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Trend Analysis of Hydrometeorological Time Series under the Scaling Hypothesis

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ABSTRACT

Mann-Kendall (MK) trend test is one of the commonly used statistical tests for detecting changes in hydrometeorological time series. The test is derived as a function of the ranks of observations making it distribution free as well as less sensitive to outliers and non-homogeneous time series. However, climatic variability which is present in such series in the form of autocorrelation violates its independent observations assumption and may lead to erroneous conclusions. The scaling hypothesis has been proposed for modeling such variability in natural time series. This study analyzed 50 years (1971-2020) observed data of rainfall, minimum temperature, maximum temperature and wind speed (obtained from NiMet Kano airport station) for statistically significant trends at monthly, seasonal and annual timescales. The data was analyzed using MK trend test and its modified versions for the effect of autocorrelation and scaling/anti-scaling behavior on the trend tests. The numbers of significant trends were found to reduce from 9, 7, 8 and 2 (when Mk trend test was used) to 9, 7, 6, and 0 (when both autocorrelation and scaling/anti-scaling was considered) for minimum temperature, maximum temperature, total rainfall and average wind speed respectively. Thus some significant trends under independent observations assumption turn out to be spurious trends when the effect of dependence was considered. Moreover all significant trends were found to be positive for rainfall and temperature series except for August that shows a negative trend in maximum temperature. On the other hand, no change in wind speed was observed at all timescales. The results thus indicated a warming and wetter climate for Kano, which will most probably influence other variables including evapotranspiration and stream flow. The results also showed the importance of considering the effect of climatic variability in climate change studies.

Keywords: Mann-Kendall, Trend, Time series, Autocorrelation, Scaling

INTRODUCTION

Over the last five decades, scientists and policy makers have put much effort into climate change with a view to identifying its causes, effects as well as possible mitigation and adaptation strategies. This has resulted in a number of global and regional climate change studies by researchers in different parts of the globe. One of the fields that received a great deal of attention is 'the detection, attribution and extrapolation of changes in past climate/hydrology'. Trend analysis has been commonly used to achieve this especially in the field of water resources and environmental engineering.

Several parametric and nonparametric statistical estimators have been used to detect trends. Most of these standard estimators are derived based on the assumption of independent identically distributed data. The Parametric tests make use of actual values of the data. They are more powerful, but require data to be normally distributed. Parametric tests such as multiple regressions also enable the incorporation of several exogenous variables that may affect the response variable. Nonparametric tests on the other hand make use of the relative values of the data rather than their actual values, thus making it distribution free, less sensitive to outliers and non-homogeneous time series. They are therefore more suitable for detecting trends in hydrometeorological time series, which are often skewed and may contain some outliers. Among the nonparametric approaches, Mann-Kendall (MK) (Mann, 1945; Kendall, 1975) appears to be the most widely used (Hamed, 2008; Gumus *et al* 2017) as well as the most promoted (Jiang *et al*, 2015).

The MK trend test was initially derived for independent data, which is seldom the case when dealing with hydrometeorological time series that are often dependent. The existence of seasonality, autocorrelation and long-term persistence (Hurst or scaling) behavior in such series will violate its independent observations assumption and may lead to erroneous conclusion. Hence, data may have to be converted to purely random for use with MK or the trend test modified to account for this dependence. Several of these approaches have been developed and applied on autocorrelated data, while little attention was given to the effect of seasonality and scaling.

The scaling behavior was first discovered by Hurst (1951) while investigating the discharge series of river Nile. It is the tendency of observed data to stay above or below its mean value for a longer period. This behavior has later been verified in several long time series of hydrometeorological and geophysical processes (Koutsoyiannis, 2006). Hurst (1951) proposed a fraction between 0 and 1 (later known as the Hurst or scaling coefficient (H)) to describe the mode of persistence of a series. An H value of 0.5 represents an independent process, otherwise it represents scaling (H>0.5) or anti-scaling (H<0.5) behavior. The anti-scaling behavior (also detected in natural processes) is characterized by long-term switching between high and low values in adjacent pairs. The presence of scaling behavior would result in underestimation of autocorrelation in the series and overestimation of the significance of MK test or vice versa (Koutsoyiannis, 2003; Hu *et al*., 2020).

Koutsoyiannis (2003) proposed the scaling modeling approach as a stationary alternative to the classical approach of modeling hydrometeorological time series. The basic hypothesis of scaling is that under stationarity assumption, non-periodic series exhibit scale invariant properties (Koutsoyiannis, 2003). Time series obeying such a hypothesis is characterized by an aggregation of large-scale stochastic fluctuations. Unlike the commonly used short range dependence models like Autoregressive (AR) and Autoregressive moving average models (ARMA), the autocorrelation function of a scaling series decays much slower with increasing lag as a result of variability at all timescales greater than the basic time scale rather than the "long term memory" that was earlier suggested (Koutsoyiannis, 2006).

Hamed (2008, 2009) modified the variance and distribution forms of MK trend test under the scaling hypothesis and proposed beta distribution as a more reasonable approximation to the exact distribution than normal distribution in case of moderate length series with scaling behavior. Hu *et al.*, (2020) also modified the variance and distribution pattern of MK under the scaling hypothesis and proposed the generalized normal distribution as a better approximation to the exact distribution for both scaling and anti-scaling characteristics.

This study examined trends in rainfall, minimum temperature, maximum temperature and wind speed at monthly, seasonal and annual timescales for a point source data in Kano, considering the effect of seasonality, autocorrelation and scaling/anti-scaling behavior. Previous studies mostly utilized original Mann-Kendall (MK) trend test (nonparametric) and least square regression (parametric test) all of which require data to be independent, a condition rarely met in hydrometeorological time series that are often dependent. None of such studies considered the effect of scaling/anti-scaling behavior. Considering this effect can cause a change in the significance of trends, thus the results from past studies cannot be relied upon. Therefore, it becomes necessary to re-analyze trends using modified versions of MK that considers the effect of scaling/ anti- scaling behavior.

MATERIALS AND METHODS

A. Description of Station

The weather station used in this study is located at Mallam Aminu Kano International Airport Kano (MAKIA as shown in Fig. 1), latitude 12^0 2'N, longitude 8^0 19'E and an altitude of 476 meters above mean sea level. It is one of the most important stations managed by Nigerian Meteorological Agency (NiMet) as it provides weather information to the airport. It also has the longest observation record among other stations in the state, hence its choice. The station is equipped with rain gauge installed at ground level, a Stevenson's screen installed at 2 meters height containing the minimum and maximum thermometers, an anemometer installed at 6 meters height, and other instruments beyond the scope of this study. The station has not been relocated since its inception, and there was no change in location, height and type of measuring instruments throughout the study period.

B. Data

Existing monthly data for rainfall, wind speed, minimum and maximum temperature that spanned for 50 years (1971-2020) was obtained from NiMet. These values are averages (temperature and wind speed data) or totals (rainfall data) computed from daily observations. The monthly data were used to form seasonal subsets to permit for analysis at the seasonal and annual time scales.

C. Software

1) PyMannKendall (Hussain and Mahmud, 2019): It is a pure python implementation of the non-parametric Mann Kendall trend analysis which brings together several types of Mann Kendall test.

2) MannKendallLTP R function in the HK process R package (Tyralis, 2016): it estimates the Hurst exponent (H) and performs Mann Kendall test under the scaling hypothesis.

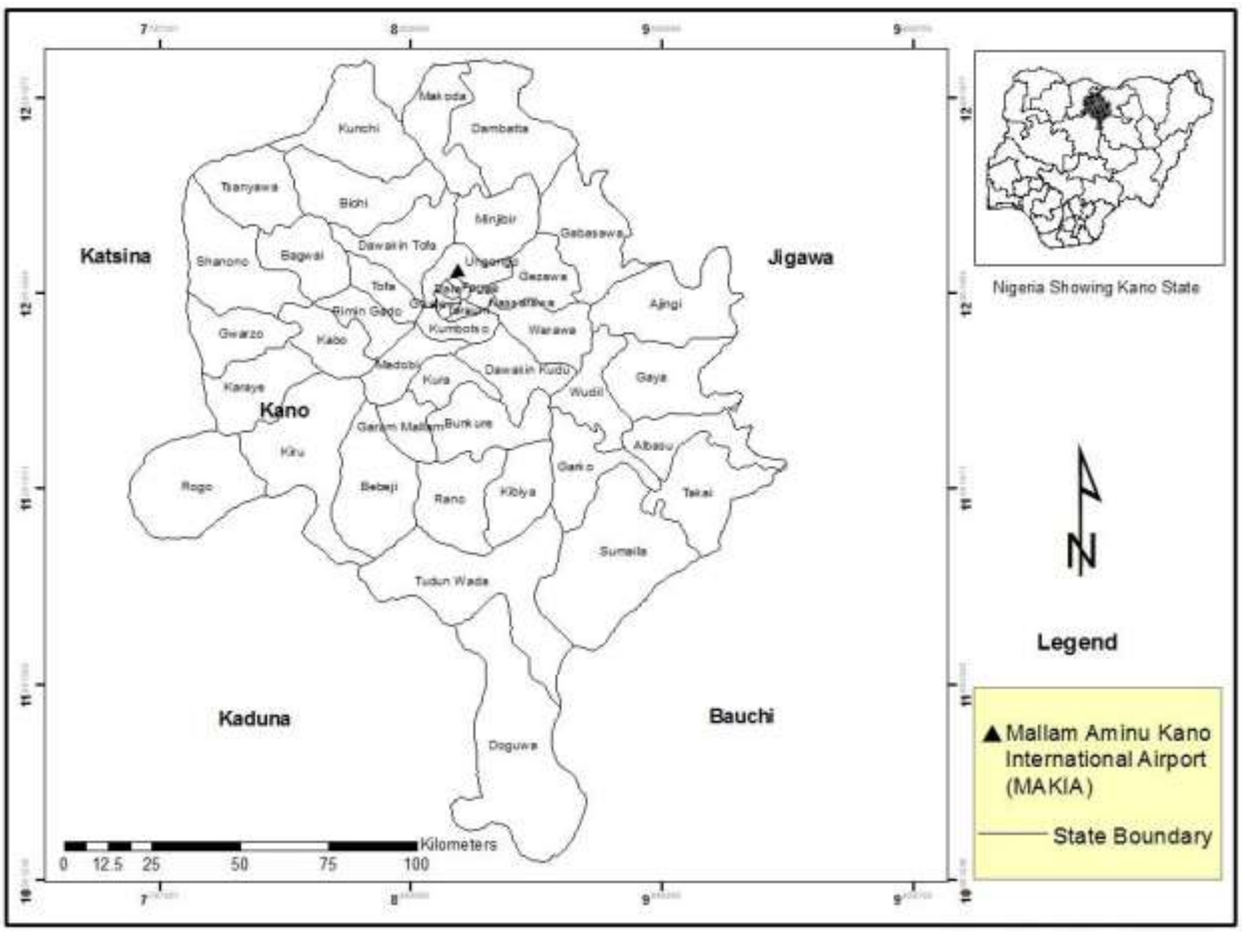

Fig.1: *Map of Kano state showing location of MAKIA (Adapted from Muhammed et al, 2015)*

D. Formation of Time Series

For each hydrometeorological variable, all values recorded at the same period were grouped into time series. Thus 12 series were obtained at the monthly timescale with one for each of the months and 4 series at the seasonal timescale. These include season MAM (March-May), JJA (June-August), SON (September-November), and DJF (December-February).

E. Autocorrelation and Scaling Test

The autocorrelation coefficient at different lags of each series was determined using the ACF function in R. The scaling coefficient was determined using MannKendallLTP R function.

E. Infilling of Missing Values

Missing values were filled using the Sum of local (one value before and one after the missing value) and sample average weighted according to lag 1 autocorrelation and scaling coefficient of the examined series (Pappas *et al.*, 2014). For continuous gaps, the available observations at the gap window boundaries were used for the estimation of the missing value at the middle of the gap window. The estimated value was then used as a proxy for applying the procedure to the new restricted gap windows. For a series $X_1, X_2, X_3 \ldots\ldots\ldots\ldots, X_{N-1}, X_N$, the estimated missing value X_t is given by:

$$X_t = \lambda\frac{\sum_{i=1}^{N}(X_{t-i}+X_{t+i})}{2N} + (1-\lambda)\frac{X_{t-1}+X_{t+1}}{2} \quad (1)$$

Where λ is the weighting factor assigned to the sample average.

G. Trend Tests

The MK test (MK, Mann, 1945; Kendall, 1975), Modified MK test that accounts for serial correlation (MMK, Hamed and Rao, 1998), and the Modified MK test that accounts for the effect of scaling/anti-scaling behavior on the estimation of the autocorrelation coefficient (MKLTP, Hamed, 2008) were utilized in this study. For each test, the effect of seasonality at the annual timescale was removed by combining the results from each of the seasons (Hirsch *et al*, 1982). The test procedure is as follows:

1) Stage one (MK test)

For the time series X =(x_1, x_2……, x_{50}), the MK Trend test statistics was computed as:

$$S = \sum_{k<l} a_{kl}$$

(2)

Where

$$a_{kl} = sign\ (x_l - x_k) = sign\ (R_l - R_k) = \begin{cases} +1, & if\ (x_l - x_k) > 0 \\ 0, & if\ (x_l - x_k) = 0 \\ -1, & if\ (x_l - x_k) < 0 \end{cases}$$

(3)

Where x_k and x_l are the ranks of the time series while R_k and R_l are the ranks of the observations.

For an independent identically distributed series (with at least 10 values) the distribution of S can be approximated by a normal distribution with mean and variance given by (Kendall, (1975):

$$E(S) = 0$$

(4)

$$V(S) = \frac{n(n-1)(2n+5) - \sum_{m=1}^{n} t_m m(m-1)(2m+5)}{18}$$

(5)

Where t_m is the number of ties of extent m, n is the sample size. The standardized test statistic Z for MK was computed by:

$$Z = \frac{S - sign(S)}{V(S)}$$

(6)

The significance of trends was tested by comparing the standardized variable Z with the standard normal variate at 5% significance level (i.e $Z_{cr} = \pm 1.96$ for a two tailed test). If $|Z| \geq 1.96$, the null hypothesis is rejected indicating the presence of a significant trend, otherwise the null hypothesis of no trend is accepted.

The presence of serial correlation in data will interfere with proper identification of significant trend by reducing (increasing) the variance of the test statistics in the case of positive (negative) serial correlation.

Therefore, data was tested again using the Modified Mann Kendall test (Hamed and Rao, 1998), which modifies the variance to account for serial correlation in data.

2) Stage two: Modified MK test (MMK)

The modified variance was recomputed as:

$$V^*(S) = V(S).\frac{n}{n_c} = \frac{n(n-1)(2n+5)}{18} \cdot \frac{n}{n_c}$$

(7)

Where ${}^{n}/_{n_c}$ represents a correction to $V(S)$ due to autocorrelation in data and is approximated as:

$$\frac{n}{n_c} = 1 + \frac{2}{n(n-1)(n-2)} \times \sum_{i=1}^{n-1}(n-i)(n-i-1)(n-i-2)r_k \quad (8)$$

Where r_k is the lag k significant autocorrelation coefficient of the ranks of the time series and is given by:

$$r_k = \frac{\sum_{i=1}^{N-k}(R_i - R_{AV})(R_{i+k} - R_{AV})}{\sum_{i=1}^{N}(R_i - R_{AV})^2}$$

(9)

Where N is the number of ranks of observations. The modified statistic Z_m was then calculated as:

$$Z_m = \frac{S - sign(S)}{\sqrt{V^*(S)}}$$

(10)

3) Stage three: Computation of the Hurst coefficient (H)

The Hurst Coefficient was estimated by using the procedure outlined below:

(1) The time series X was detrended using non parametric Theil-Sen slope β (Sen, 1968) which is given by:

$$\beta = \text{median}\left(\frac{x_l - x_k}{l-k}\right) for\ all\ k < l$$

(11)

(2) The equivalent normal variates (Z_t) of the ranks of the detrended series were obtained by using the transformation below:

$$Z_t = \varphi^{-1}\left(\frac{R_t}{n+1}\right)$$

(12)

Where R_t is the rank of the detrended observation x_t, n is the number of observations, and φ^{-1} is the inverse standard normal distribution function.

(3) The Hurst coefficient was obtained from the equivalent normal variates Z_t by

maximizing the log-likelihood function according to Mcleod and Hipel (1978) which reduces to:

$$\log L(H) = -\frac{1}{2} log|C_n (H)| - \frac{Z^T[C_n (H)^{-1}]Z}{2\gamma_0}$$

(13)

Where γ_0 is the variance of Z_t, Z^T is the transpose vector of the equivalent normal variates, and $C_n (H)$ is the correlation matrix of H given by:

$$C_n(H) = [\rho_{|j-i|}], i = 1 : n, \ j = 1 : n$$

(14)

The autocorrelation function ρ_l of lag l for a given H is independent of the time scale of aggregation and is given as:

$$\rho_l = 0.5 \ (|l+1|^{2H} - 2|l|^{2H} + |l - 1|^{2H}) \ for \ l > 1$$

(15)

$\log L(H)$ was computed for values of H between 0 and 1 at a step of 0.02. The value of H that gives the maximum value of $\log L(H)$ was noted as the H value for the given time series. The estimated H is approximately normally distributed for the uncorrelated case (i.e when true H is 0.5) with mean (μ_H) and standard deviation (σ_H) given by (Hamed, 2008):

$$\mu_H = 0.5 - 2.874n^{-0.9067}$$

(16)

$$\sigma_H = 0.77654n^{-0.5} - 0.0062$$

(17)

Then Z_H was computed as follows:

$$Z_H = \frac{H - \mu_H}{\sigma_H}$$

(18)

The significance of H was tested by comparing the value of Z_H with that of the standard normal variate at 10% significance (i.e $Z_{cr} = \pm 1.64$). If H is not significant, the decision of MK or modified MK is accepted. If H is significant, data is further tested under the scaling hypothesis.

4) Stage four: MK trend test under the scaling hypothesis (MKLTP)

A biased estimate of the modified variance under scaling behavior $V(S)^{MB}$ is represented as:

$$V(S)^{MB} = \sum_{I<J} \sum_{K<l} \frac{2}{\pi} sin^{-1} \left(\frac{\rho|j-i|-\rho|i-l|-\rho|j-k|-\rho|i-k|}{\sqrt{(2-2\rho|i-j|)(2-2\rho|k-l|)}} \right) \quad (19)$$

$V(S)^{MB}$ was corrected for bias by multiplying it by a bias correction factor B given by:

$$B = a_0 + a_1 H + a_2 H^2 + a_3 H^3 + a_4 H^4 \quad (20)$$

Where the coefficients $a_0, \dots \dots \dots \dots, a_4$ are functions of the sample size n as described in Hamed (2008). A modified test statistic Z_{MH} was then computed using the modified variance. If Z_{MH} is significant, the trend is significant, otherwise it is not. The slope of the trend was determined using the Theil-Sen approach as given in equation (11).

RESULTS AND DISCUSSION

A. Minimum Temperature

The summary of the test results for minimum temperature at the monthly, seasonal and annual timescales using MK, MMK, and MKLTP are shown in Fig. 2 together with 1.96 cut line representing the critical Z value for a two tailed test at 5% significance level. Other important statistics are presented in Table 1. From Table 1, it was observed that the S-values are positive in all but two series (Nov. and Dec.) thereby indicating the dominance of positive trends. The Hurst exponent values range from 0.27-0.69, with nine out of the sixteen series showing anti-persistence behavior (H<0.5) and the rest showing persistence behavior.

Table 1: *MK Statistics, Hurst Exponent and Sen's slope for Minimum temperature*

Time scale	MK Stat. (S)	Hurst (H)	P-Value (H)	Sen's slope (^{0}C/Yr)	Time scale	MK Stat. (S)	Hurst (H)	P-Value (H)	Sen's slope (^{0}C/Yr)
Jan	6	0.30	0.26	-----	**Oct**	143	0.36	0.58	-----
Feb	133	0.45	0.74	0.021	**Nov**	-145	0.69	0.01	-----
Mar	23	0.40	0.86	-----	**Dec**	-146	0.54	0.24	-----
Apr	238	0.37	0.63	0.015	**MAM**	262	0.45	0.72	0.016
May	352	0.56	0.16	0.027	**JJA**	444	0.66	0.02	-----
Jun	328	0.47	0.63	0.023	**SON**	57	0.56	0.17	-----
Jul	474	0.59	0.10	0.025	**DJF**	5	0.49	0.49	-----
Aug	434	0.60	0.07	0.023	**Annual**	768	-----	-----	0.010
Sep	454	0.27	0.17	0.027					

From Fig. 2, MK and MMK returns the same Z values for the months of January, June, October, December and the seasons SON and DJF, thus showing no effect of autocorrelation. The Hurst coefficients were also not significantly different from 0.5 (p-value (H)> 0.1), thus the results of MK Test were accepted for these series. The months of February, March, April, May, September and the season MAM have an insignificant Hurst coefficients and a strong effect of autocorrelation due to the observed differences in the Z-values of MK and MMK.

Thus, the results of MMK were accepted for these series. For the months of July, August and the season JJA the Z values of MK and MMK remains the same. However, the existence of significant scaling behavior for these series gives an indication of underestimation of serial correlation by MMK thus the results of MKLTP were accepted for such series. November and Annual average exhibits both significant autocorrelations and scaling behavior hence the result of MKLTP was also accepted.

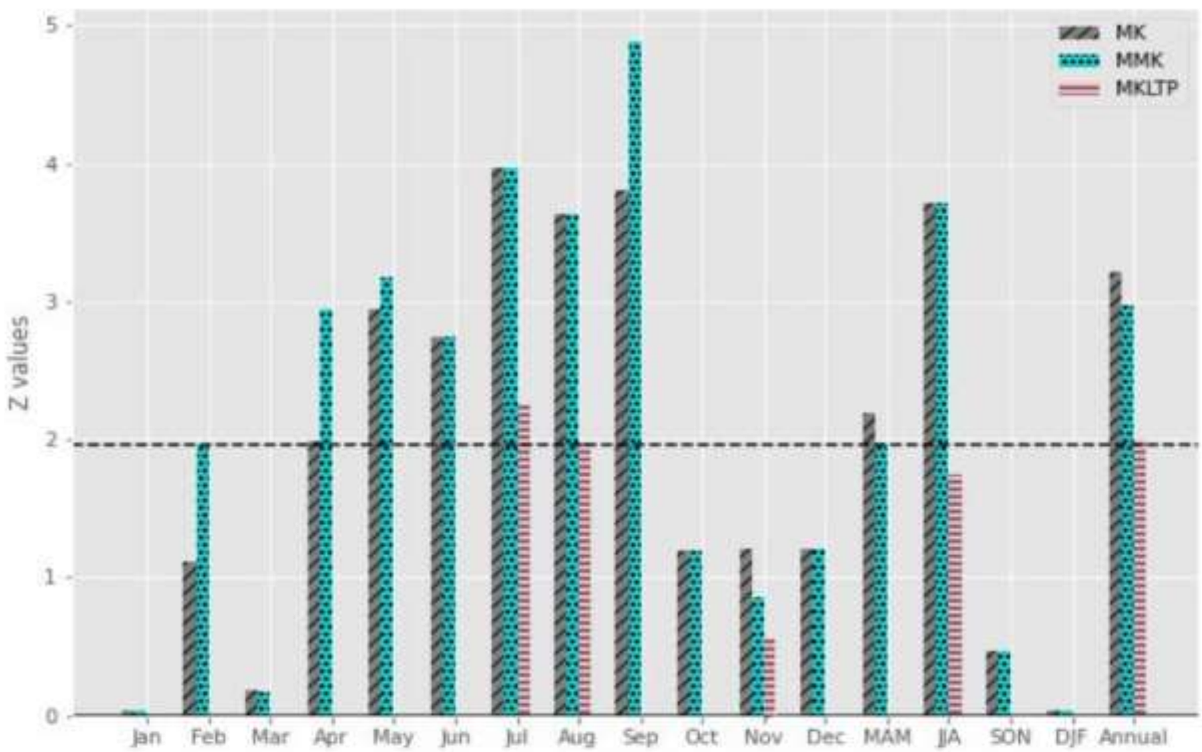

Fig. 2: *Absolute values of Z for MK, MMK, and MKLTP (Minimum Temperature)*

The number of series showing significant trends using MK/MMK/MKLTP were 9/10/9 respectively all of which are positive. While MK detects an insignificant trend for February as a result of negative autocorrelation, the trend was significant when MMK was used. On the other hand, while MK and MMK returns similar significant Z values for season JJA due to underestimation of autocorrelation caused by scaling, the trend was insignificant when MKLTP was used, thus returning the number of significant trends back to 9. Sen's slope results (Table 1) indicate the highest rate of significant change in May and September (0.027^0C/Year) while the lowest value was observed in annual average (0.010^0C/Year).

B. Maximum Temperature Figure 3 and Table 2 show the test results for maximum temperature at the monthly, seasonal and annual timescales in a similar way as it is presented earlier. The S-values were positive in all series except August, September, October, and JJA season, thereby indicating the dominance of increasing trends.

Table 2: *MK Statistics, Hurst Exponent and Sen's slope for Maximum temperature*

Time scale	MK Stat. (S)	Hurst (H)	P-Value (H)	Sen's slope ($^0C/Yr$)	Time scale	MK Stat. (S)	Hurst (H)	P-Value (H)	Sen's slope ($^0C/Yr$)
Jan	24	0.42	0.97	-----	**Oct**	-95	0.50	0.44	-----
Feb	68	0.48	0.57	-----	**Nov**	343	0.41	0.94	0.036
Mar	312	0.26	0.13	0.033	**Dec**	197	0.44	0.85	-----
Apr	274	0.14	0.01	0.020	**MAM**	444	0.48	0.56	0.033
May	261	0.41	0.97	0.027	**JJA**	-28	0.35	0.51	-----
Jun	38	0.38	0.73	-----	**SON**	138	0.35	0.49	-----
Jul	121	0.32	0.35	-----	**DJF**	152	0.43	0.94	-----
Aug	-252	0.44	0.79	-0.014	**Annual**	706	-----	-----	0.015
Sep	-54	0.37	0.65	-----					

The Hurst exponent values range from 0.14-0.50, with only October showing random behavior (H=0.50) and the rest showing anti-persistence behavior out of which only April is significant. Time series that shows no effect of autocorrelation and an insignificant anti-scaling or random behavior as observed in Fig, 3 and Table 2 are those for the months of February, June, July, October, November, December and the season MAM. The results of MK were accepted for such series. Significant autocorrelations and an insignificant anti-scaling characteristic (P-value{H}>0.1) was observed for the months of January, March, May, August, September, the seasons JJA, SON, DJF and the annual average. The results of MMK were thereby accepted for these series. For the month of April, the effect of negative autocorrelation and anti-scaling behavior was observed; hence the result of MKLTP was accepted.

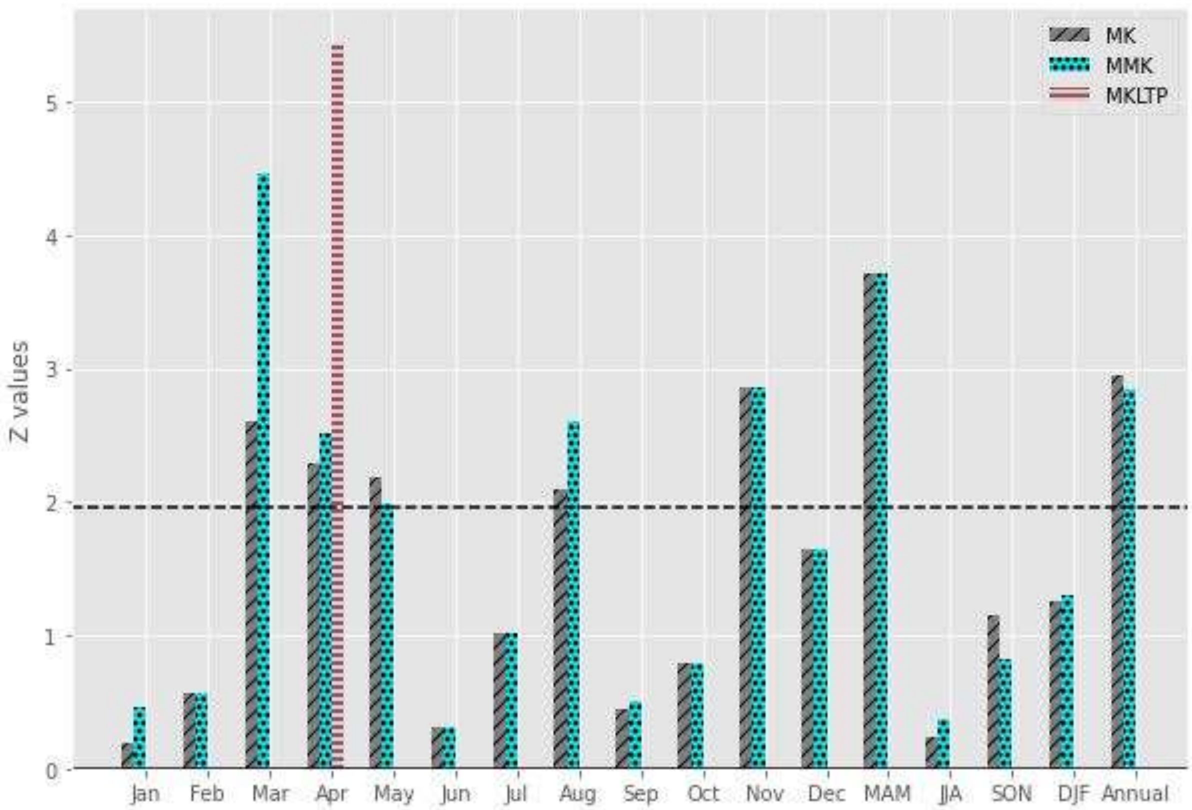

Fig. 3: *Absolute values of Z for MK, MMK, and MKLTP (Maximum Temperature)*

The numbers of significant trends using MK/MMK/MKLTP were 7/7/7 respectively. Thus, although there was change in the Z values, no change of significance was observed when the proposed modifications were used. In addition unlike minimum temperature for which all significant trends were positive, a significant decrease was observed in August for maximum temperature. The highest rate of significant change was observed in November

(0.036^0C/Year), while the lowest value was observed in August (-0.014^0C/Year).

The result of this study is consistent with the findings of Abdussalam (2015) and Dan'azumi and Ibrahim (2021) that also observed an increasing trend in annual average of minimum and maximum temperature for the same station but using a different period of study and method. It was also consistent with the findings of Rosmann *et al*. (2016) that observed predominantly increasing trend in temperature indices at different regions of the world using MK method. A dominant positive trend in annual mean, maximum and minimum values of temperature was also observed in Bangladesh when the effect of scaling was considered (Shahid *et al*., 2014).

C. Total Rainfall

Figure 4 and Table 3 show a summary of results for total rainfall at the monthly, seasonal and annual timescale. From Table 3, the S-values were positive in all but February, April, November, and season DJF thereby indicating the dominance of increasing trends. The Hurst exponent values ranges between 0.31-0.99 thus indicating the existence of persistence and anti-persistence characteristics. The Z values (Fig. 4) of MK and MMK were the same for the months of March, May, August, September, October, November and the seasons MAM and SON, thereby indicating the absence of autocorrelation. Their Hurst exponents (Table 3) were also not significantly different from 0.5, thus the result of MK is valid for such series.

Significant effect of autocorrelation and an insignificant scaling/anti-scaling behavior was observed for the series of February, April, June, DJF and the annual totals, thus the results of MMK were accepted for such series.

Table 3: MK Statistics, Hurst Exponent and Sen's slope for Total Rainfall

Time scale	MK Stat. (S)	Hurst (H)	P-Value (H)	Sen's Slope (mm/yr)	Time scale	MK Stat. (S)	Hurst (H)	P-Value (H)	Sen's slope (mm/yr)
Jan	0	0.99	0.00	……	**Oct**	231	0.53	0.27	0.15
Feb	-53	0.44	0.82	……	**Nov**	-7	0.45	0.72	……
Mar	26	0.35	0.51	……	**Dec**	0	0.99	0.00	……
Apr	-44	0.31	0.32	……	**MAM**	73	0.46	0.70	……
May	163	0.54	0.23	……	**JJA**	497	0.67	0.01	……
Jun	305	0.55	0.19	1.75	**SON**	360	0.51	0.35	2.77
Jul	370	0.60	0.08	……	**DJF**	-53	0.44	0.82	……
Aug	377	0.54	0.23	4.25	**Annual**	877	-----	-----	3.15
Sep	312	0.51	0.35	2.30					

For the months of January and December, the MK test statistic was zero while the Hurst coefficient approaches one as a result of absence of rainfall leading to long term clustering of zero values. The Z values were zero thus indicating the absence of any change. Both autocorrelation and scaling behavior was observed for the series of July and JJA, hence the result of MKLTP was accepted for such series.

The numbers of significant trends using MK/MMK/MKLTP were 8/8/6 respectively. Thus there was no change of significance when MMK was used. When scaling was considered, the number of significant trends dropped to 6. Thus while MK and MMK detected a significant trend for July and JJA as a result of significant scaling behavior, the trend was insignificant when MKLTP was used. Theil-Sen slope estimate indicated the highest rate of change in August (4.25mm/year), while the lowest was observed in October (0.15mm/year).

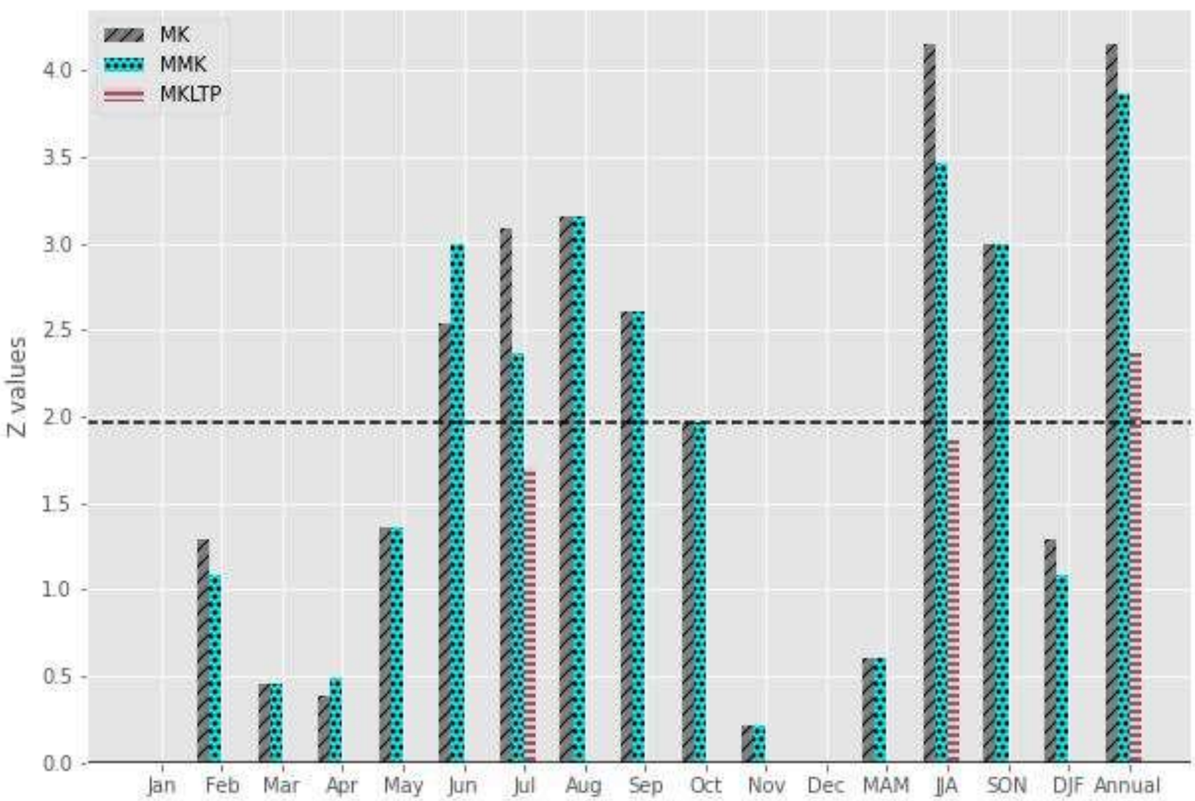

Fig. 4: *Absolute values of Z for MK, MMK, and MKLTP (Total Rainfall)*

Significant increase in total annual rainfall for this station has also been reported by Abaje *et al*. (2012), Ogunrinde *et al*. (2019) and Umar and Bako (2019), while no change was observed by Ati *et al*. (2008). Such discrepancies may be due to differences in selected period of study and method used. Fewer changes were also observed in different regions of the world using MK method (Rosmann *et al*., 2016). On considering the effect of autocorrelation and scaling, no change was observed in most stations of Bangladesh (Shahid *et al*., 2014), while a declining trend was observed in most stations of Northwest Iran (Dinpashoh *et al.*, 2014). Thus the direction of trend in rainfall is location dependent, unlike temperature which displays predominantly increasing trends globally.

D. Wind speed

Figure 5 and Table 4 show the summary of the test results for average wind speed. From Table 4, a negative S value was observed in all the series except November, thereby indicating the dominance of reduced wind speed.

__Table 4:__ MK Statistics, Hurst Exponent and Sen's slope for Average Wind speed

Time scale	MK Stat. (S)	Hurst (H)	P-Value (H)	Time scale	MK Stat. (S)	Hurst (H)	P-Value (H)
Jan	-43	0.72	0.003	**Oct**	-164	0.91	2E-6
Feb	-320	0.69	0.008	**Nov**	26	0.84	5E-5
Mar	-150	0.69	0.009	**Dec**	-194	0.74	0.002
Apr	-90	0.78	4E-4	**MAM**	-145	0.78	5E-4
May	-117	0.64	0.03	**JJA**	-192	0.81	2E-4
Jun	-105	0.71	0.005	**SON**	-95	0.92	1E-6
Jul	-94	0.74	0.002	**DJF**	-194	0.74	0.002
Aug	-174	0.79	4E-4	**Annual**	-164	-----	-----
Sep	-221	0.84	5E-5				

From Fig. 5, a difference in Z values of MK and MMK was observed in all series except May, as a result of the effect of autocorrelation. From Table 4, all the series have significant scaling behavior, hence only the results of MKLTP were accepted. No significant trend was observed at all timescales when the effect of scaling was considered.

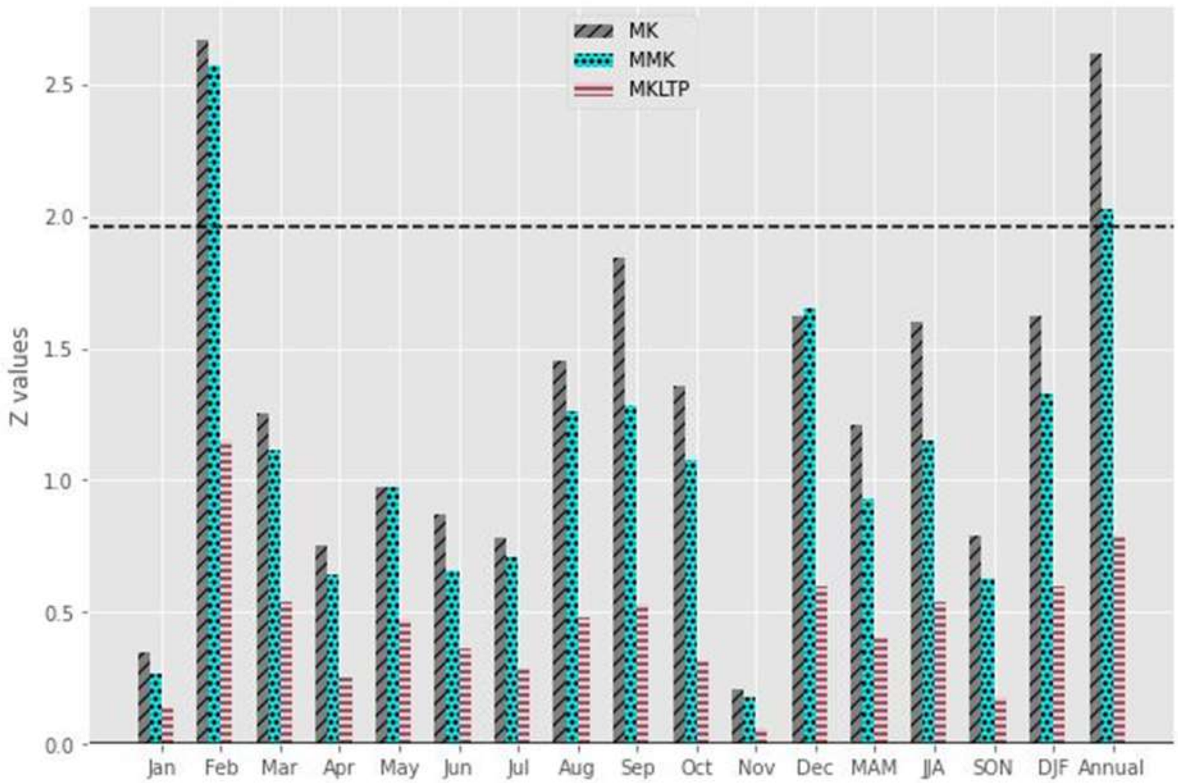

Fig. 5: *Absolute values of Z for MK, MMK and MKLTP (Wind Speed)*

The result of this study is inconsistent with the findings of Amadi and Udo (2015) that detected significant increase in annual mean wind speed for this station using MK method. The variation may be due to differences in selected period of study and method. However the result is in agreement with findings in Nigeria (Amadi and Udo, 2015), USA (Pryor *et al*, 2009), West coast of Canada (Tuller, 2004), China (Guo *et al*., 2010), Australia (Troccoli *et al*, 2011) and mainland areas of Northern Hemisphere (Vautard *et al*, 2010) where predominantly declining trend (significant or insignificant) in wind speed was observed in the last decades for selected stations across the countries/region. Guo *et al*. (2010) attributed the reduction in wind speed to changes in atmospheric circulation due to climatic changes, while Vautard *et al*, (2010) attributed it to both changes in atmospheric circulation (depending on region) and surface roughness owing to changes in vegetation cover, land use and urbanization.

CONCLUSIONS

The present study analyzed trends in time series of rainfall, temperature and wind speed at the monthly, seasonal and annual timescales for a point source data in Kano, Nigeria using MK trend test and its modified versions for the effect of seasonality, autocorrelation and long term persistence/anti-persistence characteristics. Knowledge of changes in these parameters and their expected future behavior is relevant especially to water resources planners, Agricultural industries, and Energy industries Results showed that at 5% significance level some changes had occurred over the last five decades with minimum temperature increased in the months of February, April, May, June, July, August, September, season MAM and at annual timescale. On the other hand, maximum temperature decreased in August and increased in March, April, May, November, season MAM and at annual timescale. Thus temperature change in Kano mainly follows the global warming trend which may be attributed to increased greenhouse gas emission. Total rainfall increased in June, August, September, October, season SON and at annual timescale, while there was no change in wind speed at all timescales for the study period.

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