DATA TEST AND PRE-TREATMENT FOR HYDROLOGICAL MODELLING AND APPLICATIONS

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ABSTRACT:

The proper application of meaningful hydrological model output must be preceded by use of reliable model inputs, the quality and behaviour, which must be ascertained by evaluating for any intrinsic quality problems. Long term (>40 years) rainfall hydrological data for the 5 rainfall stations situated in a catchment supplying part of the larger Nairobi metropolitan and its environs are used to demonstrate the need for data quality check. Tests for outlier analysis, trends analysis, autocorrelation and homogeneity are performed on the data. Results indicate that one station had an outlier data point. The trends analysis using the Mann-Kendal method with the Sen slope analysis using the raw data show general non statistically significant declining rainfall over the period for both annual and seasonal rainfall and significant increase in maximum temperature at 95% confidence level. Homogeneity test using the Pettit test identified break points. Trend analysis after removal of change points returns significant trends in annual rainfall for three of the five stations and several seasonal datasets at 95% confidence level. There is therefore need to pre-treat data appropriately before application in modeling and decision support simulations. Pre-treatment of data prior to use in hydrological modelling is expected to yield more reliable/accurate model predictions by reducing errors associated with model inputs.

Keywords: Quality, analysis, outlier, confidence level, hydrological data

1.0 INTRODUCTION

The growing use of modeling and simulation as a decision support tool has led to the increased use of data, both observed and remotely sensed and available through local repositories and global databases. Whereas every generator and custodian data endeavors to ensure the highest standards in data quality, the evidence of use of data, not just of questionable quality, but without the necessary pre-treatment, to support a far-reaching decision in development of infrastructure and other costly decision is not uncommon. According to Contributor (2008), George Fuechsel’s popularized “garbage in, garbage out” (GIGO) needs to be a constant reminder to all modelers on the need to pass a quality check on
the data before use. Petroski (1992), while acknowledging that engineering is a human endeavor prone to error, agrees that “some engineering errors are merely annoying while others are humanly unforgiveable”. Traditional quality management of hydrological data focuses mainly on intrinsic quality problems, such as outlier detection, nullity interpolation, consistency, completeness (Li, Hiu, & Xiaofeng, 2015).

According to Cantor, Alida; Kiparsky, Michael; Kennedy, Rónán; Hubbard, Susan; Bales, Roger; Cano Pecharroman, Lidia; Guivetchi, Kamyar; McCready (2018), data sources are diverse, spanning topics far beyond those directly related to the hydrologic cycle, such as precipitation and stream flow. Further, if commonness of use reflects importance for decision making, then it is particularly important to ensure accessibility, interoperability, and completeness for the very few data (e.g., streamflow and precipitation) that were common across many use cases, within a data system.

2.0. MATERIALS AND METHODS

2.1 STUDY AREA

The watershed is located in medium rainfall potential area of Athi Basin with moderate and reliable rainfall. It has two distinct rainy seasons: The long rains experienced in March-April-May (MAM) and short rains experienced in October and November. The mean temperature is 26°C with temperature ranging from 17.1°C in the upper highlands to 34°C in the lower midlands (Waithaka, Murimi, & Obiero, 2021). Table 1 below shows the meteorological stations within the study area for which rainfall and temperature data was used. Rainfall data was available in all the five (5) stations and the data was 100% filled with no data gaps. Temperature data was only available from Thika station (9137048).

| Station Name                        | Station ID | Data available | Altitude | Longitude | Latitude |
|-------------------------------------|------------|----------------|----------|-----------|----------|
| Githunguri Agricultural station     | 9136098    | 1970-2017      | 1999m    | 36°47'E   | 01°04'S  |
| Jacaranda Coffee Research           | 9136084    | 1970-2017      | 1608m    | 36°54'E   | 01°05'S  |
| Ndoondu Estate-Kiambu               | 9136018    | 1970-2017      | 1655m    | 36°52'E   | 01°07'S  |
| Tatu City                           | 9136092    | 1970-2010      | 1554m    | 36°47'E   | 1°08'S   |
| Thika Meteorological Station        | 9137048    | 1970-2017      | 1463m    | 37°06'E   | 1°01'S   |

2.2. GRAPHIC VISUAL INSPECTION

Often, the mere display of the data will show areas of inconsistency that would alert a user of the need for further data exploration before actual use of the data. Despite its obvious shortcomings of subjectivity and hence irreproducibility and inapplicability in large data sets, visual inspection is a “powerful expert system for simultaneous, case specific multi-criteria evaluation which provides results in close accordance with the user’s needs” (Ehret & Zehe, 2010).
2.3. Outlier Analysis

For large sample sizes (N>30), the Grubbs test (or the Extreme Studentized Deviate) tests for a single outlier is used. The Extreme Studentized Deviate procedure can detect more than one outlier. Moreover, it can detect outliers even when the one-outlier tests above do not report significance, because of so-called “masking”. The procedure starts by testing the most extreme value in the complete sample, giving a test statistic R1 (= Grubbs G). This most extreme value is then removed from the sample and the procedure is repeated until 20% of the sample has been tested (Polhert, 2016).

In the Grubbs test, the G statistics is expressed as:

\[ G = \frac{\text{max}|x_i - \bar{x}|}{s} \] ...1.1

where \( \bar{x} \) is the sample mean and s is the sample standard deviation. The critical value for G at a two-sided significance level of \( \alpha \) is given by

\[ G > \frac{N-1}{\sqrt{N}} \sqrt{\frac{t_{\alpha/(2N),N-2}^2}{N-2 + (t_{\alpha/(2N),N-2})^2}} \] ...1.2

where \( t_{\alpha/(2N),N-2} \) is the critical value of the t distribution with N-2 degrees of freedom and a significance level of \( \alpha/(2N) \). According to Polhert (2016), the Grubb test is a two-sided test, testing for presence of an outlier at either end of the range (smallest or largest value).

2.4. Trend Analysis

Trend analysis for climatic variables was based on the nonparametric Mann-Kendall test for the trend and the nonparametric Sen’s method for estimation of the magnitude of the trend. According to Salmi, Maatta, Anttila, Ruoho-Airola, & Amnell (2002), in the Mann-Kendall test, missing values are allowed, and the data do not need to conform to any particular distribution. The Sen’s method is not greatly affected by gross data errors or outliers and can be computed when data are missing. The Mann-Kendall test is used specifically to determine the central value or median changes over time (Helsel & Hirsch, 2002), and the statistic Z (or S if sample size, n<10) is given by:

\[ S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sgn}(x_j - x_i) \] ...1.1

Where:

\[ \text{sgn}(x_j - x_i) = \begin{cases} 1, & x_i > x_j \\ 0, & x_i = x_j \\ -1, & x_i < x_j \end{cases} \] ...1.2

For a time series \( x_k, k = 1, 2 \ldots n \).

When \( n \geq 10 \), \( S \) becomes approximately normally distributed with mean = 0 and variance as:

\[ \sigma_s^2 = \frac{n(n-1)(2n+5)-\Sigma t(t-1)(2t+5)}{18} \] ...1.3

Where: \( t \) is the extent (number of \( x \) involved) of any given tie and \( \Sigma \) denotes the summation over all ties.

Then \( Z_c \) follows the standard normal distribution where:

\[ Z_c = \begin{cases} \frac{(S-1)}{\sigma_s}, & S > 0 \\ 0, & S = 0 \\ \frac{(S+1)}{\sigma_s}, & S < 0 \end{cases} \] ...1.4

The null hypothesis that there is no trend is rejected when:

\[ |Z_c| > Z_{1-\alpha/2} \] ...1.5

Where, \( Z \) is the standard normal variate and \( \alpha \) is the level of significance for the test. At certain probability level \( H_0 \) is rejected in favour of \( H_1 \) if the
absolute value of S equals or exceeds a specified value $S_{\alpha}/2$, where $S_{\alpha}/2$ is the smallest S which has the probability less than $\alpha/2$ to appear in case of no trend. A positive (negative) value of S indicates an upward (downward) trend.

The Sen’s method uses a linear model for the trend. The magnitude of trend is predicted by the Sen’s estimator. The slope ($T_i$) of all data pairs is computed as:

$$T_i = \frac{x_j - x_k}{j - k}$$

...1.6

For $i = 1, 2 \ldots N$.

Where: $x_j$ and $x_k$ are considered as data values at time j and k (j>k), correspondingly.

The median of these N values of $T_i$ is represented as Sen’s estimator of slope which is given as:

$$Q_i = \begin{cases} 
\frac{T_{N+1} + \frac{T_N}{2}}{2} & \text{N is odd} \\
\frac{T_N + T_{N+2}}{2} & \text{N is even}
\end{cases}$$

...1.7

A positive value of Q indicates an increasing trend whereas a negative value indicates a decreasing trend.

2.5 AUTOCORRELATION

According to Hamed & Rao (1998) and Sheng Yue, Paul Pilon, & George Cavadias (2002), trend detection in a series is largely affected by the presence of autocorrelation. Autocorrelation is either positive or negative and is the correlation of a time series with its own past and future values. A positive autocorrelation is a specific form of “persistence”, a tendency for a system to remain in the same state from one observation to the next. With a positive autocorrelation in the series, the possibility for a series to be detected as having a trend is higher; this may not always be true. With a negative autocorrelation, the possibility of a series to be detected is less, hence an existing trend may be missed.

The graphic method(s) and the Durbin Watson (DW) statistics (Durbin & Watson, 1951) are the commonly applied methods to test for serial correlations in a time series. The graphic methods for assessing the autocorrelation of a time series are the time series plot, the lagged scatterplot, and the autocorrelation function. The autocorrelation function was carried out on evenly sampled temporal/stratigraphic data. The lag times $\tau$ up to n/2, where n is the number of values in the vector, are shown along the x-axis, the autocorrelation function is symmetrical around zero (Davis, 1985). In the DW method, the statistic $d$ provides a test of the null hypothesis $H_0: \rho = 0$ in the following specification for the error terms, $\mu_i = \rho \mu_{i-1} + \epsilon_i$. If the test is rejected, there is evidence for first-order serial correlation. By checking the DW table for critical values, the above hypothesis can be tested.

$$d = \frac{\sum(u_t - u_{t-1})^2}{\sum \mu_t^2}$$

...1.8

$$\rho = \frac{\sum(u_t u_{t-1})}{\sum \mu_t^2}$$

...1.9

Where: $\rho$ = estimated serial correlation coefficient, and $d = 2(1-\rho)$, If there is no serial correlation, $\rho=0$, then $d=2$, If there is positive serial correlation, $\rho>0$, then $d<2$, If there is negative serial correlation, $\rho<0$, then $d>2$.

In order to test for the serial correlation:

Test $H_0: \rho = 0$ against $H_A: \rho > 0$ and $H_o: \rho = 0$ against $H_A: \rho < 0$ for positive and negative serial correlation, respectively. The critical values, $d_L$ and $d_U$ at $\alpha$ of 1%, 5% or 10%, and note $k'$ is the number of coefficients in the regression excluding the constant.
For the positive correlation, the null is rejected if \( d \leq d_L \), if \( d \geq d_U \), the null is not rejected, if \( d_L < d < d_U \), the test is inconclusive, while for negative correlation, the 4-d is computed and the null is rejected if; \( 4-d \leq d_L \). If \( 4-d \geq d_U \), the null is not rejected, if \( d_L < 4-d < d_U \), the test is inconclusive. The decision zones for the DW test are summarized in Fig 7-4.

The Durbin Watson test reports a test statistic, with a value from 0 to 4, where:
- is no autocorrelation.
- 0 to <2 is positive autocorrelation (common in time series data).
- >2 to 4 is negative autocorrelation (less common in time series data).

A rule of thumb is that test statistic values in the range of 1.5 to 2.5 are relatively normal with values outside of this range being a cause for concern.

2.6. HOMOGENEITY

The homogeneity tests of time series are classified into two groups of ‘relative method’ and ‘absolute method’. In relative method, neighboring stations are used in the testing process while the test is applied for each station individually in absolute method. Although the relative method easily detects inhomogeneity, it does not show how real changes can be distinguished from random fluctuations, hence the use of Absolute method based on statistical analysis to check inhomogeneity is preferred(Chang, Ghani, & Othman, 2017).

Two commonly used tests for time series Homogeneity are the Pettitt's test and the Buishand (Buishand, 1982) Range Test. Pettitt's test is applied to detect a single change-point in hydrological series or climate series with continuous data(Polhert, 2016; Pettitt, 1979). It tests the H0: The T variables follow one or more distributions that have the same location parameter (no change), against the alternative: a change point exists. The non-parametric statistic is defined as:

\[
K_T = \max |U_{t,T}|
\]  
...2.0

Where:

\[
U_{t,T} = \sum_{i=1}^{t} \sum_{j=t+1}^{T} \text{sgn}(X_i - X_j)
\]  
...2.1

The change-point of the series is located at \( K_T \), provided that the statistic is significant. The significance probability of \( K_T \) is approximated for \( p<=0.05 \) with

\[
p \sim 2 \exp \left( \frac{-6K_T^2}{T^3+T^2} \right)
\]  
...2.3

3.0. RESULTS AND DISCUSSION

3.1. OUTLINER ANALYSIS

3.1.1. GRUBB TEST

The results indicate that all but one rainfall gauging station had data that had no statistically significant outlier points (G<3 and p>0.05) at 95% confidence level as shown in Table 2 below. Githunguri Gauging station (ID 9136165) however had outlier measures point with a G-statistic of 3.39.

Table 2: Grubb Test for Outlier Analysis (* indicate presence of outlier point(s))
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| Station ID  | 9136165   | 9136084   | 9136092   | 9137048   | 9136018   |
|------------|-----------|-----------|-----------|-----------|-----------|
| G-statistic| 3.39*     | 2.169     | 2.431     | 2.704     | 2.405     |
| P (0.05)   | 0.01432*  | 1         | 0.482     | 0.241     | 0.645     |

3.1.2 GRAPHICAL METHOD

The plot of the given data series shows consistent patterns in the rainfall data up to 2003 where the graphical display grows messy and there is no longer detectable pattern as shown in Figure 1. Similar behaviour although to a lesser extent can be visualised in the pre-1976 years. In the periods pre-1976 and post 2003, the data is meshed up in such a way that it is not possible to attribute the patterns to any global or regional hydrometeorological phenomena. Under typical conditions, within an area that does no spans over a large spatial extend, the behaviour of the rainfall records is expected to show similar or relatable response to external stimuli. For decision support and modelling purposes, the period between 1976 and 2003 provides a stable block of data where the performance can be compared within the study area.

![Graphical Method](image)

Figure 1: Time Series Plots for the Precipitation in the 5 Stations.

Analytical Method

The Grubb test outlier point in 9136165 identified in the Grubb test is also one of the noise data in the timeseries plot in Figure 1 above. This is best demonstrated in the boxplots in Figure 2 below, where the data display has been emphasized by use of the jitter and violin shapes in the boxplots. From the plots the outlier points are outside the 95% percentile.
3.1.3 TREND ANALYSIS

Trend analysis for rainfall data was performed for all the five stations since they have relatively long-term data records (>40 years). The analysis was done for seasonal and annual rainfall. Trend analysis was performed for the wet seasons of March, April, and May (MAM) and October, November, and December (OND) as well as the dry seasons June, July, and August (JJA). The summary of the results of the Mann-Kendall trends (Z) and the Sen Estimator (Q) are given in Table 3. All the stations have insignificant trends at 95% confidence level except for the JJA in Ndoondu station. The annual trends as presented Figure 3 show a fairly horizontal zen slope for all stations, implying that the rainfall patterns have not changed much over the years. Further two of the stations, Githunguri and Thika have insignificant positive trends meaning that the annual rainfall has increased over the period. The rest of the stations have a decreasing trend in the annual rainfall. The seasonal trends have mixed outcome. Except for Thika, all the other stations exhibit a downward trend in the MAM season. This being the main wet season in the study area presents a worrying trend especially since Agriculture is mostly rainfed and also the catchment serves as the source of water for large urban populations within the Nairobi metropolis. The JJA season for the stations shows a decreasing trend in rainfall. Although this is a typical dry season, the incidence of rainfall events has reduced across the study area with significant decrease (p=0.05 significance) experienced in Ndoondu. The stations with the highest Z statistic for the seasonal trends namely Jacaranda and Ndoondu are shown in Figure 4. The Zen slope is more pronounced on the seasonal graphs than on the annual.

The Mann-Kendall trend indicates that the annual maximum temperatures have increased significantly with 95% significant level for Thika, the only station with temperature data within the study area. The minimum temperature also increased albeit insignificantly. The increase in temp (both min and max) is consistent with the
changes experienced in other basins like Nzoia and Mara (Githui, Gitau, Mutua, & Bauwens, 2009; Kilonzo, 2014) and the continental decadal increases of 0.050C (Hulme, Doherty, Ngara, New, & Lister, 2001).

Table 3: Mann-Kendall (Z) and Sen Estimator (Q) Results for Selected Gauging Stations (* trend at \( \alpha = 0.05 \) level of significance).

| Period | Stations | Githunguri | Jacaranda | Ndoondu | Tatucity | Thika |
|--------|----------|------------|-----------|---------|----------|-------|
|        |          | Z          | Q         | Z       | Q        | Z     | Q     |          |
| Annuals|          | 0.47       | 0.98      | -1.31   | -3.87    | -0.68 | -1.95 | -0.30    | -0.70    | 0.78    | 1.69 |
| MAM    |          | -0.29      | -0.43     | -1.50   | -3.15    | -0.02 | -0.14 | -0.10    | -0.43    | 0.26    | 0.33 |
| JJA    |          | 0.34       | 0.14      | -1.41   | -0.73    | -2.40*| -1.10 | -0.55    | -0.30    | -1.32   | -0.34 |
| OND    |          | 0.97       | 1.59      | 0.79    | 1.16     | -0.41 | -0.61 | 0.10     | 0.28     | 0.46    | 0.45 |
| min-temp |        |            |           |         |          |       |       |          |          |         |      |
| max-temp |        |            |           |         |          |       |       |          |          |          | 2.20* |

Figure 3: Annual Rainfall Trends with the Sen Estimate Slope
3.1.4 AUTOCORRELATION

The results of the autocorrelation as determined by the DW statistics indicate that the rainfall in the study area is not serially correlated. All the five stations have $d$-values very close to the zero-autocorrelation value of $d=2$, as shown in Table 4 and Figure 5 below. This implies that the stations have time series data which satisfy.

**Table 4: Durbin Watson Statistics for the Autocorrelation Analysis**

| Station Name | D-stat  | D-lower | D-upper | sig |
|--------------|---------|---------|---------|-----|
| Githunguri   | 2.166752| 1.49275 | 1.57762 | no  |
| Jacaranda    | 1.855927| 1.49275 | 1.57762 | no  |
| Tatucity     | 1.665668| 1.44927 | 1.54895 | no  |
| Thika        | 1.582803| 1.49275 | 1.57762 | no  |
| Ndoondu      | 1.711436| 1.49275 | 1.57762 | no  |

**Figure 5: Durbin Watson Statistic Analysis Decision Chart**

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*Figure 4: Trend Analysis for Seasonal Rainfall in Two Stations*
Further, the graphical autocorrelation test (Figure 6) indicates that the data from all the stations is symmetrical around zero at a 95% significance.

A predominantly zero autocorrelation signifies random data and non-serial correlation.

![Graphical Method for Testing Autocorrelation](image)

**Figure 6: Graphical Method for Testing Autocorrelation**

### 3.1.5 HOMOGENEITY

Changepoints detection identifies different points in the time series where there is change in the data. The Pettitt and Buishand Range tests were implemented through the python code pyhomogeneity, and results are as summarised in Table 5 below. Three of the five stations have breakpoint year as 1976 and a just in the average magnitude. The remaining two stations have breakpoints at different years and show a decline in post change magnitude as shown in Figure 7. Further, two stations, Thika and Ndoondu had different change points for the Pettit and Buishand test while the rest had similar break point for both tests.

**Table 5: Homogeneity Tests Using PettitTest**

| Station    | Year of change point | Magnitude (mm) |   |
|------------|----------------------|----------------|---|
|            |                      | before         | after |
| Githunguri | 1976                 | 787            | 1023 |
| Jacaranda  | 1998                 | 1060           | 938  |
| Tatucity   | 1976                 | 967            | 1237 |
| Thika      | 1976(1987)           | 786            | 973  |
| Ndoondu    | 2010(1998)           | 1054           | 935  |
To get a true reflection of changes either in the data collection, capture and or environment conditions, statistical analyses for climate and especially rainfall time series require a homogenous dataset. To demonstrate this phenomenon, the 1976 is assumed as the changepoint for the study area and the trends analysis applied to the re-sampled data. The resultant trend analyses are shown in Table 6, Figure 8 and Figure 9 below. All the stations have a decreasing trend in rainfall. Three of the stations now show significant decrease in rainfall over the resampling study period, one at 95% confidence and two even at 99% confidence. The annual rate of decrease range is between 1mm to 8mm over the 41 yrs revised study period indicating that the annual rainfall has fallen up to 340mm. Compared to the pre-sampling period this is a 186% change in estimated decrease.

For planning of engineering and other decision support management this is a serious change in a country that’s on the verge of moving from water scarce to water deficit. Even so for rainfed agriculture, such a large change in the rainfall amounts and for the study could mean a shift in the crops being grown, the upstream area which are tea growing could be too dry for tea while the downstream coffee growing areas would require irrigation supplementation for the crops. For water harvesting and storage structures like dams and reservoirs, the drop in the rainfall amount might affect the design considerations and impair the operational efficiency of the system.
Table 6: Mann-Kendall (Z) and Sen Estimator (Q) Results for Gauging Stations after Filtering the Breakpoint at 1976 (* trend at α = 0.05 level of significance. + trend at α = 0.01 level of significance).

| Period | Stations       | Githunguri | Jacaranda | Ndoondu | Tatucity | Thika |
|--------|----------------|------------|-----------|---------|----------|-------|
|        |                | Z     | Q      | Z     | Q      | Z     | Q     | Z     | Q     |
| Annuals|                | -1.64 | -6.11  | -2.21*| -6.74  | -1.90*| -7.51 | -1.66*| -8.29 |
|        |                | -0.34 | -1.03  | +      |         |       |       |       |       |
| MAM    |                | -1.11 | -3.06  | -1.90*| -5.21  | -0.76 | -2.26 | -1.30 | -5.30 |
|        |                | -0.17 | -0.24  | +      |         |       |       |       |       |
| JJA    |                | -0.37 | -0.21  | -0.71 | -0.44  | -1.66*| -0.98 | -0.36 | -0.25 |
|        |                | 0.02  | 0.01   |        |         |       |       |       |       |
| OND    |                | -0.55 | -1.09  | -0.80 | -1.99  | -2.04*| -3.69 | -1.22 | -2.85 |
|        |                | -1.01 | -1.96  |        |         |       |       |       |       |

Figure 8: Annual Trends Analysis with Re-sampled Data
4.0. CONCLUSIONS

Depending on the end user application of data, it is necessary to ensure that some due diligence and duty of care is done. This is not only to ascertain the completeness of that data, but also some otherwise mundane data features which may look harmless but could drastically impact output on the decision process and endanger both the health of the population and the environment.

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