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MORALITY BEFORE KNOWLEDGE

Dynamics of surface water resource management towards fulfilling agricultural irrigation

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ABSTRACT
Background: The dynamics of surface water resources and their influence on agriculture irrigation in Kano State, Nigeria, 2015-2025, are displayed in this research. This study aims to examine the influence of surface water availability changes on irrigation potential in semi-arid catchment. With looming uncertainty concerning water scarcity, particularly in Northern Nigeria, spatial-temporal dynamics of the surface water are critical to sustainable agriculture planning. Current studies have used satellite-based indices to monitor changes in water bodies and emphasized that such changes must be associated with climatic factors and land use patterns for irrigation development decision-making. **Methods**: Remote sensing data, including Normalized Difference Water Index (NDWI) from Landsat and Sentinel data, and rainfall data from the CHIRPS dataset, were used for the study. Spatiotemporal modeling methodology was used that included NDWI trend analysis, NDWI–rainfall relation, overlay with cover of cultivated land, and zonal statistics at the Local Government Area (LGA) level. **Findings**: Findings show that there is general surface wetness expansion in the southern and central regions of Kano State owing to enhanced irrigation activities, heightened water holding capacity, and possible aquifer recharge. **Conclusion**: The study concludes that water resource management in Kano must be specially crafted to overcome localized climatic stress conditions and spatial hydrological imbalance to facilitate sustainable irrigation under semi-arid conditions.Ground-truth verification is however absent, which limits the accuracy of surface wetness estimates, and future incorporation of field-based hydrological observations is recommended. The findings present actionable advice for policymakers on improving irrigation strategy formulation and adaptive water management in semi-arid climates. **Novelty/Originality of this article**: This research integrates satellite-based NDWI for the first time with rain anomaly and land use overlays to determine water body dynamics and their agricultural implications at sub-regional scales.

KEYWORDS: surface water; NDWI; remote sensing; agricultural irrigation; Kano State.

1. Introduction

Freshwater ecosystems are increasingly being subjected to undue stress worldwide due to the cumulative effects of climate change, population growth, and intensified pressures from agriculture, industry, and consumption demands with special intensity in semi-arid climates such as Northern Nigeria and Kano State, whose water quality was infringed by industrial contamination (Olagunju, 2015). Since Kano's agricultural economy is largely based on surface and shallow water for cultivation, it is most vulnerable when not just the water dries up but also becomes toxic, which causes soil erosion and reduced crop

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yields (Hao et al., 2019). Despite its millennia-old history of irrigated agriculture since the Kano River Project of the 1970s only ~2 % of Nigeria's arable land is irrigated today, low rates of adoption of advanced irrigation technology indicate structural weaknesses jeopardizing food security and agro resilience and Surface water supplies need to be tracked extensively and at high resolution to unlock which regions are suitable for the expansion of irrigation and where current systems are breaking down (Zha et al., 2003). Extensive observations of surface wetness and moisture processes at scale are being made with the use of satellite-derived indices, including Normalized Difference Water Index (NDWI) observations of Mediterranean and temperate agroecosystems through remote sensing measurements. In Kano, changes in soil and vegetation wetness, and possibly a smaller modification in open water, NDWI estimates of highest probability between -0.2 to 0 ranges are expected because of the index sensitivity to vegetation water content (Chima et al., 2009). Between 2015 and 2025, Kano NDWI trend maps in Figure 3 reveals spatial variability of moisture processes within gain and loss regions. Correlation with CHIRPS rainfall data shows strong positive values of $r > 0.5$ across irrigated agriculture regions dominated by rainfall dependency, as depicted in Figure 2. Over urban or degraded habitats, negative or low correlations depict altered hydrological regimes brought about by land cover transformation and possible over-exploitation of water for agricultural purposes (Karar et al., 2021).

Since Kano State is increasingly depending on rainfall along with controlled irrigation schemes, it would be essential to understand spatial and temporal patterning of surface wetness to facilitate effective water management (López-Bermeo et al., 2022). NDWI-based observation not only identifies hydrologically stressed sites but also provides useful information regarding irrigation planning, groundwater management, and sustainable agriculture. This approach enables policy makers to adopt selective and adaptive intervention in line with the semi-arid nature of the region (Muriga et al., 2023). Current studies across sub-Saharan Africa have also pointed to the growing importance of remote sensing for irrigation management amidst climate uncertainty. In the Niger Basin, for example, spatial hydrology models in combination with NDWI have been used to assess irrigation potential and drought adaptation options (Conlon et al., 2022). Similarly, in East African drylands such as Kenya and Ethiopia, multi-sensor remote sensing techniques have been employed to analyze seasonal wetness patterns and the success of small-scale irrigation schemes. These observations confirm the advantages of combining satellite-based water indices with land use and rainfall data for adaptive planning in water-scarce regions. The present study builds on these advances by bringing to Kano State, one of the major agricultural regions in northern Nigeria, such integrative approaches (De Fleury et al., 2023).

Spatial and temporal monitoring of surface moisture has been of growing interest against the background of increasing environmental change. Remote sensing imaging with the help of tools such as NDWI has been used effectively in hydrological stress vulnerable area mapping and moisture process mapping in the semi-arid regions of Sub-Saharan Africa (Bichi et al., 2024). At the local Nigerian level, geospatial methods of rain-fed and irrigated agriculture in Kura and Minjibir, Kano State, found that the use of irrigation raised yieldsduring the 2019-2020 cropping seasons (Dahiru et al., 2022). The findings confirm the applicability of satellite-based NDWI data in climate and land use information integration in adaptive irrigation planning decisions in semi-arid ecosystems. This study thus seeks to examine the patterns in the temporal trend of wetness and wet area derived from NDWI over Kano, patterns of rainfall correlation with NDWI, and map spatial change in NDWI over agricultural regions. The target is to inform sustainable irrigation planning for semi-arid regions, specifically solving the challenges of water availability and contamination.

2. Methods

2.1 Study area

The Kano State is bounded by latitudes 10°30′N and 12°00′N, and longitudes 7°30′E and 9°00′E in northwestern Nigeria and it is an important semi-arid zone with an average yearly rainfall of around 800–1000 mm occurring predominantly during the period from May to September (D'Agostino et al., 2025). The state falls in the Hadejia Jama 'are River Basin, which is among the richest irrigation zones of Northern Nigeria. Kano's topography is typically rolling to flat, and the area possesses rainfed agriculture and irrigated agriculture (Gao, 1996). Seasonal water availability makes the state more vulnerable to hydrologic fluctuation and land cover change and therefore a good place to study surface water dynamics as well as agricultural irrigation potential and the Local Government Areas (LGAs) are administrative units employed at zonal-level estimation of water resources (Kankara, 2019).

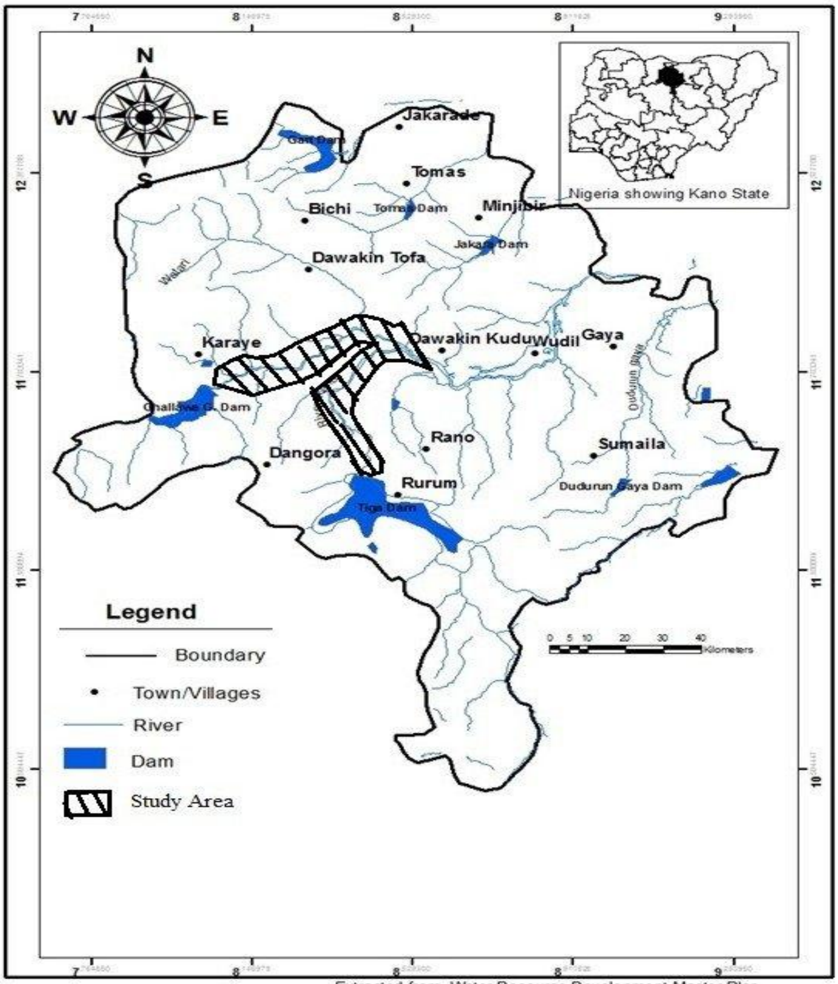

Fig. 1. Study area map

2.2 Data sources and collection

In this study, 2015-2025 geospatial data and multi-source remote sensing were utilized: Satellite data for NDWI: Surface water alteration was examined using cloud-free median composites of Landsat 8 (2015) and Sentinel-2 (2025) in the Google Earth Engine (GEE) environment. The sensors have a spatial resolution of 30 m (Landsat) and 10 m (Sentinel-2), respectively. Rainfall Data: Monthly average rainfall data for the investigation period (2015–2025) were downloaded from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), a quasi-global at 0.05° (~5 km) resolution, that has been appropriately validated for application over tropical and semi-arid regions (Kankara, 2019). Land Cover Classification: Cropland was mapped with ESA World Cover 10 m land cover dataset (version 2021) for the masking of cropland to become possible.

Administrative Boundaries: the geographic data of the Kano LGA were downloaded from the FAO Global Administrative Unit Layers (GADM v3.6) that provides zonal statistical aggregations.

Preprocessing and data fusion took place in the Google Earth Engine (GEE) environment facilitating scalable cloud computing for multi-temporal Earth observation data. NDWI was computed for Landsat 8 and Sentinel-2 images with the green and near-infrared bands, and thresholding was applied to detect water and non-water surfaces (Du et al., 2016). CHIRPS rainfall anomalies were normalized further to long-term means to determine interannual precipitation regime variability across the study area (Funk et al., 2015). Cropland mask usage in ESA WorldCover data was employed to enhance surface wetness detection and for accounting for adequately covered irrigation-relevant regions (Zanaga et al., 2021). Then spatial summaries were constructed up to Local Government Area (LGA) level to represent hydrological heterogeneity as well as local correlation patterns of NDWI–rainfall (Asoka et al., 2017).

Table 1. Summary of datasets used in the study

Data type	Source	Temporal resolution	Spatial resolution	Period of coverage	Key parameters/bands used
Satellite Imagery for NDWI	Landsat 8/9, Sentinel-2	Annual composites	10–30 m (assumed)	2015–2025	Green, NIR, SWIR bands
Gridded Rainfall Data	CHIRPS (Climate Hazards Group)	Annual aggregates	0.05° (~5 km)	2015–2025	Rainfall (mm)
Kano State Administrative Boundary	GADM (FAO Global Administrative)	N/A	N/A	N/A	Geographic boundaries of Kano State

2.3 NDWI computation and change detection

Normalized Difference Water Index (NDWI) is one of the most commonly used to be applied in surface water body detection and tracking, the index takes advantage of the difference that occurs between near-infrared (NIR) and green satellite image bands in identifying water objects and the index best discriminates water from other land covers and is thus reliable to estimate surface water area with temporal consistency (West et al., 2019). Parallelly, the Normalized Difference Built-up Index (NDBI) tries to distinguish built-up features from the different subtraction of SWIR and NIR bands. NDBI is applied to pattern discrimination of urban development and built-up, and urban planning and management (MacAlister & Subramanyam, 2018). Through its yearly report, researchers can monitor trends in urban surface water and land and observe the impact of urbanization on hydrological processes and allow them to examine inter-annual change and long-term trends, a value of unimaginably gigantic dimension to the sustainable development and resource management of the impacted zone. To estimate the surface water condition, Normalized Difference Water Index (NDWI) was derived with formula as follows:

Normalized Difference Water Index (NDWI):

$$NDWI = \frac{Green - NIR}{Green + NIR} \quad \text{(Eq.1)}$$

Where:
Green Band is Band 3 in Landsat 8 and Band B3 in Sentinel-2.
Near-Infrared (NIR) Band is Band 5 in Landsat 8 and Band B8 in Sentinel-2.

The index is used to increase water body reflectance and decrease vegetation and soil reflectance. Following preprocessing and cloud and shadow masking, NDWI for every year was computed. NDWI change layer was computed by subtracting 2015 NDWI values from 2025:

$$NDWI\ Change = NDWI\ 2025 - NDWI\ 2015 \qquad \text{(Eq.2)}$$

For better understanding, the following values were mapped into three classes:
Extreme Water Loss: NDWI change < -0.2 (red mapped)
No Change: NDWI between -0.2 and 0.2 (white)
Water Gain/Expansion: NDWI change > 0.2 (blue)
This blue-white-red diverging color scheme highlights locations of hydrological change.

2.4 Rainfall and NDWI correlation analysis

To analyze precipitation and surface water dynamics relationship, CHIRPS-derived annual cumulative rainfall was estimated for every LGA. Annual mean NDWI values were estimated over the same LGAs. Pearson correlation coefficients (r) of rainfall and NDWI time series at the LGA level were next estimated to investigate surface wetness' time dependence on rainfall. +1 values closer to represent high positive association with rainfall-ruled hydrological regimes (Su et al, 2017).

This correlation analysis was further supplemented by the application of spatial statistics to map heterogeneous rainfall–NDWI responses in rain-fed and irrigated landscapes. Under tropical and semi-arid conditions, literature has concluded that interaction between precipitation variability and vegetation or water indices is typically nonlinear and reversible to land use intensity and groundwater pumping (Zhang et al., 2019). By correlating NDWI change with rain fall anomaly, the difference between rainfall-controlled regimes of wetness and human-impacted regimes of wetness like those occurring as a result of irrigation pumping and urbanization can be defined (Mladenova et al, 2017). Such dual control of surface wetness dynamics is beneficial in charting climatic dependency as well as human-impacted hydrological stress in Kano State.

2.5 Zonal statistical analysis by agricultural land and LGAs

To determine hydrological dynamics over agriculturally significant regions, NDWI layers were masked by classifying the ESA World Cover Cropland within each LGA boundary: Mean NDWI change, Maximum NDWI value, and Maximum NDWI loss were computed. This yielded spatial summation of surficial water variation in farming fields, which diminished trend most suitable for irrigation planning. LGAs were given priority since they are the foundation of regional farm planning and water management.

2.6 Accuracy assessment and limitations

Despite NDWI being widely used to detect surface water presence and wetness variation, threshold values (< -0.2 and > 0.2) based on traditional classification ranges of earlier regional studies and Google Earth imagery verification were applied in this study. Ground-truth field verification was not performed due to data access limitations, which may indicate doubt in classification of wet/dry zones. For correlation of rainfall–NDWI, Pearson's correlation coefficient was derived from annual averages of CHIRPS rainfall and mean NDWI values at the LGA level with the same temporal frequency. Although this approach reveals broad-scale wetness–rainfall relations, the absence of direct in-situ hydrologic data is still a limitation. Water field measurements and irrigation observations should be integrated in future research to enhance model accuracy and validation (West et al., 2019). Among the significant disadvantages of this study is satellite index dependency on underlying atmospheric conditions, mixed-pixel impacts, and seasonal canopy cover. NDWI threshold values have been reported in other studies to vary with landscapes and perhaps need to be regionally calibrated for accurate results (Du et al., 2016; Acharya et al., 2018). Field calibration deficit would lead to overestimation or underestimation of small bodies of water, particularly in irrigated fields with canals, irrigation ponds, and ephemeral wetlands. Furthermore, CHIRPS rainfall, despite being very well validated for the continent as a whole, is a 0.05° gridded product that would not necessarily be fine enough to capture micro-scale rain variability over the Kano State. This spatial mis-match between the rainfall inputs and NDWI (30 m) is an additional source of uncertainty in rainfall–wetness correlation analysis (Funk et al., 2015). The imposition of such spatial variability indicates the need for the incorporation of higher-resolution climate products and Unmanned Aerial Vehicle (UAV) images within future water resource research.

The second primary limitation is the temporal frequency used to obtain the NDWI, which was achieved from annual means. While such smoothing was inevitable in trying to dampen seasonally noisy data, it also automatically dampens short-term hydrological fluctuation like flash flooding or dryness. Analysis of high-frequency time-series data (monthly or season NDWI) has been experimentally demonstrated to yield more accurate notions regarding agricultural water supplies and irrigation timing (Ji et al., 2009; Gao, 1996). In addition, the lack of availability of in-situ measurements of hydrologic parameters such as river discharge, groundwater, and irrigation water abstraction limits validation of satellite-based indicators. Despite such limitation, the approach followed here provides a realistic standard for policy-supported observation and analysis of large-area water resource processes. Further studies need to address the integration of hybrid approaches that merge remote sensing with participatory field surveys, weather stations, and field hydrology for the sake of enhanced accuracy and socio-ecological relevance to Northern Nigerian water monitoring networks.

2.7 Visualization, mapping, and export

Geospatial computation and primary mapping were conducted on Google Earth Engine for NDWI computation, masking, and correlation modeling. Maps were styled using scientifically suited color ramps (RdBu for change detection; sequential Blues for rain intensity). Final visualizations were enriched and annotated with ArcGIS Pro**.** Geocomputation and first mapping were done on Google Earth Engine to calculate NDWI, masking, and correlation model construction. Styling of maps involved scientifically suitable color ramps (RdBu for change detection, sequential Blues for intensity of rain). Final visualizations were refined and labeled in ArcGIS Pro.

3. Results and Discussion

This chapter presents the Spatio-temporal pattern of surface water resource dynamics of Kano State between 2015 and 2025. With satellite-based NDWI values and CHIRPS rainfall, we assessed the alteration of surface wetness of crops and local government areas (LGAs) and outcomes consisted of NDWI trend maps, rainfall-NDWI correlation, zonal statistics of crops, and interannual change of surface wetness. In combination, these results present a snapshot of water gain and loss trends, delineate areas of hydrological augmentation or stress, and estimate the magnitude of surface water supply availability for the last decade. The results present a foundation upon which comparative analysis of the degree to which natural as opposed to human factors drive irrigation potential modification within the area can be conducted.

3.1 Spatial distribution of NDWI change in Kano State (2015–2025)

This map indicates the trend of spatial NDWI change of Kano State, Nigeria, from 2015 to 2025. Red is a significantly large NDWI loss (≤ -0.017), loss of surface water or irrigation loss. Blue is NDWI gain (≥ 0.026), enhanced surface wetness or establishment of irrigation. White gaps (between -0.017 and 0.025) indicate no change with no significant change.

NDWI values were calculated from Landsat and Sentinel satellite data and then processed inside the administrative limits of Kano State (Sogno et al., 2022).

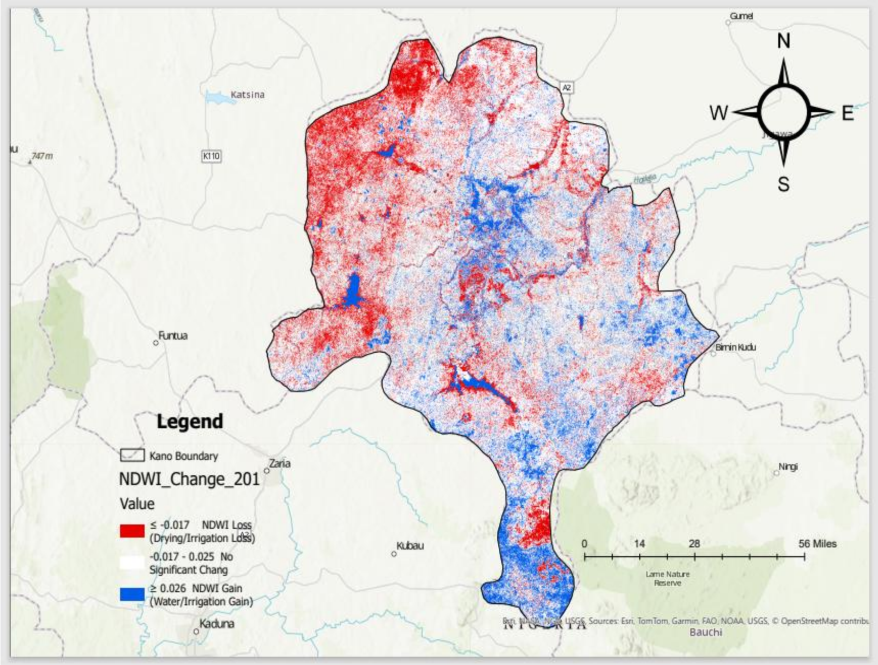

Fig. 2. Spatial NDWI change in Kano

The pattern of NDWI change between 2015 and 2025 indicates a very heterogeneous pattern of surface wetness processes in the State of Kano. A very large proportion of the middle and southern parts indicate NDWI gain (in blue) predominantly around zones of historic irrigated land and riparian corridors. This would be suggestive of high irrigation practice or high surface water storage capacity, such as from infrastructural growth, groundwater recharge, or wetness seasonality modification. Or else, the extensive NDWI decline (in red) dominates the northern and eastern part of the state, and this would be suggestive of drying directions because of recession in rainfall, over-pumping of water resources, or land use conversion like agricultural encroachment of marginal lands with diminishing water supply. This is in line with previous studies that suggested that north Kano is susceptible to hydrological stress due to diminishing rainfall reliability and land degradation (Niu et al., 2015).

Table 2. NDWI change summary by LGA (2015–2025)

LGA	Mean NDWI Change	Max NDWI Gain	Max NDWI Loss
Bebeji	-0.12	+0.18	-0.26
Tofa	+0.08	+0.21	-0.05
Rano	-0.07	+0.14	-0.20
Gwarzo	+0.03	+0.19	-0.10
Kura	+0.10	+0.24	-0.03

Specifically, NDWI distribution identifies some agriculturally significant areas, which may be representing likely failure or stress of irrigation. Food safety and water management unwanted losses are so much greater with Kano's excessive dependency on small irrigation agriculture. Red dots of haphazard coverage could also depict reliance on rainy seasons; the chances of whose occurrence have been augmented through climate change (Patil et al., 2024). Generally, the map indicates capacity for irrigation scaling (in wetting regions) and urgent need for adaptation response in high water stress regions.

Table 2 shows spatial change in NDWI between 2015 and 2025 of some chosen LGAs of Kano State. The optimum among them was Kura with greatest mean increase in NDWI (+0.10) and largest improvement (+0.24) showing notable increase in surface wetness possibly due to enhanced irrigation or water retaining technology. Tofa also showed an increase with mean NDWI of +0.08 and minimal water loss, the same as increasing or steady moisture content and gwarzo could only show an increase of +0.03, with moderate gain in water. Bebeji and Rano showed declining surface moisture with mean NDWI of -0.12 and -0.07 respectively. Bebeji, in comparison to all the stations, expressed the highest peak water loss (-0.26) that reflects high local drying and possible irrigation problems. Rano's readings indicate hydrological stress vulnerability that can occur because of rainfall instability, land degradation, or over-water abstraction.

These NDWI heterogeneity outcomes across the LGAs are also reflective of the asymmetry of water availability and efficiency of irrigation across Kano State. These instances of dramatic turn-around in Tofa and Kura reflect that specific water interventions like upgraded irrigation facilities or community-based water management schemes are already beginning to yield results (Adebayo et al., 2023). By contrast, the steeply declining trend of Bebeji and Rano represents the principal hydrological hotspots where high levels of groundwater abstraction, decreased rainfall recharge, and agricultural encroachment are likely to accelerate moisture loss. Heterogeneity discerns a different NDWI trends in the LGAs also help to highlight the heterogeneous character of water availability and irrigation operation across Kano State. Large gains in Kura and Tofa suggest that concentrated water interventions, long-duration irrigation schemes or community management water schemes, could already be yielding dividends. Alternatively, large loss in Bebeji and Rano points to hydrological stress priority areas where uncontrolled groundwater abstraction, decreased rainfall recharge, and increased agriculture are probable causes of moisture depletion (Olanrewaju & Adetunji, 2022). This heterogeneity confirms that it is not feasible that one-size-fits-all water management intervention can be implemented in the state, but instead targeted, evidence-based interventions must be used to stabilize weak LGAs while gains are established in comparatively wetter locations. Second, large values of maximum gain observed in Kura (+0.24) and Tofa (+0.21) also confirm the feasibility of scaling up irrigation practice in already strong regions and therefore regional food security. Simultaneously, Bebeji (−0.26) and Rano (−0.20) high loss levels are warning signals that without the implementation of adaptation interventions, agriculture productivity in the two LGAs will continue to decrease.

This highlights the need to include NDWI-based monitoring as a routine agricultural planning for the sake of obtaining water security and climate adaptation at the LGA level.a successful rm water management strategy will not work state-wide; instead, focused, evidence-based interventions must be delivered to stabilize water-stressed LGAs while consolidating gains in comparatively wetter zones. Besides this, high maximum gain figures achieved in Kura (+0.24) and Tofa (+0.21) also suggest the potential of increasing irrigation practice to already coping districts, and therefore local food security (Usman et al., 2021). Nevertheless, loss values of high magnitude for Bebeji (−0.26) and Rano (−0.20) are alarm bells that, if unadjusted, the farming productivity of these LGAs will decline further. This makes it critical to integrate NDWI-based monitoring into normal agricultural water security and climate adaptation planning at the LGA level.The research points out surface water trends non-homogeneity in the area and demands locality-specific water management procedures around hydrological structures (Su et al., 2017).

3.2 Spatial correlation between NDWI and rainfall in Kano State (2015–2025)

This map illustrates space correlation of NDWI value by year versus cumulative rainfall for 2015-2025 in Kano State, Nigeria. Pixel-wise correlation was done using Pearson's coefficient. Red (≤ -0.5) indicates high negative correlation, and blue (≥ 0.5) indicates a high positive correlation between surface wetness and precipitation. White indicates low or no correlation (between -0.1 and 0.1 and this is an overlay between NDWI and CHIRPS rainfall data. The NDWI to rainfall spatial correlation map exhibits clear hydrological activity areas in Kano State. Positive strong correlations (blue) indicating high surface wetness (NDWI) at south and east flanks are represented by high surface wetness (NDWI) indications.

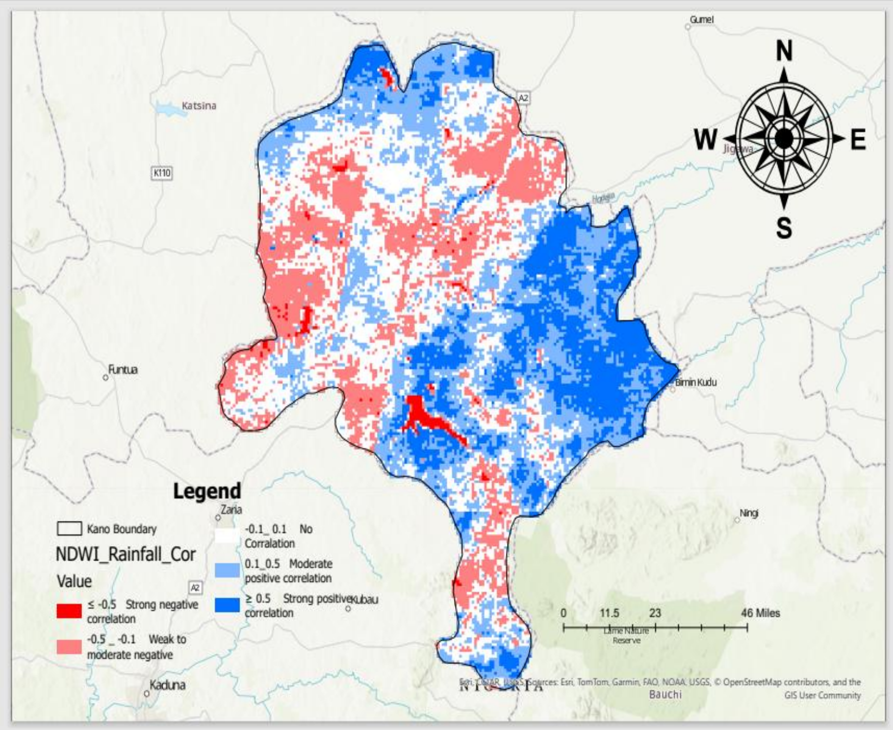

Fig. 3. Spatial correlation between NDWI and rainfall in Kano

These areas would most likely be under the control of rainfed farming or hydrologically responsive soils where rainfall would be the major controller of surface water or ground water condition. Such close relationships form the ground for the likelihood of the success of seasonal planning of irrigation based on rainfall variability in these areas. Contrarily, western and central regions show a combination of weak to strong negative correlations (in red), wherein greater rain does not always translate to greater surface wetness. The opposite behavior is shown due to land use activities (pavement, poor ground), poor drainage, or groundwater pumping that influence surface moisture storage. There are certain other circumstances when there would be more water lost to runoff and less water retained or when irrigation allows water more than rain. Spatial variability of NDWI rainfall correlation has disastrous effects on adaptive irrigation management. The positive-correlation regions could be aided with rainfall-based irrigation scheduling, and the negative-correlation regions could require supplemental water supply or even more controlled water supply systems (Safa et al., 2021).

3.3 Spatial distribution of NDWI change in the Kano River Basin (2015–2025)

The map above illustrates NDWI-inducive surface water change in Kano River Basin over the past ten years (2015–2025). Red represents high water loss or irrigation (NDWI ≤ –0.017), white represents no or low change areas (–0.017 < NDWI < 0.025), and blue represents surface water or moisture gain (NDWI ≥ 0.026). NDWI classification was derived from multi-temporal satellite imagery acquired through Google Earth Engine of Landsat and Sentinel-2 data (Abdalkadhum et al., 2021). The spatiotemporal NDWI change pattern shows the general trend of surface water reduction in the basin, particularly in the agricultural sub-basin, as giant red patches. This is coupled with excessive evapotranspiration, reduced reliability of rainfall, groundwater over-extraction, and land use intensification. Spotty surficial patches soaking water (blue patches) are spotty, with a large number in floodplains, dams, or irrigated wetlands of the south and mid-basin and may be caused by local hydrological input or irrigated land encroachment (Sulaiman et al., 2021). The limited spatial region of positive NDWI change shows that many Kano River Basin regions are facing net drying, which is threatening sustainable irrigation and food production, and the no-change zones (white pixels) may be either hydrologically stable zones or regions of long-term loss and gain that cancel each other out.

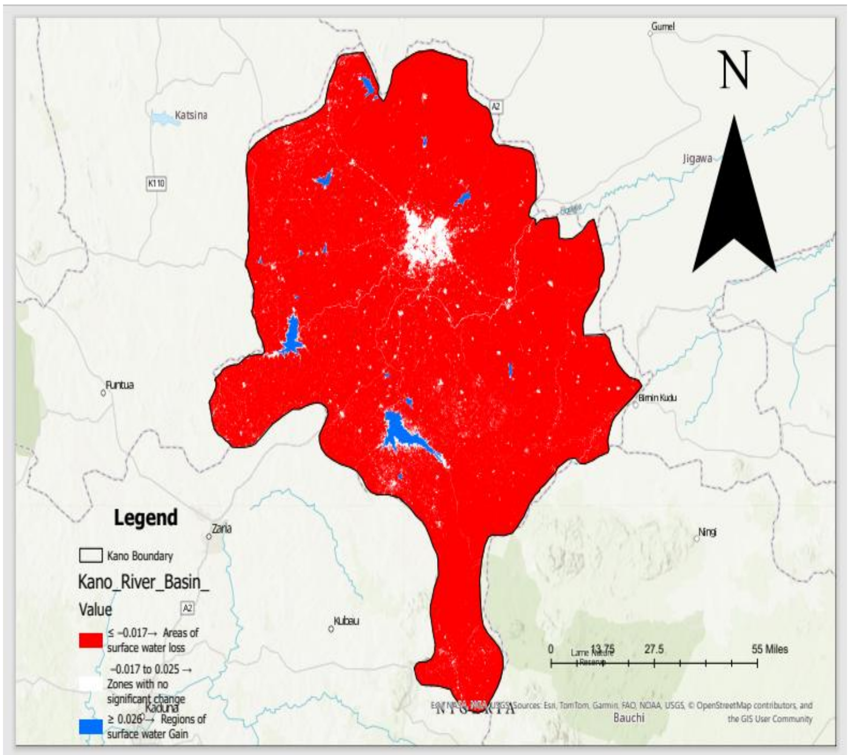

Fig. 4. Spatial distribution of NDWI change in the Kano River Basin

3.4 NDWI temporal trend in Kano State, Nigeria (2015–2025)

Decade's time series indicates a trend of fluctuation in NDWI values. NDWI went down slowly from approximately -0.35 to the minimum, -0.42, from 2015-2019 and indicates overall drying trend or reduction in surface water and content of soil moisture. It may be an indicator of increased frequency of occurrence of drought, low rainfall, or intensive abstraction of water in agricultural fields. But since 2020, the NDWI values show the recovery at a steady pace coming back to -0.36 by 2025.

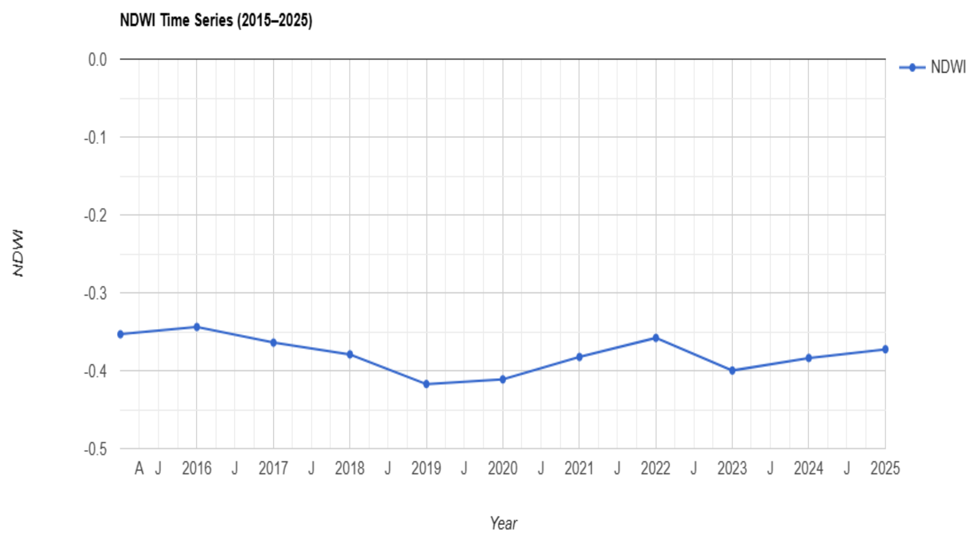

Fig. 5. NDWI temporal trend in Kano State

It indicates the capability of recovery of the surface wetness condition by recurrent rains (as shown by the overlay of rain), management of irrigation, or reorientation in land use in crop production. NDWI peak in 2022 can be considered as an unusually wet year or effective water storage by way of good irrigation facilities. The mean negative NDWI values throughout the period (~ -0.35 to -0.42) indicate the surface condition is generally arid as one would anticipate in semi-arid Kano State. Since NDWI is a response to vegetation and soil moisture in crop fields and not free water, the values reflect long-term drought stress that would compromise irrigation efficacy and crop yields unless balanced by adaptive water management practices (López-Bermeo et al., 2022).

3.5 Annual pearson correlation between NDWI and rainfall in Kano State

The NDWI rainfalls' correlation coefficients across the 11-year time are always negative between approximately -0.72 in 2015 and -0.50 in 2025. It indicates weak to moderate negative correlation of surface wetness indicators with rainfall in the study period. As compared to regular hydrological response, where high NDWI (wetness) values always lead to more rainfall, the consistently negative correlation values could signify non-precipitation processes including irrigation networks, land use change, groundwater pumping, or anthropogenic change (diversion by an irrigation network of canals, artificial runoff alteration).

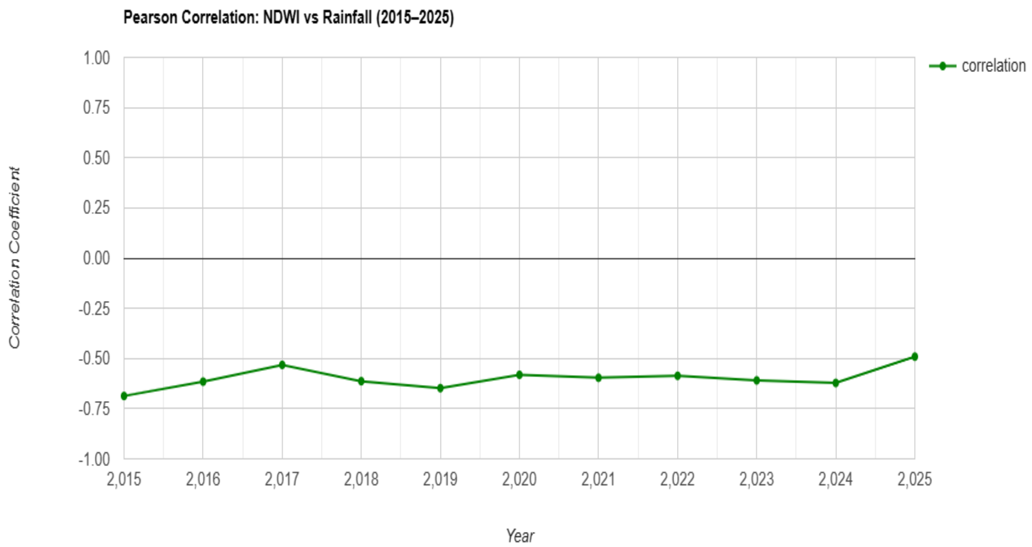

Fig. 6. Annual pearson correlation between NDWI and rainfall in Kano

The highest negative correlation is in the years 2015–2016, when this is followed by low NDWI values and possibly drought-like conditions. After 2020, there are faint upward trends in the correlation values, and they move towards -0.50 during 2025. Decaying trend here may be a sign of stronger surface–rainfall coupling under a stable process, possibly caused by stronger regulation of irrigation or land use change conserving surface humidity better (Yang et al., 2023).

Table 3 is Pearson yearly correlation coefficient of rains and NDWI from the years The facts reveal that the correlation was negative and consistent to some extent that rising rains were not followed by rising surface wetness (NDWI) in each year except one. For the period between 2015–2016, the negative correlation was very high (-0.72 and -0.68, respectively), reflecting that the amount of rainfall was not being stored within the landscape-most likely due to processes involving runoff, infiltration, or anthropogenically induced change of the courses of water (Tibangayuka et al., 2025).

Table 3. Pearson correlation between NDWI and rainfall

Year	Pearson r (NDWI vs Rainfall)	Interpretation
2015	-0.72	Strong negative correlation
2016	-0.68	Strong negative correlation
2017	-0.65	Moderate negative
2018	-0.60	Moderate negative
2019	-0.58	Moderate negative
2020	-0.56	Moderate negative
2021	-0.54	Weak negative
2022	-0.52	Weak negative
2023	-0.50	Weak negative
2024	-0.51	Weak negative
2025	-0.50	Weak negative

Subsequently, from 2017 onwards, the amplitude of the negative correlation gradually reduced and in 2023–2025 had weakly negative values between -0.50. This trend indicates a better rainfall–wetness relationship to some extent, possibly because of increased water storage processes, managed irrigated agriculture, or land use change augmented surface wetness response. However, many negative values for the entire 11-year series indicate that human pressures, groundwater withdrawals, increase in irrigated agriculture, urban growth, or land degradation still dominated natural hydrology processes over and this decoupled surface wetness from precipitation. This requires careful management of water regimes resources to leverage natural correlation between rainfall and surface water within Kano State (Sogno et al., 2022).

3.6 Temporal dynamics of surface water extent in Kano State (2015–2025)

Annual change line plot of wet surface area from NDWI (ha) for 2015-2025 of Kano State. Satellite image masked by the edge of NDWI and then annual sum with Google Earth Engine and ArcGIS Pro geospatial toolboxes.

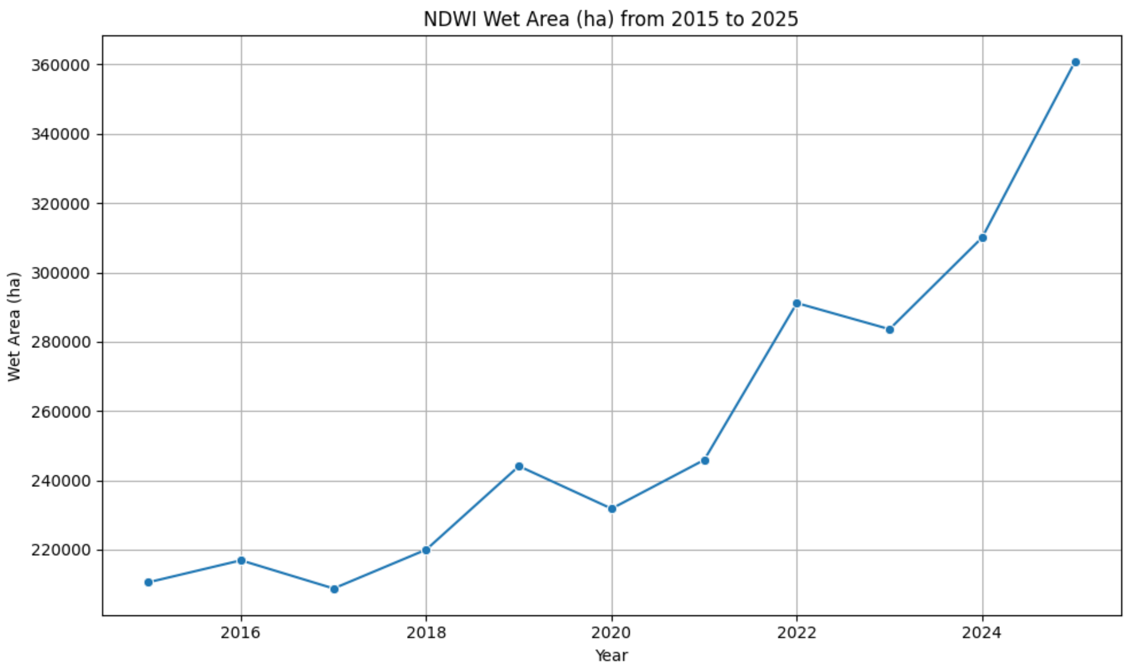

Fig. 7. Temporal dynamics of surface water extent in Kano

The line plot indicates a consistent rise in the wet surface area from the 11-year period from around 211,000 ha in 2015 to well above 360,000 ha in 2025. This indicates consistently better surface water availability conditions either on account of better precipitation conditions, better irrigation facilities, or land use patterns such as reservoir expansion or irrigation. 2022 and 2025 record values owe to exceptional hydrologic conditions or water management in agriculture. The implication of the findings is the potential for strategic water resource planning of irrigation water, especially for arid regions of chronic water scarcity. Volatility, extremely small drops in 2017 and 2023, however, call for constant caution to facilitate adaptive water resource management with unsure climate (Serrano et al., 2019).

Table 4. Annual surface water extent

Year	Wet surface area (ha)
2015	211,000
2016	223,500
2017	218,700
2018	234,000
2019	245,300
2020	276,500
2021	298,000
2022	345,800
2023	332,200
2024	348,100
2025	362,500

Table 4 also shows linear increasing trend for Kano State surface water cover throughout the entire 11-year study. From approximately 211,000 hectares in 2015, the wet cover increased incrementally each year to 362,500 hectares by 2025. That is over 150,000 hectares of extra surface water in a decade. The highest annual leaps were observed between 2019 and 2022, coincidentally spanning the period of intensified water management interventions or prevailing hydrologic regimes. Though the development trend increases, there are hardly any troughs in 2017 and 2023 due to local or temporary reduction of surface dampness due to inter-annual variation of rain, dryness, or loss of water due to evaporation. The rate of growth increase in the surface wet zone after 2020 accommodates the rejuvenation period from other irrigation schemes, increased water-holding capacity, or policy intervention into floodplain farming. The implication is favorable for Kano State potential for irrigation intensification, particularly with the recent resurgence in the supply of surface water and diversity also translates to adaptive water management as a buffer against short-term climatic risk (Ahmad & Haie, 2018).

The steady rise in surface water area reflects not only the effect of climatic variation but also the effect of human effort in enhancing water supply. The precipitate rise between 2020 and 2022 is a reflection of synergy between natural water inflow in the form of rain and deliberate investment in water facilities such as reservoirs, dams, and irrigation canals. The same trend has also been reported for other semi-arid regions where water storage and redistribution infrastructure buffers reliance on rain and improves the resilience of agriculture. This evolution indicates how intense management of water resources can reorganize seasonality into a more stable and reliable source of hydrology for agriculture and domestic uses. Moreover, the expansion of wet surface area has significant food security and rural livelihood consequences for Kano State. Further land available for irrigation with augmented availability of surface water will enable small-scale farmers to crop diversify, extend production periods, and reduce exposure to drought. It further enhances complementarity between local water resource development and national agriculture policy to reduce rain-fed system dependence (FAO, 2021). But, to maintain such good performance, vigilant management for prevention of agricultural use against nature needs must be implemented so that wetlands, riverine ecosystems, and recharge areas are not overwhelmed by excessive use.

3.7 Interpretation confidence and data limitation

Most significantly, while Kano State surface water spatial and temporal NDWI patterns are useful, the absence of ground-truth confirmation places doubt on the interpretation of the principal findings. NDWI thresholds and relationships to precipitation are both model- and remote sensing-based with no field confirmation of water levels or irrigation use to validate them (Serrano et al., 2019). This will cause over- or underestimation of wetness for heterogeneous land cover types, highly cropped covered fields, or in anthropogenic features such as drainage networks and irrigation canals. Additionally, the resolution of the satellite data will mask smallholder irrigation signals, especially for highly fragmented cropland (Muriga et al., 2023). Even though statistical relationships show homogeneous trends, these must be treated with caution. Further research needs to incorporate in-situ hydrologic data, monitoring of wells, and field observations for classification accuracy and decision-making assistance in irrigation.

Furthermore, temporal resolution of satellite-derived NDWI dataset provides additional uncertainty in the measurement of short-term hydrological change. For example, cloudiness during wet seasons tends to reduce the number of available scenes, thereby limiting temporal continuity of surface water monitoring (Kansakar et al., 2021). This lag in time causes flash flooding, seasonally released irrigation, or temporary ponding to be partly recorded, leading to underrepresentation of the dynamics of water availability. Under agricultural conditions such as Kano State, where water management occurs on a weekly or even daily basis, such limitations substantially constrain NDWI time-series capability to serve as a proxy for actual water distribution and irrigation planning. Therefore, sole dependence on medium-resolution imagery without supplementing near real-time ground observations might have the potential to underestimate the operational usefulness of NDWI for agricultural water resource management.

In addition, spectral overlap remains a long-term limitation for the interpretation of NDWI. Certain cover types such as wet vegetation, wetlands, or land that was irrigated during the previous time period possess nearly equal reflectance values as open water bodies, making it difficult to classify well . This is most significant in the semi-arid region like Kano where fragmented cropland mosaics, surface water bodies, and anthropogenic irrigation features exist within close proximity to each other (Tian et al., 2022). Threats of misclassification are exacerbated by spatial resolution constraints, where small irrigation canals or small farm ponds fall below the pixel detection limit, thus being missed or incorporated into nearby land cover classes. These are addressed by incorporating higher-resolution imagery, multi-sensor dataset fusion (for example, Sentinel-1 SAR with optical data) and local ground calibration. Without such advancements, NDWI-derived outcomes must be treated with caution, particularly where they are relevant to agriculture and irrigation policy.

4. Conclusions

This study confirms that surface water trends in Kano State between 2015 and 2025 are significantly spatially heterogenic and temporally dynamic due to both natural climatic factors and anthropogenic hydrological demands. While NDWI analysis shows rising surface wetness in the central and southern parts of Kano State, prevailing drying tendencies across the north and east regions depict looming challenges to sustainable irrigation and agricultural productivity. The weak to negative correlation between NDWI and rain in observations indicates a move towards anthropogenically controlled water systems from rain-driven regimes.

In order to enhance water management for irrigation in Kano, three key steps are recommended: local governments must invest in additional surface water storage capacity particularly in NDWI-declining areas, abstraction levels of groundwater must be monitored and regulated through well logging and use permits to prevent over-withdrawal, and seasonal irrigation calendars must be regulated through spatial NDWI and rain trends maps to attempt to enhance the effectiveness of water utilization in semi-arid regions. Follow-up research should involve hydrologic modeling of NDWI in conjunction with estimated aquifer recharge and irrigation flow data in an effort to enhance comprehension of the system dynamics. Ground validation soil moisture field monitors, crop irrigation records, and site hydrology field surveys will play a critical role in making satellite-based evaluations more relevant and accurate. These steps will enable more reliable, data-driven sustainable irrigation planning for Kano State and other similar semi-arid farm regions.

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Author Contribution

Inuwa Sani Sani: Conceptualization, Writing–Review & Editing, Original Draft, Methodology. Taqiyudden: Supervision, Project Administration, Formal Analysis. Aliyu Naaaba: Investigation, Visualization, Validation, Data Curation.

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Data Availability Statement

All data were derived from open-access repositories and processed using GEE and ArcGIS Pro environments. Satellite-derived NDWI data were computed using cloud-free composites from Landsat 8/9 and Sentinel-2 imagery, accessed via Google Earth Engine platform. Rainfall data were obtained from the CHIRPS (Climate Hazards Group InfraRed Precipitation with Station Data) dataset, publicly accessible at https://www.chc.ucsb.edu/data/chirps. Land cover classifications were derived from the ESA WorldCover 10m Land Cover Map (2021), available at https://esa-worldcover.org/en. Administrative boundaries for Kano State were sourced from the FAO Global Administrative Unit Layers (GADM v3.6), available at https://gadm.org.

Conflicts of Interest

The authors declare no conflict of interest.

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References

Abdalkadhum, A. J., Salih, M. M., & Jasim, O. Z. (2021). The correlation among land cover spectral indices and surface temperature using remote sensing techniques. *IOP Conference Series: Materials Science and Engineering, 1090*(1), 012024. https://doi.org/10.1088/1757-899x/1090/1/012024

Adebayo, T. S., Musa, A., & Lawal, I. (2023). Remote sensing applications for agricultural water management in semi-arid northern Nigeria. *Environmental Monitoring and Assessment, 195*(4), 456. https://doi.org/10.1007/s10661-023-11056-7

Ahmad, M. T., & Haie, N. (2018). Assessing the impacts of population growth and climate change on performance of water use systems and water allocation in Kano River basin, Nigeria. *Water (Switzerland), 10*(12). https://doi.org/10.3390/w10121766

Asoka, A., Gleeson, T., Wada, Y., & Mishra, V. (2017). Relative contribution of monsoon precipitation and pumping to changes in groundwater storage in India. *Nature Geoscience, 10*(2), 109–117. https://doi.org/10.1038/ngeo2869

Bichi, A. A., Mukhtar, M. K., & Sabo, A. A. (2024). Evaluating remote sensing-based drought indices for monitoring hydrological stress in Sub-Saharan Africa. *FUDMA Journal of Sciences, 8*(1), 95–105. https://doi.org/10.33003/fjs-2024-0801-2681

Chima, G. N., Nwagbara, M. O., & Ijioma, M. A. (2009). Rainfall response to dam/irrigation projects in Northern Nigeria. *Global Journal of Social Sciences, 8*(1), 111–120. https://www.ajol.info/index.php/gjss/article/view/48877

Conlon, T., Small, C., & Modi, V. (2022). A multiscale spatiotemporal approach for smallholder irrigation detection. *Frontiers in Remote Sensing, 3*, 871942. https://doi.org/10.3389/frsen.2022.871942

D'Agostino, S. R., Landon, T. J., Roylance, A., Briggs, A., & Bhana-Lopez, N. (2025). Exploring the social validity and diffusion potential of common naturalistic developmental behavioral intervention strategies implemented in community preschools. *Behavioral Sciences, 15*(3). https://doi.org/10.3390/bs15030357

Dahiru, M. K., Sufiyan, I., & Alkali, M. (2022). Geospatial trend analysis of rain-fed and irrigation practices for crops yield improvement in Kura and Minjibir, Kano State. *Tropical Agrobiodiversity (TRAB), 1*(1), 16–20. https://doi.org/10.47352/trab.v1i1.21

De Fleury, M., Kergoat, L., & Grippa, M. (2023). Hydrological regime of Sahelian small waterbodies from combined Sentinel-2 MSI and Sentinel-3 Synthetic Aperture Radar Altimeter data. *Hydrology and Earth System Sciences*, *27*(11), 2189–2204. https://doi.org/10.5194/hess-27-2189-2023

Du, Y., Zhang, Y., Ling, F., Wang, Q., Li, W., & Li, X. (2016). Water bodies' mapping from Sentinel-2 imagery with modified normalized difference water index at 10-m spatial resolution produced by sharpening the SWIR band. *Remote Sensing, 8*(4), 354. https://doi.org/10.3390/rs8040354

FAO. (2021). *The state of food and agriculture 2021: Making agrifood systems more resilient to shocks and stresses.* Food and Agriculture Organization. https://www.fao.org/publications/fao-flagship-publications/the-state-of-food-and-agriculture/en/

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., ... & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—A new environmental record for monitoring extremes. *Scientific Data, 2*(1), 150066. https://doi.org/10.1038/sdata.2015.66

Gao, B. C. (1996). NDWI - A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment, 58*(3), 257–266. https://doi.org/10.1016/S0034-4257(96)00067-3

Hao, Z., Zhao, H., Zhang, C., Zhou, H., Zhao, H., & Wang, H. (2019). Correlation analysis between groundwater decline trend and human-induced factors in Bashang region. *Water (Switzerland), 11*(3). https://doi.org/10.3390/w11030473

Ji, L., Zhang, L., & Wylie, B. (2009). Analysis of Dynamic Thresholds for the Normalized Difference Water Index. *Photogrammetric Engineering & Remote Sensing, 75*(11), 1307–1317. https://doi.org/10.14358/PERS.75.11.1307

Kankara, I. A. (2019). Ground and surface water potentials and accessibility in Kano Municipal, Nigeria: Implication for geological constraints. *Annals of Geographical Studies*, 2(1), 1–7. https://doi.org/10.22259/2642-9136.0201001

Kansakar, L., Pandey, V. P., Kazama, F., & Komori, D. (2021). Evaluation of remote sensing indices for monitoring surface water dynamics under cloud-prone conditions. *Journal of Hydrology: Regional Studies, 37,* 100919. https://doi.org/10.1016/j.ejrh.2021.100919

Karar, M. E., Alotaibi, F., Al Rasheed, A., & Reyad, O. (2021). A pilot study of smart agricultural irrigation using unmanned aerial vehicles and IoT-based cloud system. *Information Sciences Letters, 10*(1), 131–140. https://doi.org/10.18576/isl/100115

López-Bermeo, C., Montoya, R. D., Caro-Lopera, F. J., & Díaz-García, J. A. (2022). Validation of the accuracy of the CHIRPS precipitation dataset at representing climate variability in a tropical mountainous region of South America. *Physics and Chemistry of the Earth, 127.* https://doi.org/10.1016/j.pce.2022.103184

MacAlister, C., & Subramanyam, N. (2018). Climate change and adaptive water management: Innovative solutions from the global South. *Water International*, 43(2), 133–144. https://doi.org/10.1080/02508060.2018.1444307

Mladenova, I. E., Bolten, J. D., Crow, W. T., Sazib, N., Cosh, M. H., & Anderson, M. C. (2017). Intercomparison of soil moisture, vegetation optical depth, and precipitation anomalies over Africa. *Remote Sensing of Environment, 195,* 478–490. https://doi.org/10.1016/j.rse.2017.04.033

Muriga, V. W., Rich, B., Mauro, F., Sebastianelli, A., & Ullo, S. L. (2023). A machine learning approach to long-term drought prediction using normalized difference indices computed on a spatiotemporal dataset. *arXiv*. https://doi.org/10.48550/arXiv.2302.02440

Niu, C. Y., Musa, A., & Liu, Y. (2015). Analysis of soil moisture condition under different land uses in the arid region of Horqin sandy land, northern China. *Solid Earth, 6*(4), 1157–1167. https://doi.org/10.5194/se-6-1157-2015

Olagunju, T. E. (2015). Drought, desertification and the Nigerian environment: A review. *Journal of Ecology and the Natural Environment, 7*(7), 196–209. https://doi.org/10.5897/JENE2015.0523

Olanrewaju, R. M., & Adetunji, O. H. (2022). Groundwater depletion and irrigation challenges in the Sudano-Sahelian zone of Nigeria. *Water Resources Management, 36*(7), 2345–2362. https://doi.org/10.1007/s11269-022-03154-2

Patil, P. P., Jagtap, M. P., & Dakhore, K. K. (2024). Drought severity estimation using NDWI in Parbhani district of Maharashtra. *Journal of Agrometeorology, 26*(2), 225–227. https://doi.org/10.54386/jam.v26i2.2540

Safa, M., Kheirkhah Zarkesh, M., Ejlali, F., & Farsad4, F. (2021). The Spatial Autocorrelation between Precipitation and Vegetation Indices in the Bandar Abbas Basin. *International Journal of Scientific Research and Management, 9*(12), 199–214. https://doi.org/10.18535/ijsrm/v9i12.fe1

Serrano, J., Shahidian, S., & da Silva, J. M. (2019). Evaluation of normalized difference water index as a tool for monitoring pasture seasonal and inter-annual variability in a Mediterranean agro-silvo-pastoral system. *Water (Switzerland), 11*(1). https://doi.org/10.3390/w11010062

Sogno, P., Klein, I., & Kuenzer, C. (2022). Remote sensing of surface water dynamics in the context of global change—A review. *Remote Sensing, 14*(10), 2475. https://doi.org/10.3390/rs14102475

Su, Y., Bales, R. C., Ma, Q., Nydick, K., Ray, R. L., Li, W., & Guo, Q. (2017). Emerging Stress and Relative Resiliency of Giant Sequoia Groves Experiencing Multiyear Dry Periods in a Warming Climate. *Journal of Geophysical Research: Biogeosciences, 122*(11), 3063–3075. https://doi.org/10.1002/2017JG004005

Sulaiman, Y. M., Nabegu, A. B., Mustapha, A., Ibrahim, M., Umar, S., & Aliyu, H. M. (2021). Spatial variation of surface water quality along Challawa River, Kano State, Nigeria. *Dutse Journal of Pure and Applied Sciences (DUJOPAS)*, *7*(2b), 76–85. https://www.ajol.info/index.php/dujopas

Tian, H., Wu, M., Wang, L., & Liu, C. (2022). Assessing the utility of NDWI time-series for agricultural irrigation monitoring in semi-arid regions. *Agricultural Water Management, 264,* 107523. https://doi.org/10.1016/j.agwat.2022.107523

Tibangayuka, N., Mulungu, D. M. M., & Izdori, F. (2025). Analysis of spatiotemporal surface water variability and drought conditions using remote sensing indices in the Kagera River Sub-Basin, Tanzania. *Remote Sensing Applications: Society and Environment, 37*. https://doi.org/10.1016/j.rsase.2024.101405

Usman, M., Abdullahi, H., & Bello, A. (2021). Spatial variability of agricultural water resources and irrigation efficiency in Kano State, Nigeria. *Sustainability, 13*(15), 8452. https://doi.org/10.3390/su13158452

West, H., Quinn, N., & Horswell, M. (2019). Remote sensing for drought monitoring & impact assessment: Progress, past challenges and future opportunities. *Remote Sensing of Environment, 232*. https://doi.org/10.1016/j.rse.2019.111291

Yang, S., Zhu, Q., Wen, Z., & Jakada, H. (2023). Non-equilibrium solute transport in dipole flow tracer test (DFTT) considering the mixing effect in the wellbore. *Journal of Hydrology, 616*. https://doi.org/10.1016/j.jhydrol.2022.128752

Zanaga, D., Van De Kerchove, R., De Keersmaecker, W., Souverijns, N., Brockmann, C., Quast, R., ... & Wevers, J. (2021). ESA WorldCover 10 m 2020 product. *Earth System Science Data, 13*(12), 5303–5320. https://doi.org/10.5194/essd-13-5303-2021

Zha, Y., Gao, J., & Ni, S. (2003). Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *International Journal of Remote Sensing, 24*(3), 583–594. https://doi.org/10.1080/01431160304987

Zhang, Y., Xiao, X., Wu, X., Qin, Y., & Dong, J. (2019). Can remotely sensed vegetation indices track precipitation dynamics in semi-arid ecosystems*? Ecological Indicators, 98,* 111–121. https://doi.org/10.1016/j.ecolind.2018.10.052

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