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Spatial Variability of Rainfall and Classification of Peninsular Indian Catchments

M Ravi Naik, MVSS Giridhar

***Abstract:** The strength and success of hydrological analysis depend upon the quantity and quality of observed data. In the recent past, the availability of advanced computing facilities and measurement techniques had a great impact on the field of hydrology, especially in hydrologic analysis and hydrologic modeling. In spite of such growth, the present hydrologic modeling has certain challenges: complexity (involving a large number of parameters), applicability to a specific region (difficult to generalize for other regions), and lack of understanding of the connection between model theories and the actual system. The general solution of simplifying the models in terms of developing a classification framework has been discussed and focused on in the present study. It will greatly help to overcome the hydrologic modeling challenges and provides a better understanding of the hydrologic process. In general, classification is a way of grouping entities which has similar characteristics. The importance of applying nonlinear dynamics and chaos methods for classification has been realized in the recent past; since such studies provide exclusive information on hidden characteristics such as complexity, nonlinearity, dimensionality, etc. Of hydrological processes. The hydrologic processes are complex. In this study, information regarding the complexity is extracted by statistical analysis and linear methods such as Autocorrelation Function, and Average Mutual Information. 367 gridded rainfall stations over Peninsular Indian basins are used to investigate the applicability of different methods used in the study.*

***Keywords:** Peninsular India, Hydrology, Rainfall, Nonlinear dynamics, Autocorrelation, Average Mutual Information.*

I. INTRODUCTION

However, only a small fraction of water is freshwater and further a smaller fraction of it is accessible and usable for human survival and well-being. The availability of water significantly varies in space and time and, hence, water is unequally distributed over the globe. Due to this, and many other reasons such as the changes in the climate system especially the observed changes in the atmosphere, oceans, carbon and biogeochemical cycles, and temperature, the issues of water problem range in different dimensions such as flood, drought, contamination, etc., and the ability to withstand or safeguard humankind is a serious challenge. To meet the surging water demand as well as to reduce the impact of floods and droughts, comprehensive water resource planning and management is necessary.

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The availability of data is a key requirement to justify the use of such models. A large quantity of hydrological data is made available as a result of applying advanced techniques and methodologies. However, such data which represents the dynamics of water availability over space and time needs to be analyzed and synthesized to generate meaningful information through statistical and hydrological models.

II. HYDROLOGICAL MODELING

Hydrologic models have essentially simplified representations of the highly complex hydrologic cycle and associated processes. Hydrologic models can be grouped under different categories, depending upon, for example, the basis, complexity, and methodology considered: physically based models, conceptual models, lumped models (if all parameters are spatially averaged over the catchment), distributed models, linear models, nonlinear models, and data-driven models. There is already an extensive amount of literature on these various types of models and their performance for various situations, including issues related to model complexity and data requirement (Beven, 1989[1]; Singh and Woolhiser, 2002 [29]; Singh and Frevert, 2006). Physically based models, such as the one proposed by Freeze and Harlan, describe distributed mechanics of hydrologic processes. Hydrologic modeling using a physically based model can be very complex and typically requires detailed knowledge of physical processes. Such models are appropriate for studying the effects of land use changes, soil erosion, and surface water groundwater interactions because their parameters are reflected in the field measurements. In practice, however, they do not represent all physical processes in their entirety as they are purported to, especially considering the reality of significant heterogeneity in the landscape and variability in climatic inputs and, hence, their influence on water flows in the field. Conceptual models, on the other hand, provide "simplified representations of key hydrologic processes using a perceived system". Such models are well-known for their moderate data requirement. Such models rely on machine-learning approaches that attempt to learn, represent, and predict the system using observed data, through a training mechanism relating inputs and outputs. Data-driven models are widely considered to bridge the gap between classical regression and physically based models. However, such 3 models generally have limited ability to understand the details of the underlying physical processes of the system. Regardless of the type of hydrologic model, advances in computational power and data measurement techniques have created a tendency to develop more and more complex models.

While such complex models are indeed useful to better represent hydrologic systems, they also possess important limitations when applied to real situations. A particular issue associated with complex models is parameter estimation and uncertainty since such models often contain a large number of parameters to be calibrated but corresponding data are generally not available.

III. HYDROLOGIC CLASSIFICATION

Looking back into the great 18th century, Carl Linnaeus, a Swedish botanist, physician, and zoologist, laid the foundations for the modern scheme of nomenclature. Another celebrated classification system is the periodic table of chemical elements which provided an extensively useful framework to classify, systematize and compare all the many different forms of chemical behavior. Soil classification is another area where classification has played a significant role. According to Rossiter, two types of soil classification are possible: natural soil classification; technical soil classification. While "diversity is nature's principal theme", human beings have been craving the least variability and order. There exists an order in a natural process or system, which needs to be discovered or unveiled. One approach to discerning order in a heterogeneous world is through the means of classification (Gould, 1989; Wagener et al. 2007 [32][35][36][37]). Classification systems, such as taxonomy, nomenclature, categorization, and organization, all lead to naming and organizing entities or organisms into groups based on properties or relationships they have in common. Catchment classification has been traditionally carried out via Linnaeus-type analysis, mainly represented by hierarchical approaches. Classification is important to hydrologists to develop a meaningful hydrologic model for a region. Classification also provides the avenue through which research can be addressed in a rigorously systematic manner. 4 Classification is viewed not simply as a way of creating a filing system, but rather as a rigorous scientific inquiry into the causes of similarities and relationships between catchments.

A. Need for Hydrologic Classification

A catchment can be defined as "all of the upstream area, which contributes to the open channel flow at a given point along a river". Catchments are open and complex environmental systems, which are characterized by enormous variability but exhibit some degree of organization. The catchment forms a landscape element that integrates all aspects of the hydrologic cycle within a defined area that can be studied, quantified, and acted upon. On the other hand, the catchment is a self-organizing system, whose form, drainage network, ground, and channel slopes, channel hydraulic geometries, soils, and vegetation, are all a result of adaptive ecological, geomorphic, and land-forming processes. The catchment forms a landscape element that integrates all aspects of the hydrologic cycle within a defined area that can be studied, quantified, and acted upon. Catchment classification helps to organize similar units that water is drained from, as well as discover orders from the extremely heterogeneous world of hydrology. Catchment classification would provide a first-order grouping of hydrologically similar catchments with implications for hydrological theory, observations, and modeling (Gupta *et al.* 2008 [9]; McMillan et al. 2011 [22]). The lack of a generally accepted catchment classification framework brought the question of what defines hydrologic similarity to the forefront of hydrologic science. Wagener *et al.* suggested that a classification framework, which is both descriptive and predictive, can be derived if it is based on the notion of catchment function and contains an explicit mapping between function, climate, and landscape characteristics. The main drawback of these classifications is, however, their focus on individual catchment characteristics (i.e. Climate, land use, catchment response, storage, etc.). To date, no universally accepted metric or combination of metrics has been identified to quantify catchment similarity from the triple point of view of forcing, form, and function; different arguments have been made for what might constitute a useful similarity framework.

IV. STUDY AREA AND DATA

Advanced technologies and measurement devices provided a novice way to observe and measure different hydrological processes on different scales. In addition to that, a fairly large amount of observed data in terms of topology and geographical data is now digitized and made used for scientific purposes. The spread of data communication networks allows hydrological data to be obtained, analyzed, and applied to real-time forecasting over large communication networks. Extrapolating from local measurements to get a regional picture is indispensable for the water resources research enterprise of a nation. Long-term monitoring of hydrologic systems – precipitation, streamflow, groundwater levels, water lost through evaporation, and so on – and archiving the data thus collected is essential for understanding system behavior, and biological and chemical processes. Without it, there is no basis for predictive modeling.

The ultimate goal of data collection in hydrology, be it precipitation measurements, water-level recordings, discharge gauging, groundwater monitoring, and water quality sampling, is to provide a set of sufficiently good quality data that can be used in decision-making in all aspects of water resources management, in the wide range of operational applications as well as in research. Accurate assessment of water resource potential is of prime importance for developmental planning, flood protection and control, and efficient water management. Rainfall and streamflow are important processes in the hydrological cycle. Rainfall is the end product of different complex processes (Luk et al. 2001 [21]) and plays a significant role in hydrologic modeling . The information on space-time variability in rainfall is important for decision-making in meteorology, hydrology, agriculture, telecommunications, and climate research. Studies on rainfall have been studied in different aspects: input parameter in forecasting and estimation of regional parameters (Drosdowsky, 1990 [6]; Joseph et al. 1991 [16]; Kiladis and Sinha., 1991), investigation of spatial variability (Murphy and Timbal., 2007 [23]; Ntegeka and Willems., 2008 [25]) and so on.

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Similarly, streamflow is a fundamental and critical component of global and regional hydrological cycles (Makkeasorn et al. 2008 [24]). Several studies have discussed the streamflow reduction in basins (e.g., Giakoumakis and Baloutsos, 1997 [12]; Cigizoglu et al. 2005 [3]), Streamflow forecasting (e.g., Georgakakos et al. 2012 [11]; Wei and Watkins, 2011 [33]), activities that affect streamflow (e.g. Chelsea Nagy et al. 2012 [4]; Huang et al. 2012 [13]), and investigation of scaling properties in streamflow (Telesca et al. 2012 [31]). Studies in the past applied different methodologies to study different aspects of rainfall and streamflow. In recent times some attempts have been made to form a hydrologic/catchment classification which helps in modeling. For the present work, interpolated rainfall from 367 grids in peninsular India. An outline of the study area and data used for the present study is presented in Table 1.

Table 1. Details about the Data

Data Type	Region/Country	No. of Stations	Length of the Data Used
Interpolated Rainfall	Peninsular India (9 river basins)	367	1971–2005 (35 years)

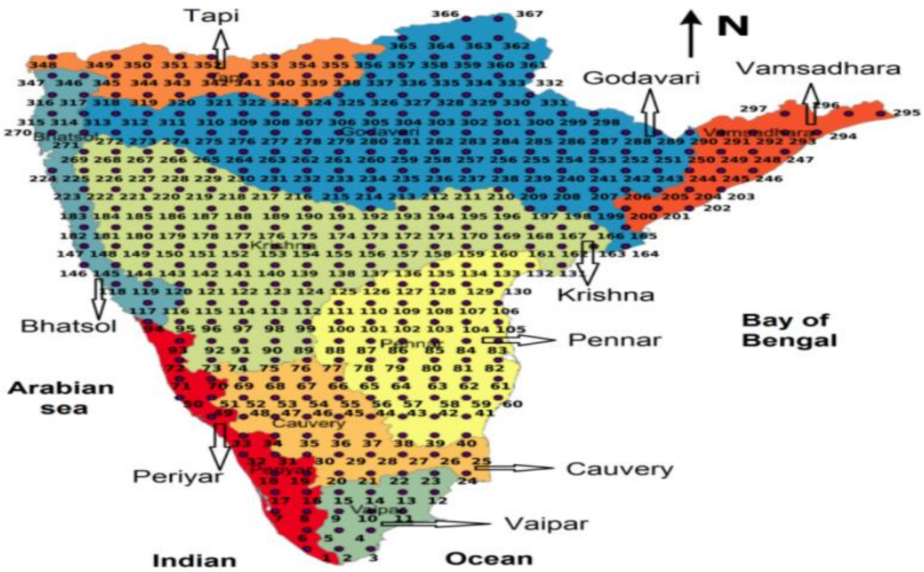

Figure. 1 Basins in Peninsular India for Analysis

A. Peninsular Indian Data

High-resolution gridded rainfall data are required to validate regional and mesoscale models and to study the intra-seasonal fluctuations. In recent years, there has been considerable interest in developing high-resolution gridded data sets (e.g., New et al. 1999 [26]; Yatagai et al. 2005; Rajeevan et al. 2006 [28]; Xie et al. 2007 [34]). Rajeevan et al developed a high-resolution daily rainfall data set for the period 1951 to 2004, which has been used in many studies (e.g., Krishnamurthy and Shukla, 2008 [19]). However, there have been demands for much higher resolution for mesoscale rainfall analysis and mesoscale meteorological applications.

For the present work, a very high-resolution monthly rainfall data set is used to find the patterns and the complexity level over the Peninsular Indian region. The high-resolution monthly gridded rainfall data set was developed using quality-controlled rainfall data from more than 6000 rain gauge stations over India. The analysis consists of daily rainfall data for all the seasons for the period 1971 to 2005. A well-tested interpolation method was used to interpolate the station data into regular grids of 0. 5 x 0. 5-degree Lat x Long. Recently, another high-resolution rainfall data set was developed at the Research 15 Institute for Humanity and Nature. The project is named Asian Precipitation-Highly Resolved Observational Data Integration Towards Evaluation of the Water Resources. Under this project, a high-resolution (0. 25 degrees x 0. 25 degrees and 0. 5 x 0.5 degrees) daily rainfall data set was developed for the Asian region. The basic algorithm adopted by them is based on Xie et al.

Some of the important characteristics of the peninsular Indian basin are represented in Table 4.4. In the present study, high-resolution gridded monthly rainfall data from nine major basins of South India have been selected, studied, and analyzed. The basins include Bhatsol, Cauvery, Godavari, Krishna, Pennar, Periyar, Tapi, Vaipar, and Vamsadhara. In total 367 grid stations in the selected areas have been analyzed. The data for a period of 35 yrs, starting from January 1971 to December 2005 has been used. The number of stations in each basin is detailed in Table 2. Rajeevan et al.have used the interpolation scheme proposed by Shepard for deriving the high-resolution gridded daily rainfall data.

Table 2. Number of Basins and their Stations

Basin Name	No. of Stations
Bhatsol	17
Cauvery	27
Godavari	110
Krishna	92
Pennar	49
Periyar	20
Tapi	21
Vaipar	13
Vamsadhara	19

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V. METHODOLOGY

Spatial phenomena in hydrology are mainly driven externally by spatial patterns in climate, soils, vegetation, topography, and geology. However, at very long timescales, a complex spatial organization develops which is created by the internal dynamics of the hydrological system. Today, the progress in hydrologic sciences is closely connected to modeling. Although experimental hydrology is extremely important, it is in combination with modeling that real new insight is achieved. Modeling is a framework for testing new theories and hypotheses to improve our understanding of hydrologic processes and how the different processes interact. One of the main tasks of time series analysis is to determine the basic properties of the underlying process, such as nonlinearity, complexity, chaos, etc. Some important analysis such as the Autocorrelation Function (ACF) and Average Mutual Information (AMI) method has been employed in this method including statistical analysis.

Among the most widely used approaches is phase space reconstruction by time delay embedding (Packard et al. 1980 [27]). Various techniques derived from the chaos theory have been applied, in the last years, in a lot of experimental fields from physics to engineering to medicine (meteorology, fluid dynamics, electroencephalography, electrocardiography, etc.) (Babloyantz and Destexhe 1986 [15], 1988 [5]; Kurths and Herzel, 1987 [17]; Lauterborn and Holzfuss, 1986 [20]; Lorenz, 1963; Hilborn, 2000; Galka, 2000 [10]; Soofi and Cao, 2002; Fan and Yao, 2003 [7]; Kyrtsou and Vorlow, 2005 [18]).

In the present study, the primary focus is on the application of the two methods mentioned already. To this end, the emphasis is on the investigation of the usefulness of the methods to the data (Peninsular Indian rainfall) Exclusive details about the data and study area can be found in the next chapter. The following parts will cover detailed information about the methods: Autocorrelation Function (ACF) and Average Mutual Information (AMI) in the results section in detail.

VI. RESULT AND DISCUSSION

Primarily basic statistical analysis is carried out for the Indian rainfall data. Some of the important details are as follows:

A. Autocorrelation Function Method

Autocorrelation, also known as serial correlation, is the cross-correlation of a signal with itself at different points in time. Informally, it is the similarity between observations as a function of the time lag between them. It is a mathematical tool for finding repeating patterns, such as the presence of a periodic signal obscured by noise, or identifying the missing fundamental frequency in a signal implied by its harmonic frequencies. It is often used in signal processing for analyzing functions or series of values, such as time domain signals. Autocorrelation refers to the correlation of a time series with its past and future values. Autocorrelation is also sometimes called "lagged correlation", which refers to the correlation between members of a series of numbers arranged in time. Positive autocorrelation might be considered a specific form of "persistence", a tendency for a system to remain in the same state from one observation to the next.

Hydrological time series are frequently auto correlated because of inertia or carryover processes in the physical system. Autocorrelation can be exploited for predictions: an auto-correlated time series is predictable, probabilistically, because future values depend on current and past values. In the analysis of a time series for the identification of dynamic properties of the underlying system, it is customary to use ACF, at least as a preliminary investigative tool, among others. The ACF is a normalized measure of the linear correlation among successive values in the time series. values in the time series. For a discrete time, series X_i, where i = 1, 2, ..., N, and for different values of lag time τ, the autocorrelation function $\rho(\tau)$ is determined according to:

$$\rho(\tau)=\frac{\sum_{i=1}^{N-\tau} x_i x_{i+\tau}-\frac{1}{N-\tau}\sum_{i=1}^{N-\tau} x_{i+\tau}\sum_{i=1}^{N-\tau} x}{\left[\sum_{i=1}^{N-\tau} x_i^2-\frac{1}{N-\tau}\left(\sum_{i=1}^{N-\tau} x_i\right)^2\right]^{1/2}\left[\sum_{i=1}^{N-\tau} x_{i+\tau}^2-\frac{1}{N-\tau}\left(\sum_{i=1}^{N-\tau} x_{i+\tau}\right)^2\right]^{1/2}}$$

The use of ACF in characterizing the dynamic properties of a time series lies in its ability to determine the degree of dependence present in the values. For instance: (1) for a periodic process, the ACF is also periodic, indicating the strong relationship between values that repeat over and over again; (2) for a purely stochastic process, the ACF fluctuates randomly about zero, indicating that the process at any certain instance has no 'memory' of the past at all; and (3) for signals from a chaotic process, the ACF is expected to decay exponentially with increasing lag, because the states of a chaotic process are neither completely dependent nor completely independent of each other. Consequently, in the specific context of hydrologic process dynamics, the ACF provides some important information regarding seasonality, annual cycle, and persistence, among others.

B. ACF Results for Peninsular Indian Rainfall

The ACF method is applied to monthly rainfall data from each of the 367 gridded rainfall of peninsular India. Figure 5.2 shows the monthly variations in rainfall for Station #1 and Station #2. Figure 5.3 shows the sample autocorrelation plots of the gridded Peninsular Indian data for Stations #1 and #2, respectively. The delay time values for these two stations are found to be 3. The delay time values from the ACF method for all 367 grids are carefully interpreted to classify the grids in terms of the entire region. Table 5.2 shows the classified stations of the gridded Indian rainfall data.

Based on the delay time values obtained from the ACF method, the 367 stations are classified into three categories. Interestingly, only one station has an ACF value of 5, and all the remaining stations are having delay time values of either 3 or 4. Figure 2. Shows classified Peninsular India based on the ACF values obtained.

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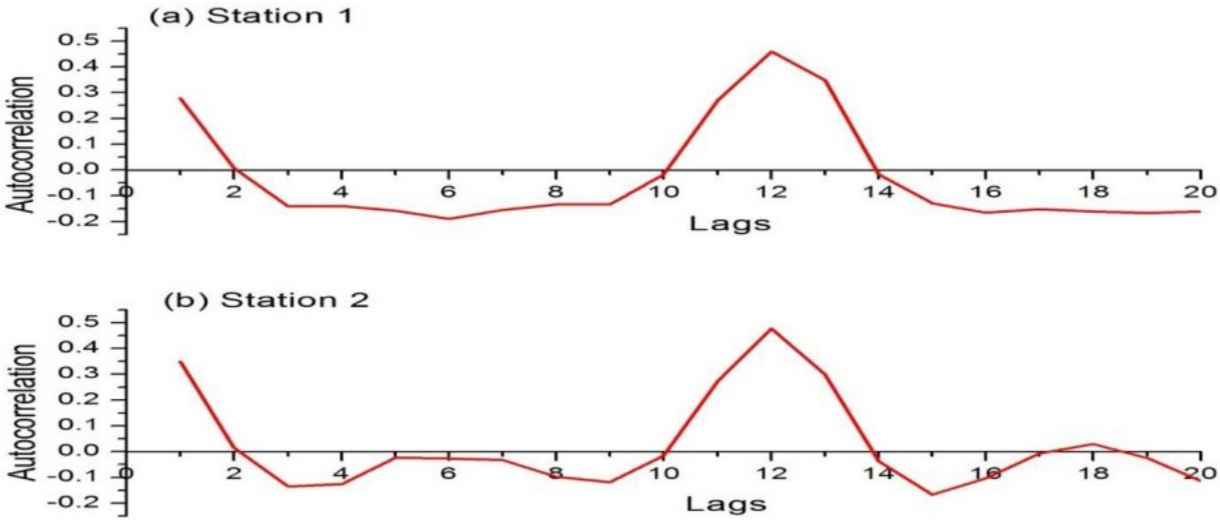

Figure. 2 Sample ACF Plots for Peninsular Indian Rainfall Data: (a) Station #1 and (b)Station #2

Table 3. Delay Time Values using ACF Method for Peninsular Indian Rainfall Data.

ACF Value	Stations	No. of Stations
3	1-3, 5, 7, 9, 10, 14, 15, 17, 18, 20, 21, 4, 25, 32-36, 39, 40, 45, 46, 49-51, 53, 55, 61, 65-68, 70-73, 82-85, 93-96, 104-108, 117-119, 128-148, 150, 152, 155-162, 166-175, 181-184, 188, 189, 191-199, 202, 206-219, 221, 223-225, 230-243, 245, 247-265, 269-271, 275-318, 320-367.	253
4	4, 6, 8, 11-13, 16, 19, 22, 23, 26-31, 37, 38, 41-44, 47, 48, 52, 54, 56-60, 62-64, 69, 74-81, 86-92, 97-103, 109-116, 120-127, 141-143, 149, 151, 153, 154, 163-165, 176-180, 185-187, 190, 200, 201, 203-205, 220, 222, 226-229, 244, 246, 266-268, 272, 273, 312, 313, 319.	113
5	274	1

From Table 3, it is found that the time delay values for peninsular Indian rainfall data vary from 3 to 5. As it is clear that almost all the stations have the ACF value of 3 and 4 which describes the extreme variability in rainfall. The northern part of peninsular India, especially Tapi, Godavari, and some stations in Vamsadhara shows clear signs of ACF values having 3. Similarly, many stations in Bhatsol and Periyar basins also have low ACF values among the stations. The central stations of Krishna, Pennar, and Cauvery basins possess slightly higher ACF values (low variability) among the stations. At the same time stations in Cauvery, Vaipar, Pennar, and Vamsadhara basins show variations in ACF values among the stations in the same basin. Significantly, only one station (Station #274) shows a high value of ACF in the Godavari basin where almost all the stations have low variability.

C. Average Mutual Information

The mutual information method is one of the important methods for determining the lag(τ) that affects the dependence of one data over another (Cover and Thomas 1991). Average mutual information, which is similar to the autocorrelation function, tries to measure the extent towhich values of $x_{i+\tau}$ are related to the values of x_i, at a given lag. It has the advantage of using probabilities, rather than a linear basis (as is done in the ACF method) to assess the correlation.If values of $x_{i+\tau}$ are strongly related to values of x_i for a given lag, mutual information is relatively high. If instead, values of $x_{i+\tau}$ are only weakly related to values of x_i at a particular lag, then mutual information at that lag is relatively low. Mutual information quantifies the dependence between two random variables (X, Y) in terms of information communicated about the value of one variable given knowledge of the other. Average mutual information (AMI) measures the dependence between pairs of random 22 variables. It has been used in many applications including blind source separation, data mining, neural synchronicity assessment, and state space reconstruction in human movement studies (Bell and Sejnowski, 1995[2]; Ye, 2003; Pikovsky et al 2003). Presently, several algorithms and computational codes exist to estimate AMI. In the AMI method, τ is chosen to coincide with the first minimum of the mutual information (Fraser and Swinney, 1986).

D. AMI Results for Peninsular Indian Rainfall

The AMI analysis is carried out on rainfall series from each of the 367 grids in peninsular India,figure 3.Shows the AMI plots for the first two stations (Station #1 and Station #2). The lag which produces the first local minima of the mutual information can be the best choice for the time lag. The delay time values obtained range from 2 to 9. Table 4 shows the AMI values for all the stations. Figure 5.6 shows the sample peninsular Indian stations having AMI values from 2 to 9.

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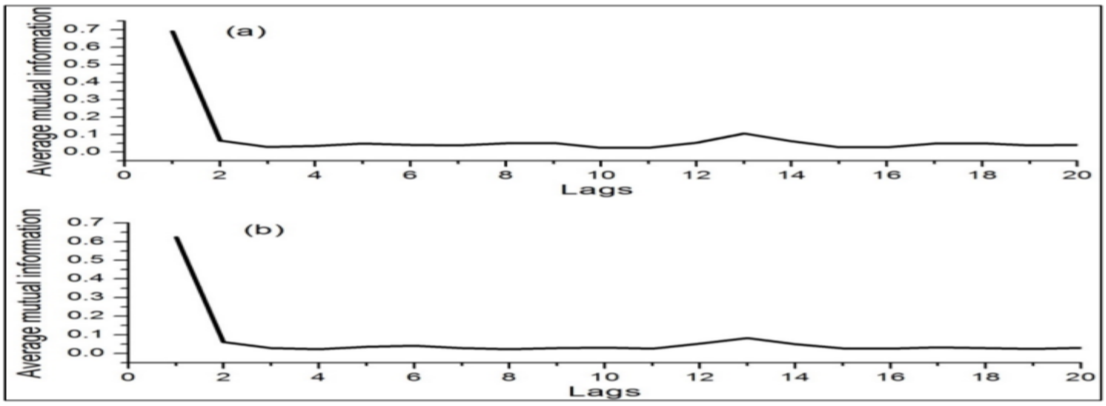

Figure.3 Sample AMI Plots Peninsular Indian Rainfall Data (a) Station #1 and (b)Station #2

Table 4. Delay Time Values using the AMI Method for Peninsular Indian Rainfall Data.

AMI Value	Stations	No. of Stations
2	266	1
3	1, 9, 10, 20, 27, 30, 32, 46, 71, 95, 122, 176, 354.	13
4	2, 7, 11, 13, 16-18, 24, 31, 34, 35, 39, 41, 49, 50, 52, 57, 59, 63, 69, 80, 83, 84, 91, 92, 96, 103-105, 108, 109, 113, 125-129, 131-137, 139-141, 146, 149, 150, 152, 154-175, 177, 180, 184, 188-218, 224, 225, 229-265, 269-271, 274-311, 313-353, 355-367.	241
5	3-5, 8, 19, 21, 22, 33, 38, 40, 42-44, 51, 53-55, 58, 60-62, 64-68, 70, 72-75, 77-79, 81, 82, 85-90, 93, 94, 97-102, 106, 107, 110-112, 114-120, 123, 124, 130, 138, 142-145, 147, 148, 151, 153, 178, 179, 181-183, 185-187, 219-223, 226, 228, 268, 272, 312.	92
6	23, 25, 26, 29, 37, 45, 48, 56, 76, 121, 273.	11
7	12, 14, 15, 28, 36, 47	6
9	6, 227, 267	3

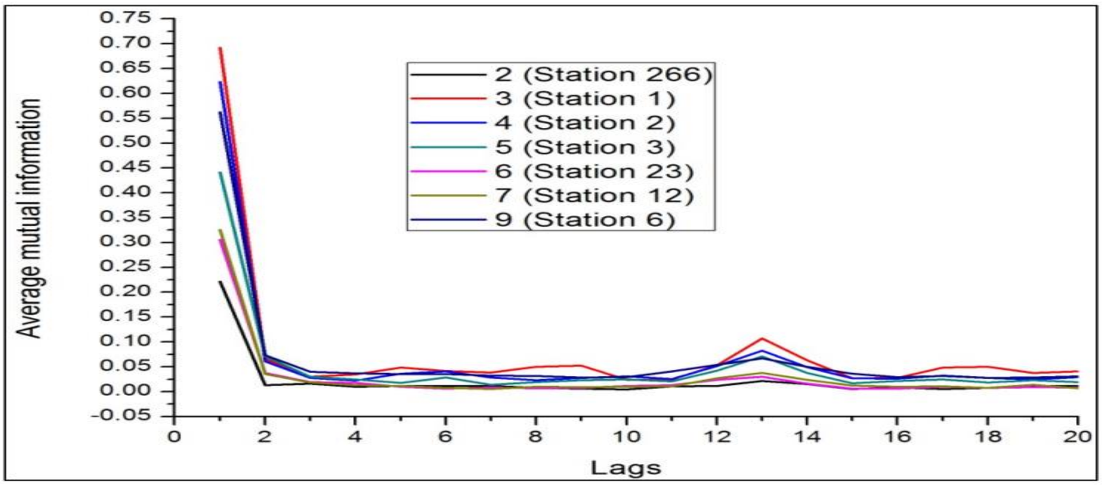

Figure.4 Sample AMI Plots for Peninsular Indian Rainfall Data Showing Each of the Time Delays.

It is very clear from the number of stations in both low and high delay time values is less compared to the medium time delay values (in this case, the low and high delay time values are considered as 2 and 9 respectively). 90% of the stations have moderate variability as their delay time values are found to be 4 and 5. This is very significant when these results are compared with the ACF results of peninsular Indian rainfall data.

Figure 4 describes the clear indication of the separation of delay time values (i.e. region specific or basin-specific). For instance, almost all the stations of Tapi, Godavari, and Vamsadhara have a delay time value of 4 and many stations in Bhatsol and Pennar basins have a delay time value of 5. The stations of the Krishna basin are found to have different delay time values. Similarly, the results of Cauvery, Vaipar, and Pennar also possess significant differences in the delay time values.

E. Summary

The requirement for effective hydrologic modeling is an accurate understanding and acquiring information on the streamflow as well as rainfall dynamics. There are a large number of models which were developed in the past which certainly provided a better understanding of hydrological processes or catchments. The developed models also had a relative amount of complexity in them requiring a greater number of data, involving a large number of parameters, and so on.

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In addition to that, the models are subject to catchment-specific, region-specific, and process-specific. It is very much essential for a wide range of purposes such as the identification of the appropriate complexity of the model and interpolation/extrapolation of the data. Several approaches have been proposed and applied to study the variability of streamflow and rainfall, including catchment classification. Recently the specific task of developing a catchment classification framework based on dynamics which helps in effective and efficient modeling practice has gained great interest (Hrachowitz et al 2009 [14], Sivakumar et al 2015 [30]). The present study is focused on the application of two different methods: Autocorrelation Function and Average mutual Information to study rainfall variability. It is aimed to analyze the dataset: Interpolated rainfall Peninsular Indian gridded rainfall 367 stations.

VII. CONCLUSION

Primarily ACF method was used to find the time delay (τ) which is further used as a metric in classifying the stations. The delay time (τ) is chosen based on the lag time where ACF first crosses zero (Holzfuss and Mayer-Kress, 1986). For peninsular Indian rainfall, the range is still lower and the ACF value ranges from 3 to 5 which shows high variability in gridded rainfall data also. A nonlinear method, AMI is applied to find the delay time (τ), and based on the AMI value, the stations are classified. Delay time (τ) is chosen to coincide with the first minimum of the mutual information (Fraser and Swinney, 1986 [8]). The AMI values for peninsular Indian rainfall AMI range from 2 to 9 in which the separations of delay time values are region-specific. For instance, the number of stations in basins such as Tapi, Godavari, and Vamsadhara almost has the same delay time.

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Conflicts of Interest	No conflicts of interest to the best of our knowledge.
Ethical Approval and Consent to Participate	No, the article does not require ethical approval and consent to participate with evidence.
Availability of Data and Material	Not relevant.
Authors Contributions	All authors contributed to the study's conception and design. Material preparation, data collection and analysis were performed by M Ravi Naik,. The first draft of the manuscript was written by M Ravi Naik.,guided by Prof. MVSS Giridhar and all authors are commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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This work presents a supervised classification and accuracy assessment of LU/LC satellite data, and Channel Dynamics of Musi River. Skills in remote sensing and data using satellite images were acquired in this work. The present work leaves a wide scope for future investigators to explore many other aspects of Environmental uncertainty and risk assessment.

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