 3. Full visual description for our land use classification and cropping intensity model. Each pixel from each composite goes through the XGBoost model. These multi:softprob outputs are used as starting probabilities for the HMM model, which determines the most likely hidden states for each pixel sequence over the nine years of observation. These generated cultivated rice masks (per year, y_t) are used to mask EVI, NDYI, and VH time-series, which is smoothed. These time-series are used to create images through a Gramian Angular Summation method, which can be used to classify cropping type (double, dry, wet, fallow) for each year.

3.3. Land-use classification

Recognising the limitations of global land use products in sub-Saharan Africa (Potapov *et al* 2022, Kerner *et al* 2023, Nakalembe and Kerner 2023), we developed a specific XGBoost model (Chen and Guestrin 2016) for rice cultivation classification, trained with the data mentioned in section 2.3. We used the Python packages SCIKIT-LEARN (Pedregosa *et al* 2011) and XGBOOST (Chen and Guestrin 2016) to achieve this. The model's objective was set to `multi:softprob` for pixel classification, with hyper-parameters optimised through cross-validation. A stratified K-fold cross-validation was used in this case combined with a randomized grid search. For our cross-validation a traing-test split of 80-20 was used. This approach was chosen for its relevance to the specific environmental and agricultural conditions of the region.

In assessing model performance, we prioritised precision, recall, and the f1-score over accuracy alone, as accuracy can overestimate performance, particularly in cases with large class sizes like bare land and wetlands (Powers 2020). Our findings indicated an overall accuracy of 96%, with a precision of 85%, a recall of 99%, and a f1-score of 92% for rice classification. This high recall rate suggests a tendency towards false positives in rice identification, rather than false negatives. Consequently, our land-use classification provides an upper bound for rice production in each region, highlighting areas where rice cultivation is most likely, albeit with some overestimation. We chose a model with higher recall over precision as our resulting agricultural mask will be refined further using a HMM (detailed in section 3.4) with this output being used to analyse cropping practices in section 3.5. While we are confident in the results of this model for the SRV, we would be less so in non-arid climates (i.e. some of the largest rice producing regions are grown in tropical and sub-tropical climes).

3.4. HMM

HMMs are powerful tools in time series analysis, often used in areas like natural language processing and biomedical applications. A HMM interprets sequences of observations by inferring hidden states and transition probabilities between them. In our study, we utilised a HMM to detect improbable class transitions and ensure consistent temporal progressions in land cover classifications (Abercrombie and Friedl 2016, Higginbottom *et al* 2023). This model was applied to each pixel in our dataset for the years 2015 to 2023, each containing 9 data points. Starting probabilities were derived from our classification model's output, with transition probabilities set at 0.1, following the approach in both Abercrombie and Friedl (2016) and Higginbottom *et al* (2023).

3.5. Cropping intensity analysis

Historically, SRV agriculture primarily involved wet season cropping of rice from October to February. To understand the dynamic aspects of agricultural practices, we employed a time series-to-image algorithm to investigate this further. For pixels within the classified dry season crop mask, we used time series data from MODIS EVI, Landsat 8 NDYI, and Sentinel-1 VH, converting them into 3-channel images using the Gramian angular field summation (GAFS) algorithm.

GAFS transforms time series into a matrix of temporal correlations. This involves scaling the time series, converting them to polar coordinates, and then computing the cosine of the sum of angles. PYTS (Faouzi and Janati 2020) was used for this transformation.

Subsequently, a supervised CNN classified these images into categories: fallow rice, single crop dry rice, single crop wet rice, or double crop rice. Our focus remained on the dry season rice cultivation, aligning with the intervention's goal to enhance dry season agricultural productivity.

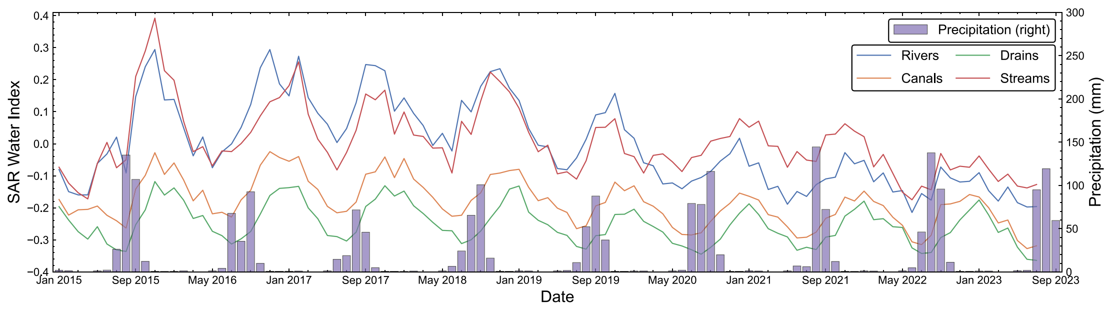

Figure 4. Sentinel-1 smoothed SWI for rivers, streams, canals and drainage in the Intervention Delta region since 2015. Larger values here indicate higher water levels. Bar chart shown along the bottom in purple is the measured precipitation levels in the region for each month.

The CNN architecture (displayed in figure 3) uses the re-scaled vegetative indices images as input, and through multiple `Conv2D` and `MaxPool2D` layers with `ReLU` activation, achieves 4 output nodes corresponding to our cropping classes. To avoid over-fitting we utilised dropout layers and L1 regularisation. The model achieved an accuracy of 98% when tested on 2000 random samples. The Python package KERAS (Chollet *et al* 2015) was used to create and train this model.

3.6. Irrigation analysis

To map and characterise the total irrigation component of the SRV area, we extracted any objects labelled as waterways by OpenStreetMaps (OSM; OpenStreetMap contributors 2017). These waterways can be seen in figure 2. This included natural waterways such as rivers and streams, as well as man-made waterways like canals and drains. We applied a 20 m buffer to streams, canals and drains and a 50 m buffer to the rivers. The Sentinel-1 water index (SWI; Tian *et al* 2017) was then used to analyse water levels at these loci. This index was calculated after applying the Analysis-Ready-Data framework for Sentinel-1A backscatter in the GEE Python API (Mullissa *et al* 2021). This pre-processes the data by applying border noise correction, speckle filtering and radiometric terrain normalization. Finally, the SWI data was exported for each water-body type and each region outlined in figure 2 from 2015 to 2023.

3.7. Climate stress analysis

Identifying climatic stress events within the SRV was implemented by quantifying precipitation, air temperature and evapotranspiration anomalies using archived meteorological data. Rainfall data (UCSB-CHG/CHIRPS/PENTAD) was aggregated into an annual sum for the years 1983–2023 and then the rainfall anomaly index, developed by Van–Rooy (Costa and Rodrigues 2017) was calculated. These values were then normalised so that -1 indicated the driest conditions based on the last 40 years, while the positive values indicated above-average rainfall. A slightly adapted formula was applied to evapotranspiration (FLDAS) and temperature (ERA5 Daily Aggregates) datasets to create a time series of annual anomalies for all three primary potential climate shock indicators. An additional metric was included for temperature to capture the extremes where we calculated the annual percentage of days above 30 °C, as this information may not have been well represented by a deviation from the historical mean if paired with exceptionally low temperatures. These values were then normalised from −1 to 1, with the negative values indicating drought conditions such as low actual evapotranspiration and increased temperature anomalies. The results are plotted in figure 4.

4. Results

4.1. Identification of absolute areas under rice cultivation 2015–2023

In figure 5 we present the total cultivated rice area for each of the regions delineated in figure 2 as determined from our HMM model for the years 2015–2023. An example output for the year 2019 is shown in the top panel of figure 6. The data highlights the intensified activity in the Intervention Delta—which covers areas impacted by the MCC work—yielding conspicuous year-on-year improvement in cultivated area to 2020, with a subsequent drop. West Mauritania and North West Delta show significant decreases post 2020, and the Middle Delta region expanding substantially between 2015–2020, before stabilising around 5000 ha yr^{-1}. Relative performances within each region compared to their 2015 baseline are plotted in figure 7. The transformation of the Middle Delta region post-2015 is striking, evolving from a largely fallow area to one of increasing cultivation, thanks to investment from the public-private partnership: '*le Projet de Promotion du Partenariat Rizicole dans le Delta*' (3PRD; Sylla *et al* 2023b).

Other trends in figure 7 include the marked decline in rice production area in the West Mauritania and the North-West Delta regions starting from 2021,

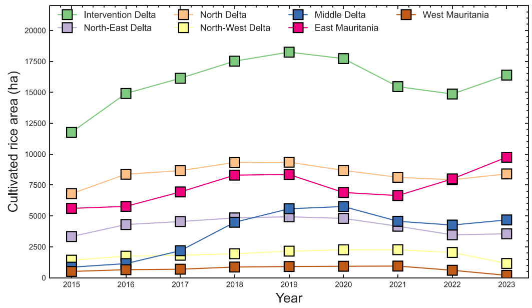

Figure 5. Output of the HMM model for absolute rice areas per region of interest between 2015–2023.

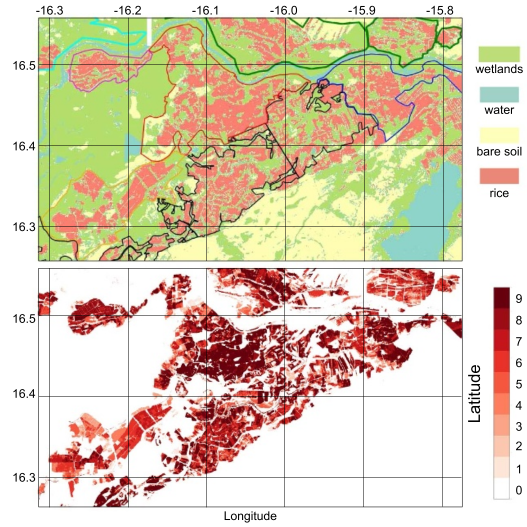

Figure 6. *Top:* Output from rice classification model for the year 2019, zoomed into the Central and Intervention Delta. *Bottom:* Number of cropped years over previous 9 years from 2015–2023. Darker regions show heavily cropped land in the last decade.

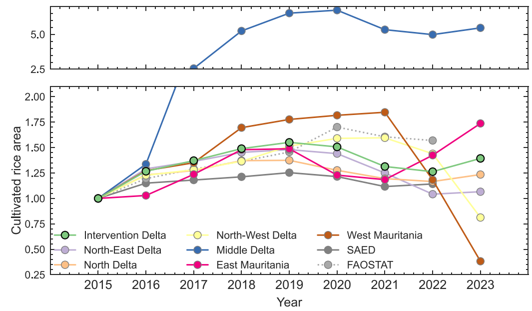

Figure 7. Output of HMM for rice area per region of interest normalised to the first year of analysis, 2015. Note the extended discontinuous y-axis in the top panel of the figure. Grey points show national statistics of cropped area over the same period from SAED and FAOSTAT (FAOSTAT 2024, SAED 2024).

with the decrease in 2023 for both particularly stark in comparison to performances of the other regions. Notably, in West Mauritania, the overall rice production is modest relative to the region's size, meaning that even minor changes can significantly impact the area's production-to-size ratio, as depicted in figure 7. Perhaps most interestingly is the trend associated with the Intervention Delta region whose functional form essentially mirrors that of the North Delta, North-East Delta and East Mauritania regions, with a consistent increase in rice cultivation up until 2019/2020, with a subsequent drop in 2021/2022 and then recovery from 2022 onward, with East Mauritania's recovery particularly noticeable from 2021. The Intervention Delta displays a recovery that is acceptable in comparison to others, although not as impressive as that of East Mauritania. Figure 6 shows a stark divergence of rice production among all areas in 2023, while the Intervention Delta remains stable. However, this year is 8 years after the conclusion of the intervention and so it is difficult to conclude the reasons for this. Additionally, the Intervention Delta is the largest region and had the most rainy season crop in 2015, possibly skewing this figure. The recovery of East Mauritania is noteworthy however, and perhaps policies and practices implemented here could be used in Senegal.

It is worth noting in figure 7 that most regions in the SRV outperformed the regional trend of rice grown (SAED 2024), but not the national trend reported by the FAO (FAOSTAT 2024). This could be due to differences in regional and national trends. It is possible that while the northern region of Senegal (the SRV) increased rice production, that the other primary rice growing region in Senegal (primarily across the south of the country) was accelerating more rapidly in production levels, however we have not verified this hypothesis.

4.2. Rice cropping practices 2015–2023

Using the output generated from our trained CNN classifier allowed us to characterise regional rice cropping practices over the same temporal baseline, as shown in figures 8 and 9. Figure 8 shows the output for 2019 for a central portion of the SRV. Note MODIS resolution (250 m) was used for this analysis due to computational resource constraints. We can see that double cropping dominated during this year and region. Whilst generally mirroring trends visible in figure 6, the data in figure 9 allow us to articulate how effective the impact of the MCC works were within the Intervention Delta region post-completion from 2015 to 2023. A priority for the MCC project was the greater frequency of cultivation within the Intervention Delta. The data as presented for this region shows how cultivation patterns did indeed evolve from 2015–2019, with a gradual increase in double, dry and rainy season cropping, a distinct change in 2020 to fallow status, with rainy season cultivation dominating beyond 2021, and some recovery of dry season cropping coincident with consistent but

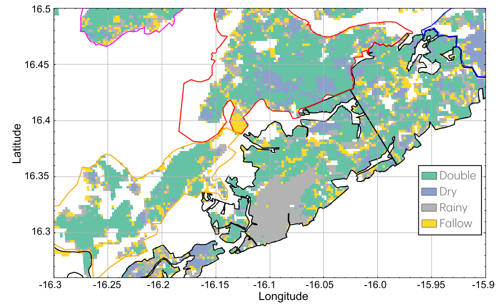

Figure 8. Central delta plot showing the cropping calendar type for 2019. Types of cropping include double (green), single (dry; blue or rainy; grey), and fallow (no crop; yellow).

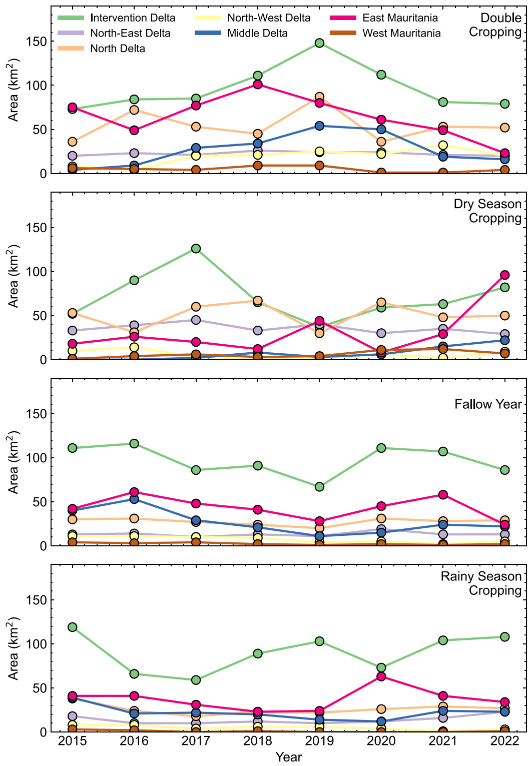

Figure 9. Areas of rice cultivation per year per cropping practice measured in km^2. Note that double cropped areas here are not double counted in the dry or rainy season crop.

lower levels of double cropping than had been the case in 2019 where year-on-year increases were apparent. An examination of the other region annual patterns shows little or no similarity to the trends apparent for the Intervention Delta region, other than a perturbation common to all between 2019–2020.

4.3. Precipitation and irrigation trends in the Intervention Delta 2015–2023

In figure 4 we plot the composite Sentinel-1 Water Index (SWI) time-series for rivers, drains, streams and canals identified within the Intervention Delta region, with the precipitation data from CHIRPS superimposed. Each year the canal SWI value peaks at the beginning of each dry season (March) sometime after the precipitation peak evident each rainy season, primarily a consequence of dam management, as water levels are kept low at this time to mitigate flood risk (Sall *et al* 2020). These data indicate a systematic decrease in SWI for all water bodies over this 8 year period, and a lack of apparent precipitation between 2016–2020 compared to other years. However the SWI measure for the canal network within the Intervention Delta manifests a more consistent relative temporal signature. Note that areas with increased SWI are not necessarily indicative of increased water volume. This is pronounced with the lack of dredging described earlier. Build-up of silt on water beds could cause over-estimation of water levels in a waterway. Our calculations of trends of water levels are most accurate assuming waterway volumes stay consistent.

4.4. Climate anomalies in precipitation and evapotranspiration in the SRV

In figure 10 we display a bar chart of the normalised climate anomalies in precipitation and evapotranspiration for the SRV from 1983–2023, which capture climatic trends and in particular drought stress events that would be expected to impact regional agricultural production. One of the most severe droughts in recent years occurred in 2014 and was quickly followed by four successive years of drought conditions starting in 2016 and breaking with a typical rainy season in 2020. This provides important contextual information on the background climate behaviour while analysing the trends in rice cultivation in the SRV. We highlight the acceptable performance of the region given these harsh climate conditions. However this is a clear warning to food security in the region as climate conditions continue to worsen.

4.5. Technical and data validation

To validate our labelling of rice for our training data, the data was labelled by a team member, reviewed by 2 other technical expert team members, and finally reviewed by a agricultural expert on sub-Saharan agriculture. Additionally, our model results on land use classification are reported in section 4.1. We define our model performance metrics for XGBoost which fulfilled our expectations as regards performance. These full metrics are supplied as supplementary data. Additionally, we compare our result to the most recent ESA 10 m WorldCover map for 2021. With a total overlapped cultivation area of 386 km^2, our model has an accuracy of 69%, a precision of 55%, recall of 87% and an f1-score of 68%, assuming ESA Worldcover is entirely accurate. The large disagreement is primarily with the West Mauritania region, which ESA Worldcover labels as cropland. However it is clear from RS data from 2021 that this is almost entirely fallow for 2021, emphasising the need for better temporal crop classifications.

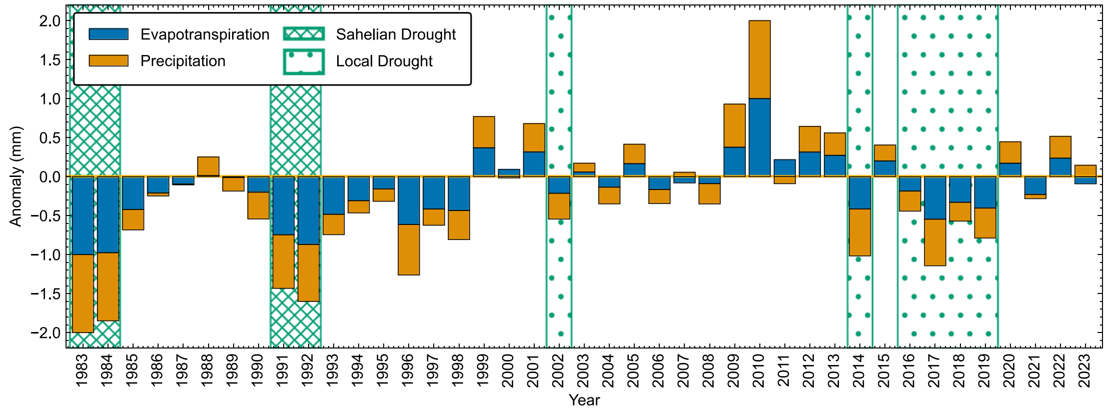

Figure 10. Normalised climate anomalies in precipitation and evapotranspiration. Vertical regions in green show local (dotted) and Sahelian (hatched) scale droughts in the region. Droughts coincide with low precipitation and low evapotranspiration.

Unfortunately, measuring the HMM model performance is not as straightforward. This is even more pronounced with the cropping intensity model. Our training data for this was labelled by hand by a technical expert. This involved labelling 2 thousand pixels on a yearly basis to analyse their seasonal phenology. We did not validate our labelling of waterways from OSM beyond measuring the actual water content of the canals in Sentinel-1/2 using NDVI, NDWI, and SWI. We highlight the need for better geospatial local open data of an agricultural nature by national institutions below in section 5.

To validate our climate analysis, we reviewed documented extreme climate events over the past four decades from sources like FEWS NET, ReliefWeb, and the FAO (FEWSNET 2014, ReliefWeb 2018, 2020). This review confirmed both local and Sahelian scale droughts visible in our data (highlighted as hatched regions in figure 10). Further details on other climate risks, such as storms, floods, and epidemics, are publicly available at World Bank (2023).

5. Discussion

A holistic view of our AI-enabled satellite RS analysis combined with the ground truth climate context of the region allowed us to assess the long term impact of the IWRM component of the USAID-funded MCC's Senegal Compact. This provides evidence of a successful irrigation management system, albeit not restricted to the Intervention Delta region. We deem success as the relative stability of rice cropping given the local drought over four years directly preceding a global pandemic. However, the lack of continued dredging practices in the region could have effected our measure of water content in the canals, effectively causing our results to be a best case scenario as the canal bed rises/becomes blocked. Therefore irrigation management in this case would be simply adequate given the background scenario. We point out in our results that the SRV outperformed regional rice cultivation trends, but not national ones. It is also worthy to note the FAO report a decline in national rice yield per area, yet an overall increase in cultivated area and rice production. This could indicate either recent irrigation practices are having a positive impact, or conversely, newly added rice cultivation is of low quality, thereby producing very low yields.

From our analysis, it is clear that seasonal land use classifications/labels are required to make accurate assessments of practices in the region. Using a temporally static crop mask which is out of date by a single season leads to miscalculation of total crop production. While this can be achieved through RS as demonstrated in this paper, it underscores the need to strengthen national institutions to effectively address record deficiencies for agri-environment schemes. Integrating RS techniques with significant improvements of local agri-climate data from national institutions offers the best path forward for the implementation of responsive policies at scale to foster climate-resilient agrifood systems.

Redicker *et al* (2022) has shown that most (86%) irrigation schemes across sub-Saharan Africa have been under-performing over several decades, with most proposed schemes over-promising results that have not been shown to materialise post-intervention. Our results show the longevity of the MCC intervention is trending in the wrong direction, although disentangling the success of irrigation intervention from climate degradation is a difficult and nuanced problem. As mentioned previously, planned sustained maintenance of irrigation works that meshes with local smallholders and fits with their livelihood goals is essential. It is imperative both economically and socially we develop methods to quantify and disentangle the negative effects of climate change and any positive effects of interventions.

Mateos *et al* (2010) highlights the need for appropriate sustained maintenance procedures for irrigation canals in smallholder rice farming (studied nearby, upstream in Mauritania), rather than sporadic rehabilitation, highlighting some issues with small-scale irrigation. We see limited success of this large-scale intervention, especially monetarily. Adams (1991) discussed the predominant issues with large-scale irrigation projects. García-Bolaños *et al* (2011) show using ground data that nearby irrigation projects upstream on the Mauritania side of the Senegal River show vastly different rates of deterioration, with a lack of water delivery and system maintenance leading to low productivity. It is clear from our results, analysed at a much larger scale, that this variation could exist, but is lost at this scale. Generally, the regions that produced the most rice at the beginning of our analysis, continued to do so. For an in depth economic analysis on the rice value chains in Senegal we direct the reader to Miklyaev *et al* (2017).

Any resilience to climate stress and shock events from this investment can most likely be attributed to the hydrological infrastructure—the Manantali and Diama dams—which were put in place to artificially control flooding of the delta, provide low flow support in the dry season, and prevent seawater intrusion (DeGeorges and Reilly 2006). On a more local scale, the sluice gates at Ronkh regulate the flow of water into the irrigation canal network (Morén and Andersson 2014) whose effectiveness in supporting local crop production is dependent on regular maintenance, such as dredging.

All regions experienced a significant perturbation of cultivation practices in 2020/21 - this was independent of climatic conditions or water availability as is clear from the data. The most likely cause was the impact of the COVID-19 global pandemic disrupting supply chains critical to supporting agricultural activities in the SRB area, the processing and sale of any resulting crops, not to mention the healthcare implications for the local population (Diarra *et al* 2023, El Bilali *et al* 2023, Jha *et al* 2023). This is supported by the increase in fallow cropping classification in figure 9. However, previously funded programmes prior to the pandemic had aimed at building sustainable agricultural communities in the same region. For instance, USAID's *Feed the Future Senegal: Naatal Mbay* (2011–2015) and *Finding the Best Fit: Nataal Mbay* (2015–2019) focused on promoting the development of value chains. These programs emphasized socio-economic resilience for communities dependent on the cultivation of irrigated rice in the SRV (USAID 2016, Manfre 2022). Such initiatives were predicted to lay the groundwork for a strong recovery in the 2021 season (Latané *et al* 2021). Note these did not take place in the SRV but elsewhere in Senegal. We did not see sufficient evidence for a bounce back in 2021 with less total productive rice cropped area in 2021 (392k ha) than in 2020 (397k ha) across the entire region.

However, over 2021–2023 there is RS evidence for a general recovery for all regions in the central SRV, with the Intervention Delta stabilising overall rice production to the peak level in 2017. In terms of cropping practices, the data indicates that within this region, double cropping and dry season cropping have yet to fully recover from their pre-2020 peaks, with a greater reliance on rainy season production. The decline in total dry season cropping from 2020 (dry cropped and double cropped areas) is of relevance with regard to the increasing lack of funding available for maintaining the irrigation canals, with the total dredged kilometres dropping from 102 km in 2016 to 31 km in 2020 (Harris *et al* 2021). The decreasing trend in maintenance is reflected in the persistent decline in SWI of the irrigation canal networks (figure 4) and is consistent with a significant decrease in flow reported by water user association members (Harris *et al* 2021), indicating that sufficient access to irrigation water is becoming more limited.

While we examine some trends in this work, a more causal analysis of the link between climate, biotic factors and rice production in this region would help in deciphering the most important factors, it is however beyond the scope of this study. This would provide critical decision making factors for organisations and farmers on the ground trying to sustain and enhance rice production in the SRV.

6. Conclusion

We present an EO based analysis of rice cultivation practices in the SRV between 2015–2023 using both Landsat 8 and Sentinel-1A data and ML methodologies to identify rice growing regions, determine rice cropping practices and assess the impact of irrigation over this time. Our motivation for this study was to assess the long term performance and local impact on rice production in the regions targeted by the IWRM work component of the USAID-funded MCC Senegal Compact. The methods used in this research offer a cost-effective solution for monitoring and evaluating large interventions by minimizing the need for extensive field data collection. This approach aids in strategically targeting and prioritizing investments, thereby enhancing decision-making processes related to resource allocation, ultimately maximizing the impact on smallholders' livelihoods.

We confirm a distinct increase in cultivated rice area across several designated regions within the SRV immediately post project completion, despite the wider region suffering long term drought conditions over the same period. An analysis of contemporary climatic data substantiates both a decline of local precipitation and lowering river-associated SWI, implying a clear climate adaptation benefit based on community irrigation management. All regions exhibited a negative perturbation in rice cultivation in 2020, likely a consequence of the COVID-19 pandemic, but the central SRV regions in particular all recovered to their pre-COVID levels by the conclusion of our study in 2023. It is very likely that USAID programmes from

2010 onward that focused on the socio-economic resilience among these same farming communities may have played a role in recovery.

For the IWRM intervention region, a cost to value estimate can be deduced by taking the growth from 2015 in cropped area and assuming a yield production rate of 5.5 tons ha^{-1} for Senegal specifically (Global Yield Gap Atlas 2023, SAED 2024). We find an additional total area of cultivated rice of 37 117 ha over the 8 years following 2015, or 4640 ha per year on average. This potentially results in an additional yield of 25 520 tons of rice per year from within the intervention area, equal to a market value (Soullier *et al* 2020) of approximately US$ 5.1 million per year, or US$ 40.8 million total, since 2015. This calculation underestimates the monetary return since it ignores the increase in double cropping that was observed. Including the total increased double cropping area (18 900 ha), from figure 9, we can increase this total estimate to US$ 61.6 million. To provide context, this represents approximately 13% of the total value of rice imported into Senegal in 2021. This value estimate does not include the future lifetime impact of the intervention, nor does it include the possible decline in rice production in the absence of the intervention. This represents 36% of the total IWRM investment. Excluding unforeseen events such as the COVID-19 pandemic, and assuming similar trends into the future, it is anticipated that the benefits of the intervention will offset its cost within the next 15 years.

However, we note with some concern, evidence of a deteriorating irrigation network from our RS data, which is consistent with the ground truth audit data up to 2019. Our findings clearly demonstrate the importance of the irrigation infrastructure in sustaining rice production despite local climatic extreme conditions, and highlights as a priority long-term planning for their maintenance so as to sustain productivity and resilience of rice cultivation for communities in the SRV.

Real-time longitudinal analysis into the long-term sustainability of climate adaptation interventions (such as irrigation) through satellite RS, extending past the initial funding phase, provides the opportunity to measure climate change adaptation and resilience of agricultural systems, in the presence and absence of climate adaptation investments and interventions.

Data availability statement

The data cannot be made publicly available upon publication because the cost of preparing, depositing and hosting the data would be prohibitive within the terms of this research project. The data that support the findings of this study are available upon reasonable request from the authors.

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Author contributions

A G, C S, A M L and L R conceptualized the research, supervised, and acquired funding. D O F, M G, J O F, R T and Y T conducted data curation, formal analysis, software, methodology, and investigation. DOF created visualisations. P C conducted project management. All authors participated in writing the paper.

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