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Modeling water table dynamics of tropical wetlands in North Central Nigeria

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Abstract The increasing frequency of drought, hunger, migration, malnutrition, including societal unrest has been linked with cases of water stress and climatic aggravation on the Earth's water resources. As a targeted strategy to contribute towards integrated water resources management, this study emerged as a tool to model and predict cultivable wetland potential for water sustainability. The study took an empirical approach, where the experimental site was studied for its water resources availability and sustainability. Stratified random sampling techniques were applied to delineate ten sites within the University of Abuja landmass, where study wells were hand-dug to assess the wetland water table of North Central Nigeria. Descriptive statistics, and autoregressive modelling in time series analysis were conducted for predicting the water table dynamics and temporal dynamics in the wetland. The date and site interaction showed a significant difference between the means across all sources of variation. Significant variations in water table depth across ten sampled wells were found, with a first-order autoregressive model: $X_t = 4.6312 + 2.008x$ which indicated a high correlation ($r = 0.9114$) between predicted and observed values. The combination of field experimentation and statistical prediction in this study remains critically novel in the assessment of water table dynamics towards integrated water resources dynamics. The study remains significant as a tool for assessing wetland suitability for water-return sustainability.

Keywords: Autoregressive model, water-table modelling, wetland dynamics.

1 Introduction

The increasing frequency of drought, hunger, migration, malnutrition, and societal unrest has been linked to water stress, aridity, and climatic aggravation on the Earth's water resources. About 80% of the global population has been stressed over the past century and becoming worse in the 21st century on the issue of drought and high impact stress on water resources, thereby complicating water resources management (FAO 2016, Vitousek 2017, Schuerch *et al.* 2018, UN-Water 2022). Water stress worsens drought and hunger globally with expected high-frequency projections estimated for semi-arid regions (FAO 2016). Wetlands hold significant food production potential (Mitsch *et al*. 2015). Autoregressive modelling has been used to predict water dynamics (Baareh *et al*. 2006a), however, extensive empirical studies on the Guinea Savannah region of North-Central Nigeria wetlands' cultivable potential are inadequate.

The sustainability of our water resources is critical for life on earth, and holds the key to the development and prosperity of the global community. If we must sustainably combat and adapt to the earth changing climate, then it is critical to closely look into sustainable modalities we could take to strengthen the global monitoring systems in-order to reawaken the earth integrated water resources and develop sustainable approaches we could use to modulate the earth system towards global climate action. Sustainable food remains a critical gap to close the link between hunger, environmental balance and poverty, which are key targets of the Sustainable Development Goals. The challenges to ensure adequate availability of water have become compounded by climate change (Bunn and Arthington 2014, Davidson 2014, FAO 2021).

Cultivation of wetlands presents a significant opportunity to enhance food production and improve rural livelihoods in developing nations. However, realizing this potential requires navigating a critical challenge: balancing agricultural use with the conservation of the wetland's core ecological functions. The imperative for this balance is well-established in literature emphasizing sustainable wetland management (Mitsch and Gosselink 2015). The primary ecological value of these systems is intrinsically linked to their hydrology (Lloyd *et al*. 2013, Mitsch *et al*. 2013). Therefore, any agricultural development must prioritize the protection of the water regime to ensure long-term productivity and ecosystem health. Sustainable wetland cultivation requires optimal management of the water table and soil moisture characteristics to achieve significant crop production. The influence of water table and its fluctuations in the wetland is critical to the maintenance and management of soil moisture which determines the available water for crop production. This requires a reliable tool, especially in the management of the spatially heterogeneous ecosystem.

Autoregressive model $AR_{(P)}$ is an extension of the random walk model, and it is defined as a linear combination of previous values at times/locations $i=1, 2, \ldots, p$. It is a widely used stochastic model that can be extremely useful in representing certain practically occurring series. Autocorrelation is the degree of linear association between pairs of values separated by a given distance, which is obtained from self (Nielsen and Wendroth 2003). In contrast, autocorrelation length is defined as the separation distance beyond which the autocorrelation is considered nil because it is not significantly different from zero. The autoregressive model is one of the most well-known models among the traditional linear models. Autoregressive model $AR_{(P)}$ of the order p for the time space/space dependent property A is;

$$A_i = \emptyset_1 A_{i-1} + \emptyset_2 A_{i-2} + \ldots . \emptyset_p A_{i-p} + \omega_i \, w \; ---------- \; (1)$$

where $\varphi_1, \varphi_2 \ldots\ldots \varphi_p$ are auto regressive coefficients and A_i is the value at a certain time of the order (Nielsen and Wendroth 2003). Findings of Baareh *et al.* (2006a) and Kisi (2005) have expressed views that the application of autoregression model is productive in evaluating parameters at a location with time about the subsequent location.

As a targeted strategy to model and predict the cultivatable wetlands to find sustainable remediation and contribute to global climate action towards sustainable food production and integrated water-soil-ecosystem management nexus, this study aims at (1) modelling and predicting the water-table dynamics of wetlands using autoregression techniques, and (2) assessing the cultivable potential of wetlands for sustainable water management by analyzing water-table performance.

2 Material and Methods

2.1 Study area

A wetland Fadama field being cultivated by farmers was chosen for the study due to the interest of the farming communities in utilizing the wetland resources for the dry season farming with little or no irrigation. The Fadama field is within the landmass of University of Abuja and Nigerian Army Range, and Farms located at the Federal Capital Territory of Nigeria (09° 00' 09.9''N 007° 09' 52.9''E and 08° 59' 17.9''N 007° 09' 17.0''E), with an elevation of 246m and 236m respectively. The river Usuma (or locally called Rinpa river) which passes through the area, often serves as a source of water for supplementary irrigation when the soil moisture is no longer sufficient to sustain crop production. The temperature of the area ranges from 25ºC– 27ºC. The highest annual rainfall of the area is 1632mm. The area has recorded the highest relative humidity at 20%. The upland soils of the area under the basement complex formation are generally deep, weakly to moderately structured, sand to sandy clay in texture with gravel and concretionary layers in the upper or beneath the surface layers.

2.2 Experimental design

Stratified Random sampling procedure was adopted, where sites for water wells in the study were selected in the Fadama area to address wetland heterogeneity, improve measurement accuracy, and ensure representation of diverse conditions relevant to water sustainability.

2.3 Population and sample size

The landmass of the University of Abuja covers about 11,800 hectares, of which segments containing wetlands within the habitable areas, particularly near river Usuma were utilized for the study. The sample size was 10 wells which were located on the depression (lower slope) of the catena in the Fadama area of the River Usuma. The positions of the hand-dug wells were selected based on visible catenas that appear naturally in the wetland areas.

2.4 Water table monitoring

Monitoring wells were installed on a 30 m x 30 m grid. Prior to installation, the initial depth to the water table was measured at 1.2 m below ground level (BGL). Wells were constructed using an electric powered hand auger to drill through the unsaturated zone until a continuous, low-permeability clay layer was encountered at approximately 1.8 - 2.0 m depth. This clay layer was penetrated using an electric powered percussion driver and a post-hole digger to access the shallow aquifer beneath it. The final well depth was 3.0 m. A 5.1 cm (2-inch) diameter PVC piezometer was installed, with a slotted screen positioned to span the water-bearing zone of the aquifer. The annular space around the screen was filled with sand pack, and a bentonite seal was placed above it to prevent surface contamination. The general installation procedure followed Ridder (2006).

2.5 Observation and data collection

The water table was recorded at two-week intervals between October 2018 and March 2019 using a manual water level sounder. This six-month study period, encompassing the active farming season, resulted in 13 discrete measurement events.

2.6 Data analysis and computation

Descriptive statistics, including mean, coefficient of variation, and standard deviation were calculated. Autocorrelation and autoregression analysis were conducted on the observed and predicted variables.

Autocorrelation

Autocorrelation explores the relationship between a variable at time x_0 and the same variable at time x_{0+1}. Similarly, autocorrelation length of the variable was determined on the autocorrelation plot.

Stochastic Modelling

Stochastic model was computed using the linear autoregression model given as;

$$Y = \propto + \beta X + e - - - - - - - - - - (2)$$

*w*here, Y = water table at present (variable 1), x = water table at the preceding time (variable 1-1lag), α and β =intercept and slope, e is assumed to be identically and independently distributed and with the validity of the assumption: $l = 0$ and (2) becomes;

$$Y = \propto + \beta X ------------- (3)$$

The model parameters were estimated using Least Square Estimate (LSE).

Computation

The residual of the model prediction, the F-Statistics and the Coefficient of Determination were computed.

3 Results and Discussion

3.1 Applying autoregressive model to assess water availability in the study area

The significant variability in average water table depth between wells (ranging from 5.744 cm to 6.928 cm) highlights substantial spatial heterogeneity across the wetland. This indicates that local subsurface conditions, rather than a single regional water table, dominate hydrologic behavior at this scale (Table 1). The variance in depth measurements for each well further reveals differences in water table stability. Well 2 (σ^2 = 10.775) experienced the most fluctuation over the study period, suggesting it is highly responsive to external drivers like precipitation or pumping. In contrast, the water level in Well 10 (σ^2 = 3.697) remained relatively stable, likely due to local conditions that dampen these external influences, such as tighter soil porosity or lower hydraulic conductivity.

Table 1: Descriptive statistics of the water table depth for the wells.

Well	$\bar{x}$	Sum	Pi	$\boldsymbol{\sigma}^2$	Range	STD	CV(%)
1	7.111	128.00	0.506	7.832	9.100	2.799	39.355
2	8.022	144.40	0.839	10.775	15.100	3.283	40.918
3	7.362	132.52	0.456	6.957	8.200	2.638	35.827
4	6.056	109.00	0.389	6.010	7.000	2.452	40.485
5	6.083	109.50	0.433	5.698	7.800	2.387	39.239
6	7.128	128.30	0.450	6.093	8.100	2.468	34.631
7	6.928	124.70	0.522	7.514	9.400	2.741	39.568
8	7.067	127.20	0.389	3.871	7.000	1.968	27.842
9	5.744	103.40	0.444	4.882	8.000	2.210	38.466
10	6.789	122.20	0.372	3.697	6.700	1.923	28.320
Total		1229.22					

STD=standard deviation, CV=Coefficient of Variation

From these, it is apparent that water table depth for each well varied significantly from one time to the other and it is independent of the distribution of the sample mean, $\bar{x}$

(i.e. the mean, $\bar{x}$ are independent of each other in terms of variability). This finding aligns with the research findings of Donald and Thomas (1997), Wang *et al*. (2022), Xu *et al*. (2020), Zedler and Kercher (2005), and Zhang *et al*. (2021) whose studies also reported fluctuations in water table in upland and prairie-pothole wetland of a tropical region.

The Analysis of Variance (ANOVA) for the site and the interaction between date and site are shown in Table 2. A significant difference exists between the means for all sources of variation.

Table 2: ANOVA for water table parameters.

Source of Variation	Degree of Freedom	Sum of Squares	Mean Sum of Squares	F-Statistics
Date	17	8922.84704	524.8733	0.56^{NS}
Site	9	152483.001	16942.5556	18.081^{**}
Date × Site	153	1360582494	8892696.0390	9490.139^{**}
Error	162	151801.4327	937.0459	
Total	341			

NS = Not significant (p > 0.05; no effect.); * = Significant (p < 0.05; sites differ)
**= Highly significant (p < 0.05; interaction drives variation); Error = Unexplained variation; Total: Overall DF.

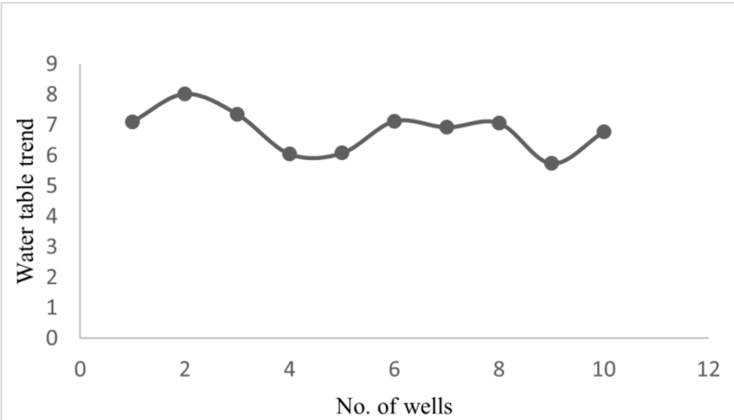

Fig.1: Mean water table of the area (commencing from October 2018 and at every other day till May 2019)

A significant F-statistics was observed 18.081 for site and 9490.139 for Interaction between date and site. The observed F-statistics were significant for both site (F = 18.081) and the date × site interaction (F = 9490.139). Both values exceeded their respective critical F-values at the 0.05 significance level: F(17, 1.96) = 0.560 for site and F(9, 2.71) = 18.081 for the interaction. The mean water table (Figure 1) for the different dates for each well were subjected to autocorrelation analysis because of the mean separation partition of the dates into different classes. The autocorrelation diagram indicated a near-real-life of the water table of the area (Figure 2). The outcome of this study is an indication of deterministic trend of the observation, and hence the data could also be viewed in terms of local correlation. These findings align with the research output of Donald and Thomas (1997) who reported fluctuations with correlative output in wetland water table.

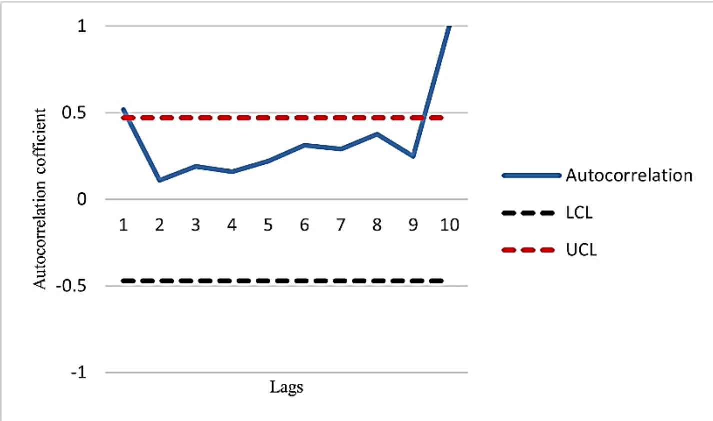

Fig. 2: Autocorrelation function plot for total of wells (LCL = Lower Confidence Level; UCL = Upper Confidence Level)

The methodological approach of this study complements the work of Baareh *et al*. (2006b). While they demonstrated the efficacy of non-parametric models for forecasting water resources, application of a similar model in the present study successfully predicted water table fluctuations in a wetland agricultural context, confirming the model's versatility. Furthermore, key finding that the water table depth exhibits significant spatial autocorrelation directly supports the conclusions of Theib and Ahmed (2006). Their investigation into using correlation for irrigation planning established the principle, while this research provides a concrete case study demonstrating that this spatial dependence must be accounted for to accurately assess water table deficits across a field.

The autocorrelation values of the water table data in the area included both positively and negatively returns, indicating the randomness of the values falls to the range $\pm \frac{2}{\sqrt{n}} = (-0.4714, 0.4714)$. This suggests that the autocorrelation data need no form of adjustment. The autocorrelation length (lag 10) identified in the correlogram corresponds to the number of monitoring wells in the study (Figure 3). This finding methodologically aligns with previous research that successfully employed autocorrelation analysis to understand groundwater dynamics (Zhang and Schilling 2006). Studies of Kisi (2005), IFPRI (2008), IPCC (2022), Junk *et al*. (2013), Kirwan *et al*. (2010), Kisi and Shiri (2011) and Koutrakis (2019) also demonstrated the efficacy of correlative and autocorrelative processes for identifying temporal patterns and spatial dependencies in water table behaviour.

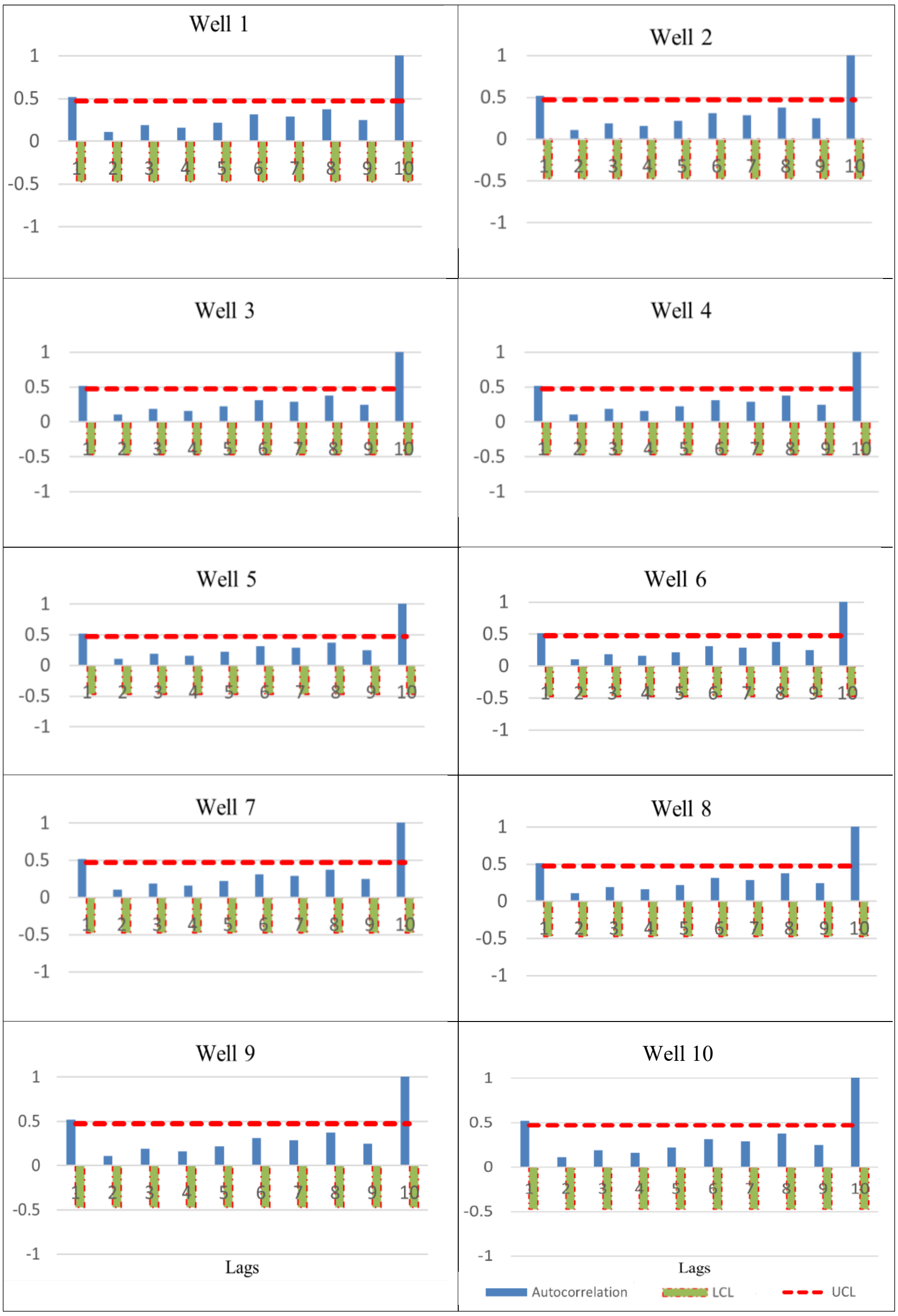

Fig 3. Autocorrelation function plot for each well separately (X-axis: autocorrelation coefficient, and y-axis : the lags)

The Stochastic model for the first order autoregressive model is given as; $Y_t = 4.63102X + 2.008$, where; Y_t=water table depth at current date, while X = water table depth at preceding date. The correlation coefficient (r) for this model is 0.9114 and there is a relatively high F-statistics, which is significant at 0.05% probability level. This implies that there exists a significant difference between the means of both dependent and independent variables. Also, the variance of estimation indicated a significant level of variability in the prediction of the water table depth.

The plot of the actual verses predicted values of the autoregressive model showed a significant correlation. The strong correlation between actual and predicted values in the autoregressive model (Figure 4, Table 3) demonstrates its effectiveness for forecasting water table dynamics. This adds to a body of work, such as Donald and Thomas (1997), which successfully used linear models to describe trends in wetland water levels, confirming that statistical modeling is a viable approach for these systems. The sum of residuals $\Sigma_r = 5.130116$ was higher than zero. This is an indication that the predicted model and the observed model differ. The significant spatial variability in water table depth observed in this study aligns with the fundamental principle established by Donald and Thomas (1997) and Rosenberry and Winter (1997) that wetland hydrology is highly heterogeneous. Furthermore, the high predictive accuracy (r = 0.91) of the developed autoregressive model supports the findings of Pickens *et al*. (2020) that such time-series approaches are effective for modeling complex wetland systems.

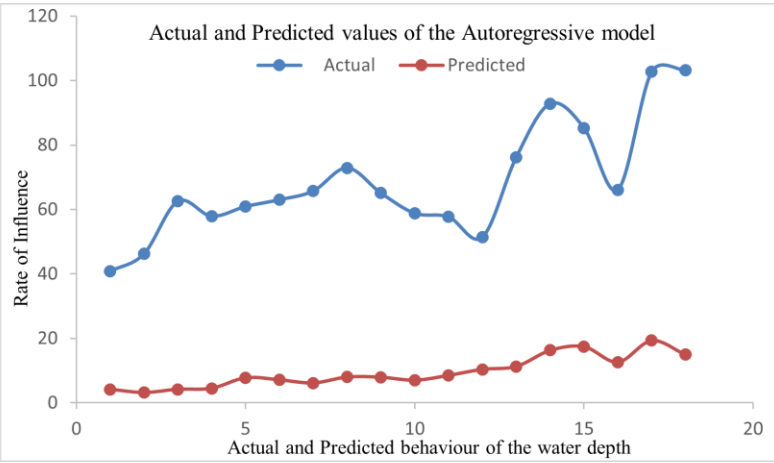

Fig 4. Actual and predicted values of the Autoregressive model (x-axis is periodic date at every other day)

Table 3: Actual and predicted autocorrelation behavior of the wetland water table characteristics.

Week	Actual	Predicted
1	40.80	4.196176468
2	46.20	3.186058351
3	62.52	4.193464224
4	57.90	4.499060863
5	60.90	7.768333754
6	63.00	7.145251471
7	65.70	6.169276769
8	72.90	7.987736923
9	65.10	7.950673834
10	58.80	7.02175293
11	57.70	8.511200227
12	51.40	10.40023116
13	76.20	11.29958208
14	92.80	16.29298774
15	85.30	17.46503362
16	66.10	12.63808115
17	102.70	19.33791434
18	103.20	14.93718409

4 Conclusions

A first-order autoregressive model effectively predicted water table depth in the studied tropical wetland, demonstrating high accuracy ($r = 0.91$) between predicted and observed values. This shows that autoregressive modeling is a practical tool for managing water resources in such environments. The outcome of this study highlighted the potential of wetlands to sustain water availability for food production and for ecosystem management services, hence, standing as a tool for adaptation for integrated water-soil-ecosystem management. The autoregressive model developed in this study proved to be an effective tool for predicting local water table dynamics. This approach can inform water resource management within the specific wetland area studied, potentially increasing its resilience to water stress.

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