

Engineering Hydrology

Week-11

CHAPTER-5 STOCHASTIC HYDROLOGY

Sisay Demeku Derib (PhD, PE)

Sisay.demeku@aastu.edu.et

Addis Ababa Science and Technology University (AASTU),

Department of Civil Engineering

May, 2025





CHAPTER-5 STOCHASTIC HYDROLOGY

5.1 Introduction.

5.2 Time Series

5.3 Analysis of Hydrologic Time Series

5.4 Time Series Synthesis

5.5 Some Stochastic Models



Home assignment:

Based on the last week part of this chapter lecture, I hope you are sure you area able to exercise on:

- Discuss on analysis of hydrologic time series
- Describe time series synthesis
- List some stochastic models



Lecture Learning Outcomes

Course Learning Outcomes: After completion of this Lecture, you will be able to:

CLO-1: Apply measurement techniques of the components of the hydrologic cycle, water balance and filling of missed data;

CLO-2: Examine rainfall-runoff relationship and hydrograph;

- Apply flood routing

CLO-3: Examine the probability of occurrence;

- Analyze of hydrologic time series
- Compare some stochastic models

;

CLO-4: Analyze the water movement in to, over, and through the soil surface;

CLO-5: Design capacity of reservoir;

CLO-6: Design runoff volume and time of distribution of the runoff hydrograph from urbanization effect.



Lecture contents of the week (Week-11)

CHAPTER-5 STOCHASTIC HYDROLOGY

On this second part of the chapter, we will cover details of:

5.3 Analysis of Hydrologic Time Series

5.5 Stochastic Models comparison



Revision: Time series

- A time series is a sequence of data points recorded over a period of **time**, usually at regular intervals (hourly, daily, monthly, annually).

Characteristics and Concepts:

- **Order:** It is **ordered** by time, making it distinct from other types of data where the **order is not significant**.
- **Interval:** It is often collected at **regular** intervals.
- **Pattern/trend:** Time series can exhibit patterns like trends, seasonality, and cycles, which are important for analysis and forecasting.
- **Application:** Time series analysis is used in diverse fields like finance, weather forecasting, healthcare, and marketing.



Time Series

Examples of time series data:

- Hydrograph, hyetograph,
- Hourly temperature readings from a weather station.
- 5 minutes rainfall data from AASTU weather kit
- Daily stage measurements of a river gage station

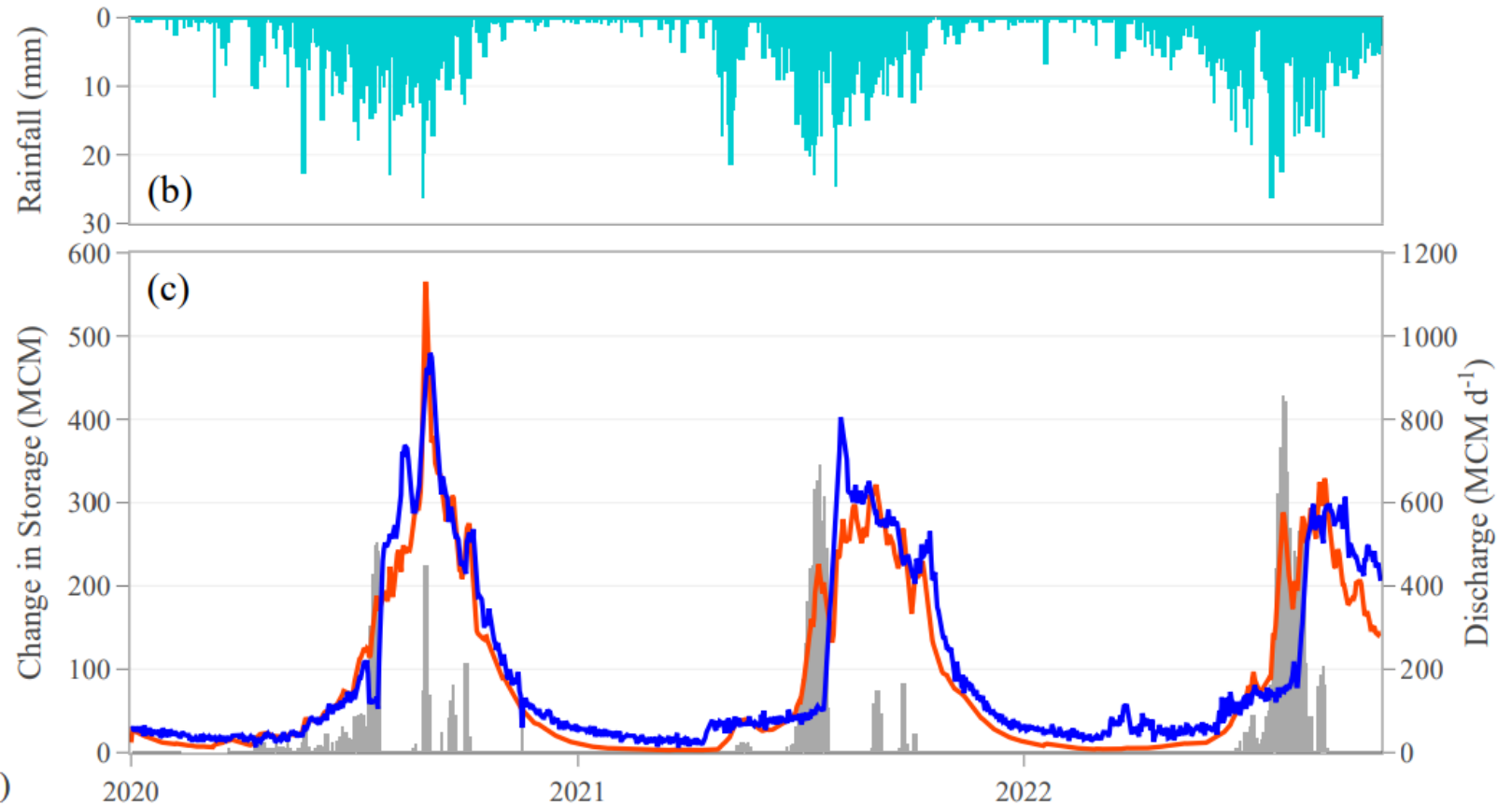
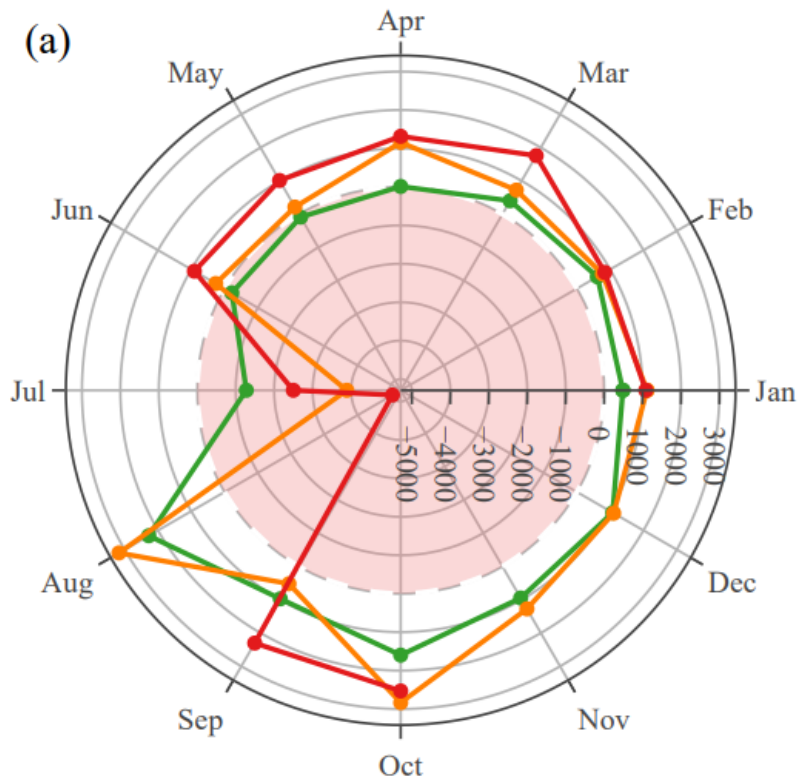
Others:

- Daily stock prices of a company.
- Monthly sales data of a product.
- Patient heart rate over time during a medical procedure.



Time Series

Examples of time series data: GERD filling on inflow to Sudan [1]





Analysis of hydrologic time series

- Hydrologic time series analysis involves examining patterns and trends in hydrological data over time, such as:
 - Precipitation, river flow, temperature, hydrographs over time.
- It helps to understand the variability and behavior of hydrological processes,
- It is crucial for **water resource** management, **flood** and **drought** prediction, and understanding the impact of **climate change**.
- It needs historical data collection, data cleaning like:
 - Address missing values, outliers, and inconsistencies in the data to ensure accuracy and reliability of the time series data before analysis.



Analysis of hydrologic time series: **Trends**

Detecting and analyzing **trends in hydrological** time series, e.g., :

- increasing or decreasing precipitation patterns for understanding long-term climate change impacts.
- to identify trends in river flow, potentially indicating changes in water availability or flood frequency.
- Examining changes in groundwater levels over time to detect trends related to groundwater depletion or recharge.
- changes in evaporation rates, which can be influenced by temperature and other factors, to assess their impact on water balance.
- Analyzing temperature trends, often alongside rainfall trends, to assess the influence of climate change on hydrological processes.
- Analyzing historical flood records to determine if the frequency or magnitude of floods has changed over time, potentially due to climate change or other factors.



Analysis of hydrologic time series: **Trends**

Tools and Techniques trends in hydrological time series, e.g., :

- 1. Non-parametric** tests like the **Mann-Kendall test** are commonly used to detect monotonic trends in these time series data.
 - Parametric tests assume specific distributions (like normality) and use parameters like the mean with larger samples,
 - Non-parametric tests don't make those assumptions and can be used with various data types, including nominal and ordinal with smaller samples.



Analysis of hydrologic time series: Trends

Mann-Kendall test statistic, S , is calculated using given equation ,

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i)$$

where,

- n is the number of data points.
- X_j and X_i are the data value in time series i and j ($j > i$), respectively, and,
- $\text{sgn}(X_j - X_i)$ is the sign function as: .

$$\text{sgn}(x_j - x_i) = \begin{cases} +1, & \text{If } x_j - x_i > 0 \\ 0, & \text{if } x_j - x_i = 0 \\ -1, & \text{if } x_j - x_i < 0 \end{cases}$$

Source: (Kamal, Neel and S. Pachauri, 2018)



Analysis of hydrologic time series: Trends

2. Sen's Slope Estimator:

- Is used to estimate the magnitude of the trend in time series data.
- is a robust nonparametric method for estimating the slope of a linear trend in time series data
- the estimation of the slope of a trend in the sample of N pairs of data:
- Calculates slopes for each pair of X_j and X_k , where $j > k$, calculate the slope (Q_i) using the formula: $Q_i = (X_j - X_k) / (j - k)$.



Analysis of hydrologic time series: Trends

2. Sen's Slope Estimator:

- Q_i are ranked from the least to the highest and the median slope or Sen's slope estimator was calculated as:

$$Q_{\text{med}} = \begin{cases} Q\left[\frac{N+1}{2}\right], & \text{if } N \text{ is odd} \\ \frac{Q\left[\frac{n}{2}\right] + Q\left[\frac{N+2}{2}\right]}{2}, & \text{if } N \text{ is even} \end{cases}$$

- A positive Sen's slope indicates an increasing trend, while a negative slope indicates a decreasing trend.

Source: Frimpong et al. (2022)

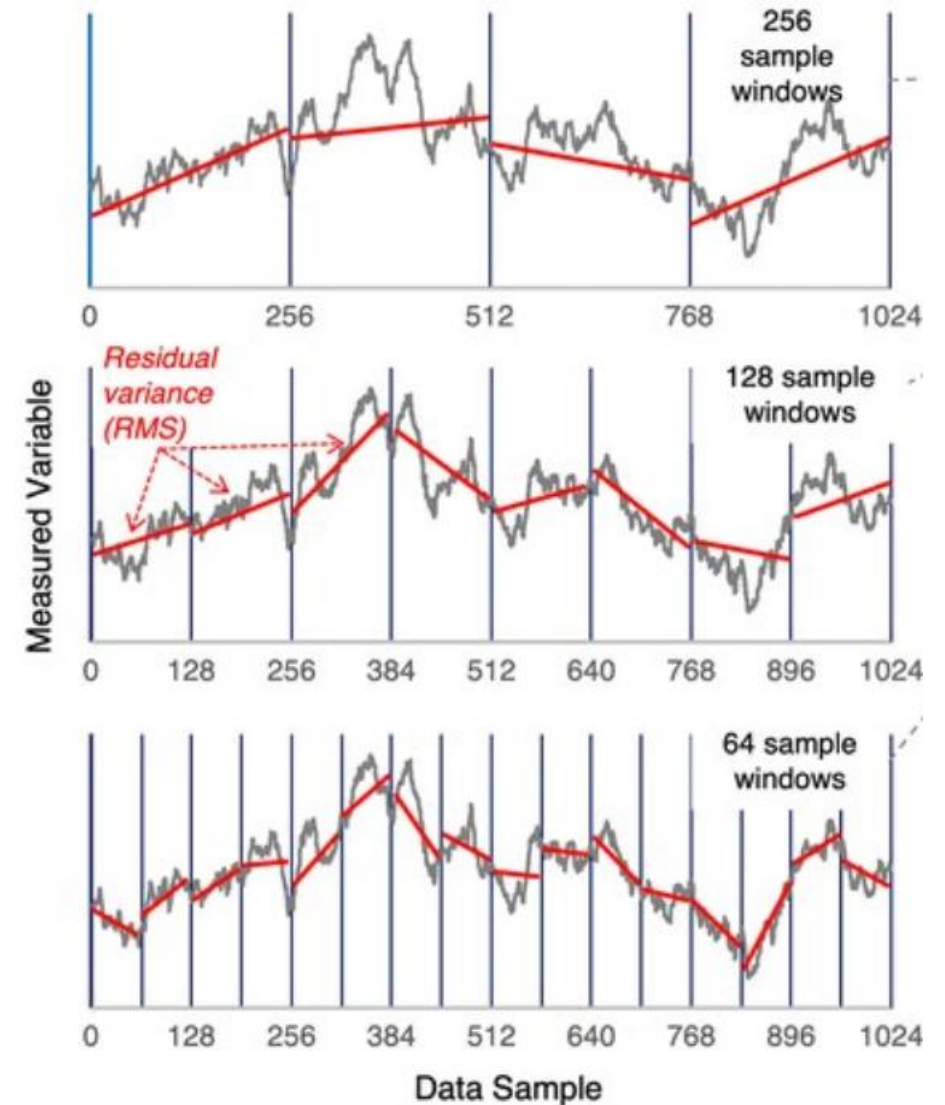


Analysis of hydrologic time series: Trends

3. Detrended Fluctuation Analysis:

- A method for analyzing the long-range dependence of time series data.
- It involves partitioning a time series into windows and quantifying the fluctuations within each window, taking into account local trends.

Illustration of Detrended Fluctuation Analysis (DFA) (Source: Rigoli et al (2020))





Analysis of hydrologic time series: Trends

Statistical Packages:

- like **R** or **Python**, with libraries like *statsmodels* or *pandas*, are used for performing trend analysis and data visualization.
- R boasts a wide array of specialized packages for time series analysis, including `forecast`, `tseries`, and `xts`, which offer advanced statistical models and functionalities.
- R's `ggplot2` package provides excellent data visualization



Analysis of hydrologic time series: **Trends**

Statistical Packages:

- Python has a large and active community with many libraries and frameworks,
 - including `pandas`, `statsmodels`, `scikit-learn`, and `Prophet`, which are widely used for time series analysis.
- Python has a **more readable** syntax and a smoother learning curve compared to R, making it easier for beginners to pick up.



Covariance and correlation

Covariance:

- Covariance measures how much **two variables vary together**.
 - A tendency to increase or decrease when the other variable increases or decreases
- A **positive covariance** means that as one variable increases, the other also tends to increase, and as one decreases, the other tends to decrease.
- A negative covariance means that as one variable increases, the other tends to decrease, and vice versa.



Covariance and correlation

Covariance:

- Is calculated using a formula that involves the expected value of the **product of the deviations** of each variable from their respective **means**.
- $Cov(X, Y) = E[(X - \mu_X)(Y - \mu_Y)]/N$, where X and Y are the random variables, μ_X and μ_Y are their means, and E represents the expected value.



Covariance and correlation

Example 1: Calculate the covariance of X and Y:

X	Y	X - μ_X	Y - μ_Y	$(X - \mu_X) * (Y - \mu_Y)$
1	2	-1.5	-4.5	6.75
2	5	-0.5	-1.5	0.75
3	8	0.5	1.5	0.75
4	11	1.5	4.5	6.75
				15

Step 1: Calculate the means of X and Y :

- Mean of X (μ_X) = $(1+2+3+4)/4 = 2.5$
- Mean of Y (μ_Y) = $(2+5+8+11)/4 = 6.5$

Step 2: Calculate the deviations:

- $(X - \mu_X) = \{1-2.5, 2-2.5, 3-2.5, 4-2.5\} = \{-1.5, -0.5, 0.5, 1.5\}$
- $(Y - \mu_Y) = \{2-6.5, 5-6.5, 8-6.5, 11-6.5\} = \{-4.5, -1.5, 1.5, 4.5\}$

Step 3: Multiply the deviations and sum them:

- $\sum[(X - \mu_X) * (Y - \mu_Y)] = (-1.5 * -4.5) + (-0.5 * -1.5) + (0.5 * 1.5) + (1.5 * 4.5) = 6.75 + 0.75 + 0.75 + 6.75 = 15$

Step 4: Divide by the sample size minus 1 (for sample covariance) or the sample size (for population covariance):

- Sample covariance ($\text{Cov}(X, Y)$) = $15 / (4 - 1) = 5$
- Population covariance ($\text{Cov}(X, Y)$) = $15 / 4 = 3.75$



Covariance and correlation

Covariance: Example 1: Calculate the covariance of X and Y:

X	Y	X - μ_X	Y - μ_Y	$(X - \mu_X) * (Y - \mu_Y)$
1	2	-1.5	-4.5	6.75
2	5	-0.5	-1.5	0.75
3	8	0.5	1.5	0.75
4	11	1.5	4.5	6.75
				15

- Sample covariance (Cov(X,Y))
- = $15 / (4 - 1) = 5$
- Population covariance (Cov(X,Y))
- = $15 / 4 = 3.75$

Interpreting the covariance

Consider two variables: X: Rainfall (in mm) and Y: Humidity (in %).

If we find a positive covariance between X and Y,

- it suggests that high rainfall amount tend to be the larger the humidity of the air, and vice versa.
- A covariance of zero would suggest no linear relationship between rainfall and humidity.



Covariance and correlation

Correlation:

- quantifies both the direction and the strength of the linear relationship between two variables.
 - A correlation of +1 indicates a perfect positive linear relationship.
 - A correlation of -1 indicates a perfect negative linear relationship.
 - A correlation of 0 indicates no linear relationship.
- Covariance alone doesn't tell us how strong the relationship is, while correlation does, giving us a standardized measure of strength and direction.



Covariance and correlation

Example 2: Calculate the correlation of X and Y:

X	Y	$(x - \bar{x})^2$	$(y - \bar{y})^2$	$(x - \bar{x})(y - \bar{y})$	r
1	2	2.25	20.25	6.75	
2	5	0.25	2.25	0.75	
3	8	0.25	2.25	0.75	
4	11	2.25	20.25	6.75	
2.5	6.5	5	45	15	0.07

Step 3: Calculate the sum of cross-products:

- $\Sigma(x - \bar{x})(y - \bar{y})$

Step 4: Calculate the correlation coefficient:

- $r = \Sigma(x - \bar{x})(y - \bar{y}) / \sqrt{[\Sigma(x - \bar{x})^2 * \Sigma(y - \bar{y})^2]}$
- $r = 15 / (5 * 45) = 0.07$

Step 1: Calculate the means of X and Y :

- Mean of X (μ_X) = $(1+2+3+4)/4 = 2.5$
- Mean of Y (μ_Y) = $(2+5+8+11)/4 = 6.5$

Step 2. Calculate the sum of squared deviations:

- $\Sigma(x - \bar{x})^2$ and $\Sigma(y - \bar{y})^2$

Interpretations:

- A correlation coefficient of near 1, suggests a very strong positive relationship, while -1 indicates a very strong negative relationship.
- A value of 0, like on this example, indicates no correlation.



Covariance and correlation

Covariance:

- Is calculated using a formula that involves the expected value of the **product of the deviations** of each variable from their respective **means**.
- $Cov(X, Y) = E[(X - \mu_X)(Y - \mu_Y)]$, where X and Y are the random variables, μ_X and μ_Y are their means, and E represents the expected value.



Autocovariance and autocorrelation

- are both statistical measures that quantify the relationship between a **time series** and its **lagged versions**.
- Autocovariance measures the covariance between a **time series** at **different points in time**, while
- Autocorrelation is a standardized measure of autocovariance, making it easier to compare across **different series** and interpret.



Autocovariance and autocorrelation

Autocovariance:

- Measures the covariance of a **time series** with itself at different **lags (time intervals)**.
- It quantifies how much the values of a time series at **one point** in time are correlated with its values at **past or future time** points.



Autocovariance and autocorrelation

Autocorrelation:

- Autocorrelation is a **normalized version** of autocovariance, typically expressed as a coefficient between -1 and 1.
- It is denoted as $\rho(k)$, $\rho(k) = \gamma(k) / \gamma(0)$, where $\gamma(0)$ is the variance of the time series.
- Autocorrelation is widely used in time series analysis for **forecasting, modeling**, and identifying **patterns** in time series data.



Autocovariance and autocorrelation

Interpretation:

- A high **positive autocorrelation** (close to +1) means that **past** values tend to **predict future** values.
- A high **negative autocorrelation** (close to -1) means that past values tend to be **negatively correlated with future** values.
- A **low autocorrelation** (close to 0) means that past values are **not strongly related** to future values.



Some stochastic models

- Models may be broadly classified, based on three different criteria used to generate synthetic sequences:
 1. Based on No. of variables: **univariate** models or **multivariate** models
 2. Based on the time interval: [**annual** model or **seasonal** model].
 3. Based on the choice of model: [autoregressive (**AR**), moving average (**MA**), autoregressive moving average (**ARMA**) models, autoregressive integrated moving average models (**ARIMA**), fractional Gaussian noise (**fGn**) models, etc]
- Are models used in time series analysis to forecast future values based on past observations



Some stochastic models

AR (Autoregressive) Model:

- predicts future values based on the linear combination of **past values** of the same time series.
- It assumes that the current value of a time series is **linearly dependent** on its previous values.
- Example:
 - An AR(1) model might predict tomorrow's climate based on today's climate.
 - An AR(2) model would use today's and yesterday's climate to predict tomorrow's climate.
- The 'p' in AR(p) represents the **order of the model**, indicating the number of past time steps to be considered in the prediction.



Some stochastic models

MA (Moving Average) Model:

- predicts future values based on the **linear combination of past errors** (differences between the observed values and their predictions).
- It's characterized by its reliance on **lagged error terms (residuals)** rather than past values of the series itself, unlike Autoregressive (AR) models.
- The 'q' in MA(q) represents the **order** of the model, indicating the **number of past errors** to be considered.



Some stochastic models

ARMA (Autoregressive Moving Average) Model:

- combines both **AR** and **MA** components.
- It predicts future values based on both **past values** of the time series and **past errors**.
- An ARMA model is denoted as $ARMA(p, q)$, where 'p' represents the order of the AR component and 'q' represents the order of the MA component.



Some stochastic models

ARIMA (Autoregressive Integrated Moving Average) Model:

- extends the ARMA model by including an **integration** (differencing) component denoted by 'd'.
- It combines autoregressive (**AR**), integrated (**I**), and moving average (**MA**) components to model the relationship between a variable's current value and its past values, errors, and lagged forecast errors.
- **Differencing** involves subtracting consecutive observations to remove trends and seasonality, making the series stationary (meaning its statistical properties like mean and variance are constant over time).
- An ARIMA model is denoted as $ARIMA(p, d, q)$, where 'p' represents the order of the AR component, 'd' represents the order of differencing, and 'q' represents the order of the MA component.



Home assignment:

Make sure that you can :

- Analysis of hydrologic time series
- Compare some stochastic models



References

- Ali, A.M. Lieke A. M., and Adriaan J. T. 2023. Inferring reservoir filling strategies under limited-data-availability conditions using hydrological modeling and Earth observations: the case of the Grand Ethiopian Renaissance Dam (GERD), *Hydrology and Earth System Sciences (HESS)*, 27(21): 4057–4086
- Kamal, Neel and S. Pachauri. 2018. Mann-Kendall Test - A Novel Approach for Statistical Trend Analysis, *International Journal of Computer Trends and Technology (IJCTT)*, 63(1): 18-21. Mann-Kendall Test - A Novel Approach for Statistical Trend Analysis
- Frimpong, B.F., A. Koranteng, and F. Molkenthin. 2022. Analysis of temperature variability utilizing Mann–Kendall and Sen’s slope estimator tests in the Accra and Kumasi Metropolises in Ghana, *Environmental Systems Research*, 11(24):1-13. <https://doi.org/10.1186/s40068-022-00269-1>
- Rigoli, L. M., T. Lorenz, C. Coey, R. Kallen, S. Jordan & M. J. Richardson. 2020. Co-actors Exhibit Similarity in Their Structure of Behavioural Variation That Remains Stable Across Range of Naturalistic Activities, *Scientific Reports*, 10(6308) | <https://doi.org/10.1038/s41598-020-63056-x>



Thank you very much for your active attendance!!

Prepared By: Sisay Demeku Derib (PhD, Practicing Hydraulics Engineer, Assistant Prof.)

Affiliated to: Addis Ababa Science and Technology University –AASTU, Department of Civil Engineering

[Scopus](#) [WOS](#) [ORCID](#) [ResearchGate](#) [Google Scholar](#) [LinkedIn](#) [YouTube](#)