COMPARISON OF SPATIAL INTERPOLATION METHODS FOR ESTIMATING THE RAINFALL IN LUMBINI PROVINCE, NEPAL



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Submitted by

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DECLARATION

This thesis entitled, "COMPARISON OF SPATIAL INTERPOLATION METHODS FOR ESTIMATING THE RAINFALL IN LUMBINI PROVINCE, NEPAL" which is being submitted to the Central Department of Hydrology and Meteorology, Tribhuvan University, Nepal for award of the Degree of Master of Science in Hydrology and Meteorology, is a research work carried out by me under the supervision of Assistant Professor Damodar Bagale. The research results presented in this study are original and have not been submitted earlier in part or full in this or any university or institute, here or elsewhere for the award of any degree or for publication in any journal and there is no potential conflict of interest. All the reference sources of information have been properly and fully acknowledged.

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RECOMMENDATION

It is certified that **Ms Yojana Bastakoti** has carried out the thesis work entitled, "COMPARISON OF SPATIAL INTERPOLATION METHODS FOR ESTIMATING THE RAINFALL IN LUMBINI PROVINCE, NEPAL" for the achievement of Degree of Master of Science in Hydrology and Meteorology under my supervision. To my knowledge, this work has not been submitted to any other degree.

We, therefore, recommend the dissertation for acceptance and approval.

.....

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CERTIFICATION

The dissertation entitled, "COMPARISON OF SPATIAL INTERPOLATION METHODS FOR ESTIMATING THE RAINFALL IN LUMBINI PROVINCE, NEPAL" submitted to the Central Department of Hydrology and Meteorology for partial fulfillment of a degree in Master of Science, is a research work carried out by Ms. Yojana Bastakoti under supervision of Assistant Professor Damodar Bagale, Central Department of Hydrology and Meteorology, Kritipur, Kathmandu. This work is my own genuine work and has not been submitted anywhere for the award of any degree.

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ABSTRACT

For strategic management and long-term use, it is important to have a better understanding of the spatial distribution of rainfall data. The current study assesses the geographic distribution of rainfall over Nepal's Lumbini Province, 39 data sites were used for the study. The spatial distribution of rainfall was obtained by interpolating the observed data using the various geostatistical interpolation algorithms offered by ArcGIS. The Ordinary Kriging (OK), Simple Kriging (SK), Inverse Distance Weighting (IDW), and Radial Basis Function (RBF), spatial interpolation methods were investigated. Based on the crossvalidation results and the statistical parameters Correlation (R) and Root Mean Square Error (RMSE), the performances of different interpolation algorithms were assessed with R and RMSE values of 0.61 and 26.35 respectively. The Ordinary Kriging seems to have performed well for the region. The Ordinary Kriging interpolation method was used to map the spatial distribution of rainfall over the low and high lands of Lumbini Province. The results showed that the average annual rainfall during 22 years period ranged between (1058 to 2555 mm). At the Meantime, province's southwest region has lower rainfall of 1058 to 1431 mm, whilst high rainfall in the range of 2046 to 2555 mm occurs in the province's northeast region and appears to be gradually decreasing towards the lower altitude. Additionally, seasonal precipitation range of pre-monsoon, monsoon, winter monsoon and post monsoon are observed. Furthermore, pre-monsoon, monsoon and winter monsoon follow the highly similar pattern of overall precipitation pattern throughout the years. However, distribution of post monsoon rainfall pattern is discreate over the territory.

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LIST OF ABBREVIATIONS

R	Correlation
IDW	Inverse Distance Weighting
OK	Ordinary Kriging
RBF	Radial Basis Function
RMSE	Root Mean Square Error
SIMs	Spatial Interpolation Methods
SK	Simple Kriging
UK	Universal Kriging
GW	Ground water

Chapter 1

1.1 INTRODUCTION

Rainfall is considered as one of the world's most prominent, renewable, and existent sources of water supply. The knowledge of rainfall patterns over an area can have significant applications on decision making processes in the development of hydrological, agricultural and water supplies program and policies as well as in many natural resource management investigations. Rainfall is considered a crucial component in the hydrological cycle and changes in its spatial pattern directly influence the water resources. It is the most important climatic variable in hydrology and in water resources management due to its critical effect on the spatial pat- terns of water availability. Precipitation data is an important parameter in environment studies such as climatic modeling and hydrological modeling (Antal et al., 2021; Yang et al., 2021). Precipitation has a structure varying at spatial and temporal scale. Understanding this variation of precipitation has a significant role in the applications of hydrology, climatology, agriculture, ecology, and other environmental sciences. It is difficult to make a correct forecast for precipitation and to reveal its spatial distribution in areas in which topography varies in short distance and there is an insufficient number of stations.

Precipitation plays a key role in the hydrological cycle, a determinant of the global climate system and participates in the dynamics and atmospheric composition (Ahmed et al., 2014). Many uncertain factors including topographic factors such as latitude, longitude, altitude, slope, and largescale circulation have variable effects on the spatial distribution of precipitation. Therefore, it is necessary to conduct a detailed study to improve the accuracy of such analysis. Spatial interpolation schemes are required to provide accurate spatial distribution of rainfall.

The spatial distribution of rainfall is an aspect important that requires detailed scientific research since regions with rainfall measurements scores are taken by raingauge network which can often be sparse and irregular. Hence there is necessity for spatial interpolation process where points with known values are used to estimate unknown values at other points. The spatial distribution of rainfall is a per amount for water related researchsuch as hydrological modeling and watershed management. The use of different interpolation methods in the same area may cause large differences and deviations from the real spatial distribution of rainfall, these differences depend on the type of chosen model, its mode of geographical management and the resolution used.

Spatial distribution of rainfall should be properly continuously monitored in order to determine the extent of rainfall fluctuations with seasons and years for its optimal use and to realize a realistic development planning. Such monitoring has not been possible in many developing countries including Nepal compared to the developed countries due to lack of trained manpower and facilities. Adequate information on spatial variation of rainfall distribution is prerequisite to the proper planning, risk assessment and decision making for the sustainable development of water resources. A regional scale assessment of rainfall distribution with the conventional method of direct measurements to generate dense data may not be viable as they are inherently expensive and time consuming. However, recent advancement in numerical interpolation techniques have made it possible to realize a realistic assessment with sparsely available observation data.

Several studies have demonstrated an efficient and reasonably accurate assessments of regional scale spatial distribution of rainfall distribution using the limited number of observed data from the area (Silva et al., 2019; Fanet al., 2021; Drynas et al., 2007). A robust interpolation technique that works on sparsely sampled data to predict and map the spatial distribution of rainfall data at unsampled locations is needed. Geographic Information System (GIS) is one of the widely used computerbuilt tools to estimate and map the rainfall distribution over an area of interest. The numerical interpolation techniques that it incorporates are considered highly efficient and fairly accurate. Furthermore, the Geostatistical analysis module in GIS is the reliable way to reveal the spatial correlation and is used extensively for incorporating and analyzing spatial data with other data. This particular module of GIS can greatly help simplify arrangement of resource expansion, ecological safety and logical investigation (Njeban, 2018). Inrecent years, the use of GIS has grown rapidly in various studies related to rainfall distribution.

Spatial distribution of groundwater depth is often assessed by performing

interpolation of sparsely monitored depths. Different interpolation techniques are applied. Each technique has some strengths and weaknesses and, depending upon the characteristics of the land-surface, one or another technique predicts relatively more representative groundwater level distribution. Some of the widely used interpolation techniques are implemented in the Geographic Information System (GIS). The interpolation methods can be broadly categorized into the deterministic and the stochastic. The Inverse Distance Weighting (IDW) and Radial Basis Function (RBF) methods are example of deterministic whereas the Kriging, which is further classified into three methods, namely, Ordinary Kriging (OK), Simple Kriging (SK) and Universal Kriging (UK) are the example of stochastic (Varouchakis and Hristopulos, 2013).

A study on comparison of various interpolation methods over the Mining oasis of northwest China revealed that among various interpolation techniques, the optimal technique can only be obtained by comparing their results in a variety of geomorphological settings (Sun et al., 2009).

The spatial distribution of precipitation plays an important role in hydro-logical modeling, disaster prediction and watershed management. A better scientific understanding on spatial variation of rainfall is required to lay out a concrete plan for future planning and strategies. The study aims to evaluate the four different interpolation methods two stochastic (Ordinary Kriging (OK)and Universal Kriging (UK)) and two deterministic (Inverse Distance Weighting (IDW) and Radial Basis Function (RBF)) from the 40 rainfall stations data of lowlands and highlands of Lumbini Province. The accuracy of the interpolation method is evaluated to outline a spatial variation of rainfall of Lumbini Province based on one of the accurate methods. The dissertation is divided into five chapters, each containing the required and crucial descriptions. The first chapter discusses the motives that motivated us to undertake this study, as well as the study's objective. The study's aims are clearly stated here. Other sections of this chapter address the research area's broad geographical and climatic aspects and the variation of rainfall according to the geography as well the interpolation techniques studied over the world in the field of Meteorology and Hydrology. The specific technique used throughout the investigation is given in full in chapter three. The study's findings are rationally organized and nicely reported in the

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fourth chapter. At last, in the fifth and last chapter, some concluding observations on certain key results and ideas for future study are summarized.

1.2 Motivation and Purpose

Since accurate geographical and temporal representation of the precipitation is crucial to predicting rainfall distribution throughout the region, precipitation data serves as the primary input parameter. Interpolation techniques are employed to carry out an accurate spatial representation of rainfall and, as a result, to enhance the existing data. The spatial interpolation of precipitation in Nepal has received far less attention than other regions. Understanding how rainfall data are spatially interpolated throughout the study region to estimate the amount of precipitation in 22years is improved by this research.

Contrary to other meteorological parameters, the pattern of rainfall is rather inconsistent. The terrain of the province of Lumbini is varied, ranging from high hills to low flatlands. This area is highly populated andknown as the country's agricultural and tourist powerhouse. Therefore, a thorough analysis of this region's rainfall distribution is required. The most accurate method to forecast the distribution of rainfall over time in the research region may be spatial interpolation. By combining geospatial technology with a statistical technique, this work aimed to fill a gap in the literature by developing a robust tool for tracking the spatial interpolation frainfall data over the province of Lumbini. This study is meant to act as a foundation for additional in-depth spatial analysis studies.

1.3 Description of Study Area

Lumbini Province is in western Nepal. It borders Gandaki Province and Karnali Province to the north, Sudurpashchim Province to the west, Uttar Pradesh and Bihar of India to the south. Lumbini is the third largest and the third most populous province among the Nepali provinces comprising 12 districts. This region covers 22, 288 square kilometers and accounts for around 15% of Nepal's total land area. The southern portion of this regionis Terai, which is connected to Uttar Pradesh in India, the central section is hilly, and the northern high hills added a plus decorum of the province geography. There are additional steep hills and tarsand foothills between the Mahabharat and Chure mountains. The vibrant land terrain ranges from 60 to 7000 meters above mean sea level. This region is drained by major rivers, like Rapti, Babai, Madi, Banganga etc, as well as includes the famous pilgrimage of buddist Lumbini and Nepal second International airport Gautam Buddha International Airport (*https* : *//en.wikipedia.org/wiki/Lumbini province*).

The province of Lumbini has a humid subtropical climate with four dis- tinct seasons. The summer season runs from March through May, while the monsoon season runs from June through September after the winter months of January and February.

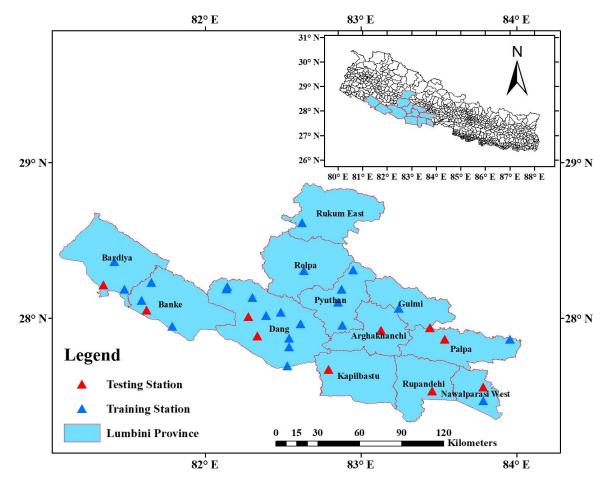


Figure 1: Map of Study Area

1.3 Scope and Objectives of study

The study aims at achieving the following main and specific objectives:

1.4.1 General Objectives

• To understand, model, predict and map, the spatial distribution of rain fall data over 22 years in the flat and high land of Lumbini Province, Nepal.

1.4.2 Specific Objectives

- To compare the performance of different spatial interpolation modules and to identify the optimal interpolation module for the Lumbini Province.
- To evaluate the spatial distribution of rainfall over Lumbini province from 2000 to 2021 with Seasonal distribution as well.

1.4.3 Research Questions

- What is the best interpolation method for interpolating rainfall over the low and high land of Lumbini province?
- Which interpolation method has low Root Mean Square Error (RMSE) and High correlation(R) in between actual and predicted data?
- What is the average rainfall distribution over Lumbini province over 22 years?
- What is the range of Seasonal (Summer, Winter, Pre monsoon and Post monsoon) average rainfall distribution over 22 years?

Chapter 2

2.1 Literature Review

The measurement of every rainfall data station using Raingauges is necessary in order to comprehend the spatial variance of rain-fall data in the region. Data collection on rainfall is difficult, time-consuming, and expensive at every location. Using geostatistical methods, geoscientists produce spatial maps of rainfall interpolation. Using a variety of interpolation techniques, the datacollected from the sampled sites are utilized to forecast values for unsampled spots. It is possible to use a stochastic (OK, UK, simple kriging (SK) or deterministic method to interpolation (IDW, RBF, Natural neighbor etc.). The choice of interpolation approach is causing more concern, and numerous researchers have used different methodologies to determine the best interpolation method. Interpolation method in GIS has been widely used to map the spatial variability of rainfall levels. However, the determination of ideal interpolation procedure is of serious concern. Different interpolation methods were compared by Caruso and Quarta discussing their advantages and disadvantages (Caruso et al., 1998)

A study by Phillips shows that geostatistical prediction techniques are one which provide better estimation of rainfall (Phillips et al., 1995). Next study by Pirani compares deterministic and geostatistical methods for rainfall estimation (Pirani et al., 2020). A study by Daly and Borrough showed that if data are abundant the interpolation method give the best result (Daly et al., 1994; Burrough et al., 2001). A study by Yang spatially interpolates daily rainfall data between (1950-2009) and (2040-2059) over greater Sydney region resulting Inverse Distance Weighting (IDW) method better than other interpolation (Yang et al., 2015).

The spatial interpolation method mapping rainfall in Indian Himalayas after cross validating the available data found that Radial Basis Function with Thin plate spline function as the best interpolation techniques with R as 0.78 and RMSE 33.63 (Kumari etal., 2016).

Pareira spatially interpolates the rainfall variation using 300 rain gauges data in Sri lank. The paper compared five interpolation methods resulting in the best interpolation method as Radial basis function with thin plate spline function (Pareira et al., 2021).

Bakis researched on comparison of spatial rainfall distribution using interpolation method in Turkey and had shown that correlation R as 0.7118 with RMSE 33.359, showing Kriging as the best interpolation method (Bakis et al., 2021).

Ceron in his journal compared spatial interpolation methods for annual and seasonal rainfall in 2 hotspots of South America. In this research geostatistical and deterministic approaches were compared by cross validation resulting in Kriging with Spherical model as the best interpolation with high R and lower RMSE (Ceron et al., 2021).

Kharel in 2021 spatially analyzed the temporal rainfall variation in Pokhara with data ranging from 1999 - 2019 using Inverse distance weighting method with R 0.68 with lower RMSE 22.34 (Kharel et al., 2021).

S. Wang and Huang compares the interpolation for estimating spatial distribution of precipitation in Ontario Canada and obtaining ordinary kriging obtain optimal result and better interpolation (Wang et al., 2014).

"A Comparison of IDW, Kriging and RBF Methods for Interpolation of Rainfall Data" by De Piazza and V.Voila in (2012) compares the performance of IDW, Kriging, and RBF interpolation methods for estimating rainfall data in a study area in Italy. The study found that the Kriging method performed the best, followed by the RBF method, and then the IDW method (Piazzaet al., 2011).

Interpolation of Rainfall Data Using IDW, Kriging and RBF Methods: A Comparative Study" by S.K. Singh and P.K. Singh in (2011) compares the performance of IDW, Kriging, and RBF interpolation methods for estimating rainfall data in a study area in India. The study found that the Kriging method performed the best, followed by the RBF method, and then the IDW method (Singh et al., 2011).

Arslan measured groundwater level of 59 wells in Carsamba Plain, Turkey and attempted to interpolate for the prediction of spatial distribution groundwater level using nine different interpolationtechniques and examined their performance. Analyzing the yields of R, MAE and RMSE, he concludes that RBF method was the

optimal module to estimate the groundwater level for Carsamba Plain (Arslan et al., 2014).

Adhikary and Dash compared different interpolation modules available with GIS. They examined the deterministic modules such as IDW and RBF and stochastic modules such as OK andUK for the study of groundwater level in Delhi region as per the year 2006 using the groundwater level data from 110 different lo- cations. They found that OK and UK modules outperformed the IDW, but the RBF performed better than OK in predicting the groundwater levels over the Delhi region (Adhikary et al., 2017). Sun compared the accuracy of the interpolated values obtained from several interpolation techniques. The study presents SK to be optimal interpolation method for interpolating depth to GW data in Mingin oasis at Northwest China. Further, the study discusses the spatial and temporal variation of GW level based on optimal interpolation method (Sun et al., 2009).

Yao inspected the performance of several deterministic and stochastic interpolation methods-IDW, global polynomial interpolation, local polynomial interpolation, Regularized spline (Rspline), Tspline, OK, UK, SK. The OK and UK were selected as the optimal interpolation as a result of orthogonal validation possessing less RMSE and higher correlation (R) (Yao et al., 2013).

Karki in 2015 study kriging interpolation technique to interpolate climatic variables and Bhattarai in 2022 compares stochastic and deterministic approach to show the best interpolation technique for ground water also (Karki et al., 2015; Bhattarai et al., 2022). Review of publications suggests that an optimal interpolation method to map the spatial distribution of rainfall data over Lumbini Province is yet to be identified. Nevertheless, the optimal method for the province can be identified and adopted by looking at the statistical measures between the different interpolation method.

2.2 Semivariogram Analysis

Before Kriging is performed a valid semi-variogram model is to be explored. The theoretical building of semi-variogram is derived from the variogram. The variance of the difference between two field values $\gamma(S_i, S_j)$ at any two locations say S_i and S_j is called semi-variogram.

$$\gamma(S_i, S_j) = var\left[\left(Z(S_i) - Z(S_j)\right)\right] \tag{1}$$

and semi-variogram defined as:

$$\gamma\left(S_{i}, S_{j}\right) = \frac{var\left[\left(Z(S_{i}) - Z(S_{j})\right)\right]}{2} \tag{2}$$

If we consider 'n'be the pair of sample points separated by the vector distance 'h' then equation 1 and 2 can be re-written as:

$$\gamma(h) = \frac{\sum_{i=1}^{n} [Z(S_i) - Z(S_i + h)]^2}{2n}$$
(3)

 $\gamma(h)$ is a semi-variogram which is the function of lag distance orseparation distance 'h' (Taee et al., 2018).

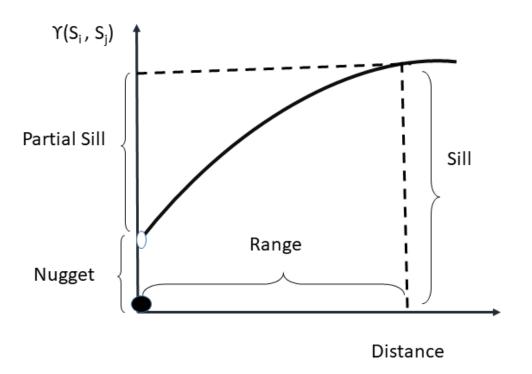
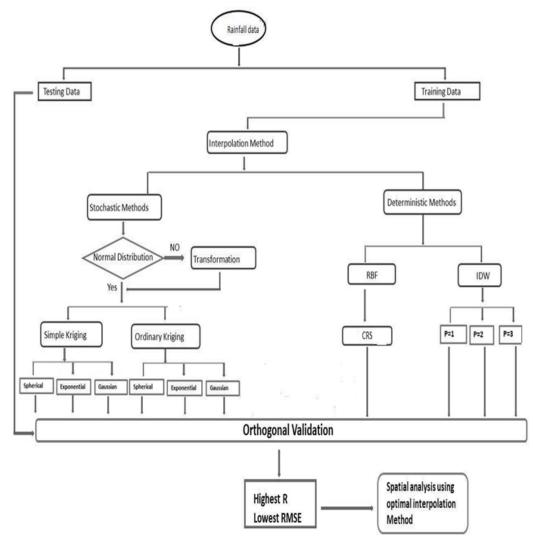


Figure 2 : The general anatomy of semivariogram.

Chapter 3

3.1 Methodology

This chapter introduces the methods and methodology adopted in the study. The study of spatial variation of Rainfall distribution in lowlands and high lands of Lumbini province is based on the data collected by rain gauges at 39 different meteorological stations over the area. The collected data was organized, interpolated, and analyzed using MS Excel 2013 and ArcGIS 10.6. The details of the methods/procedures adopted in realizing the



present study is summarized in figure.

Figure 3: A block diagram showing the research methodology.

3.2 Data Collection

For the study, the rainfall observations from 39 stations governed by Department of Hydrology and Meteorology (DHM) Nepal have been taken. For aiming to capture different climatic zones data set used in this work included lowlands and high lands. For this study data from 2000-2021 were employed, all the stations contain regular data with no missing values for the years. Average rainfall data for 22 years has been used for the study.

3.3 Spatial Interpolation Methods (SIMs)

ArcGIS interpolation algorithms are frequently used to forecast the values of raster cells from a small number of sample points. Based on known sampling data from the nearby grid points, such techniques accurately forecast unknown values for every geographic grid point. Some SIMs are identified by several terms, such as "deterministic" and "stochastic", "interpolating" and "non- interpolating", "interpolators" and "non- interpolators" and so forth (Lu and Wong, 2008).

Examining and identifying the best interpolation technique that gives the most accurate spatial distribution of GW over the study region is one of the specific goals of the current study. In this study, we assess the effectiveness of some of the interpolation methods that are frequently used. The two main types of interpolation algorithms are deterministic and stochastic. While approaches like Ordinary Kriging and Universal Kriging are known as stochastic interpolation techniques, Inverse Distance Weighing (IDW) and Radial Basis Function (RBF) are regarded as deterministic methods.

Based on either the degree of similarity (IDW) or the degree of smoothing, deterministic interpolation algorithms generate sur- faces from sample points using mathematical functions (RBF). These techniques don't require complicated mathematical algorithms and are rather straightforward and basic. The idea of randomness is incorporated into stochastic procedures.

These techniques anticipate values at all points in the region of interest using mathematical and statistical algorithms, and they provide probabilistic assessments of the interpolation's quality based on the spatial autocorrelation of the data points. The interpolated surface is thought of as one possible observation among many, all of which could have given rise to the known data

points. Thenext subsections offer a brief description of the SIMs used in thestudy.

3.3.1 Inverse-Distance Weighting (IDW)

The IDW is one of the deterministic models which is exact and convex. The details of IDW are discussed elsewhere. This particular method, a standardized formulation available in almost all the GIS packages, is widely used by geoscientists. It estimates the value at some unsampled location $Z(S_0)$ at a distance S_0 as a linear combination of weights λ_i and observed Z values sampled at locations S_i such that:

$$Z(S_0) = \sum_{i=1}^n \lambda_i Z(S_i) \tag{4}$$

with λi defined as,

$$\lambda_i = \frac{d_{0i}^{-\alpha}}{\sum_{i=1}^n d_{0i}^{-\alpha}} \tag{5}$$

and,

$$\sum_{i=1}^{n} \lambda_i = 1 \tag{6}$$

The numerator in equation (5) is the inverse of distance d0i between S0 and Si with power ' α ' and denominator is the sumof all inverse distances.

The mathematical relation can be written as:

$$Z(S_0) = \sum_{i=1}^{n} \frac{d_{0i}^{-\alpha} Z(S_i)}{d_{0i}^{-\alpha}}$$
(7)

The weight ' λ_i ' depends upon the distance between S0 and S_i, smaller the distance between them larger the weight and vice- versa. The arbitrary choice of the weighting function is the major limitation of the IDW interpolation method (Virdee and Kotte- goda, 2008; Wackernagel, 2003).

3.3.2 Radial Basis Function (RBF)

The RBF is also a widely preferred SIM's for large number of poorly distributed data sets. The most commonly used RBF methods are; the multiquadric (MQ) and the Thin Plate Spline (TPS) method. The TPS uses the spline-based technique for data interpolations and smoothing. The RBF

approximation at S0, based on the set of sample locations reads as:

$$Z(S_0) = \sum_{i=1}^n \lambda_i \varphi(d_i^*)$$
(8)
$$d_i^* = \sqrt{\theta_1 (x_0 - x_1)^2 + \theta_2 (y_0 - y_1)^2}$$
(9)

 $\theta 1$ and $\theta 2$ being fixed positive scalars. The weight factor λi is estimated such that the observed value and approximated value exactly matches at point *Si*. TPS uses the function $\psi(t) = t^2 \log(t)$.

3.3.3 Ordinary Kriging (OK)

The kriging method, in all of its varieties, has been extensively studied in a number of research. It is an interpolation technique based on the stochastic spatial variation model, and it is like to be reliable due to its unbiased estimates and known minimum variances. It offers benefits, particularly when there is considerable natural data fluctuation. Kriging can be thought of as a point interpolation technique that takes a point map as input and outputs a raster map with estimates. The OK is a popular stochastic model for estimating value at a point in an area where the variogram is known, and it is dependent on local data at the place of the estimation. The value $Z^{*}(s0)$ at point "s0" is estimated by using the data values from 'n' neighboring sample points which is just a linear combination of known input values advantaged by minimum error estimates (Cressie, 1988; Adhikary and Dash, 2017; Cressie, 2015).

$$Z^*(S_0) = \sum_{i=1}^n \lambda_i Z(S_i) \tag{10}$$

In the above equation 'S' is the position vector, Z(S0) is the interpolated value of any hydro geological variable and λi is the weight factors. For the estimator Z^* to be unbiased:

$$< Z^{*}(S_{0}) - Z(S_{0}) > = 0$$
 (11)

and weights must sum to unity i.e

$$\sum_{i=1}^{n} \lambda_i = 1 \tag{12}$$

3.3.4 Simple Kriging (SK)

Simple kriging assumes the model

$$Z(s_0) = \mu(s_0) + \epsilon(s_0)$$
 (13)

Where,

Z(s0) is the variable of interest, $\mu(s0)$ is some deterministic function and $\epsilon(s0)$ is random variation. The symbol SO indicates the location. In the above figure, the observed data are given by solid circles. A second order polynomial is the trenddashed line which is $\mu(S0)$. The errors, assumed to be random, are obtained by subtracting $\mu(S0)$ from original data. The mean of all $\epsilon(S0)$ is zero. However, instead of assuming that the errors $\epsilon(s0)$ are in- dependent, they are modeled to be auto correlated. In equation (12), $\mu(s0)$ is defined as drift in some references. The average value of the distributed points is modelled by the drift, which is a straightforward polynomial function. If the surface is not stationary, the kriging equations can be enlarged to estimate the drift concurrently, removing the drift and bringing the surface tostationary. At each grid node, kriging will estimate the drift and residuals from the drift so they may be mapped. The surfaces representing the estimated drift and the estimated residuals are combined to get the best approximation of the original surface. Theoretically, kriging is the only method of grid generation that can generate estimates that are superior (in the sense of being unbiased and having least error) in the form of a mapped surface. The correct specification determines how well the technique works in practice (Olea, 1999; Clark, 1977).

The experimental semi-variogram $\gamma(h)$ can be fitted to different theoretical models such as linear, exponential, circular and gaussian etc. to generate three main parameters of semi-variogram Nugget(*C*0), sill (*C*0 + *C*) and range(*R*0) as shown in

Figure 2 (Arslan, 2014).

3.4 Semivariogam model selection

The experimental semivariogram is fitted to three different theoretical models Exponential, Spherical and Gaussian as preferred in most of the studies.

The RMSE and R are the major statistical parameters computed to determine the best fit theoretical semi-variogram model. The RMSE and R of observed and interpolated(predicted) data sets for various models are individually computed and the one with lowest RMSE and highest R is selected as the best fit (Jian et al., 1996). The model parameters shown in Table 1 are fine- tuned to minimize the error and spatial association of data set is comprehended from corresponding sill, nugget and range. The best fit semi variogram model is shown in Figure 4.

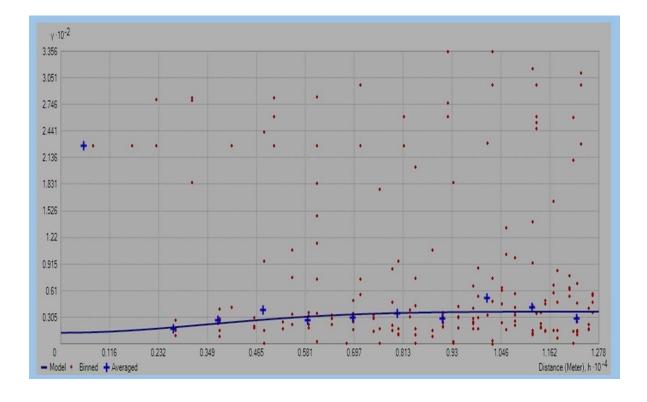


Figure 4: Semivariogram of best fit model.

List of	Data	The	The	Direction
Interpolation	conversion	Maximum	minimum	search angle
Methods		predicted predicted		
		points used in	points used in	
		search raduis	search radius	
IDW	None	5	1	45
ID W	none	5	1	45
TPS	None	5	1	45
OK	BOX-COX	5	1	45
SK BOX-COX		5	1	45

Table 1: Parameters used in interpolation of data.

3.5 Selection of optimal interpolation method

The observed data set is statistically analyzed, and normality of the distribution is assured by box-cox transformation with power parameter, $\lambda = 1$. Out of 39 observations 29 observations (75%) classified as training data set was used to develop the interpolation model and remaining 10(25%) were classified as testing data. The testing data was randomly assigned to validate the model. The study used 75% as testing and 25% as training data. The cross-validation method is used to test the model's ability to predict the unknown values correctly. As different interpolation techniques are used to predict spatial rainfall distribution data, their accuracy can be estimated by using orthogonal validation. In this study RMSE, an error-based measurement is the major parameter to test the accuracy of the model. It can calculate the forecasting errors within the data set and is computed using the formulation.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (z_i - z_i^*)^2}{n}}$$
(14)

where, Z_i is the observed value at the sampling points i, Z_i^* is the predicted value and 'n' is the number of training samples.

Another criteria to evaluate the cross-validation is the computation of R which is the square of correlation calculated as:

$$R = \frac{\sum Z_i Z_i^* - \frac{\sum Z_i Z_i^*}{n}}{\sqrt{\left[\sum Z_i^2 - \frac{\sum Z_i^2}{n} \left[\sum Z^2 - (\frac{\sum Z^2}{n})\right]\right]}}$$
(15)

The model that yields the lowest RMSE and higher R has been chosen and is expected to produce the most representative spatial distribution of rainfall data over the study area (Yao et al., 2013).

CHAPTER 4

4.1 Result and discussion

The primary findings of the study are addressed in the next many sections and subsections. In this chapter, we explain the explanation for the expected spatial distribution of rainfall data over the low and high lands of Lumbini province.

4.2 Statistical Analysis

The 39 separate stations' data collection was limited to their physical positions inside the study region. First, before spatially correlating the data, the average of the 22 years of data was calculated in order to interpolate using various statistical and geo- statistical techniques. 22 years average data has been designed according to the locations. Average data is thus separated using GIS subset feature. The whole data is distinguished between Training 75% and Testing 25%. The Training data is used in interpolation while testing data is used in validation.

To perform further interpolation, the data must be regularly distributed. Since the data were not normally distributed, the Kolmogorov-Smirnov (K-S) test was used to determine whether the data set was normally distributed. In light of these factors, the stochastic interpolation approach may be unable to accurately replicate the geographical distribution of rainfall across the research area without ensuring the normal distributed data. Box-cox transformation with parameter $\lambda = 1$ testing ensures that the data set is normal and produced a normalized skewness value of 0.0515 and a kurtosis value of 0.328 be unable to accurately replicate the geographical distribution of rainfall across the research area without ensuring the normal distribution of rainfall across the research area stransformation with parameter $\lambda = 1$ testing ensures that the data set is normal and produced a normalized skewness value of 0.0515 and a kurtosis value of 0.328 be unable to accurately replicate the geographical distribution of rainfall across the research area without ensuring the normal distribution of data sets. According to reports, this specific approach performs better with regularly distributed data.

Box-cox transformation with parameter $\lambda = 1$ testing ensures that the data set is normal and produced a normalized skewness value of 0.0515 and a kurtosis value of 0.328.

22 years average data has been designed according to the locations. Average data is thus separated using GIS subset feature. The whole data is distinguished

between Training 75% and Testing 25%. The Training data is used in interpolation while testing datais used in validation.

4.3 Performance analysis of interpolation methods

The data must first be divided into two subsets, training, and testing data, with 29 data serving as the training data set and the remaining 10 serving as the testing data set. The training data is then subjected to interpolation, as mentioned earlier in the process. Data must be interpolated using deterministic and stochastic approaches for the interpolation techniques to be estimated accurately.

4.3.1 Cross validation of deterministic model using IDW

Three different spatial interpolation techniques were investigated and contrasted in this study. Cross-validation is frequently used to evaluate the precision of different interpolation techniques. Each time, a data point is eliminated from the data sets, and values are predicted using the remaining measured points. Following that, the anticipated value at the deleted point and the measured value can be compared. In this study, cross-validation was used to validate the interpolation results. Mean, root-mean-square error (RMSE), and square of degree of correlation R were determined to assess the goodness-of-fit. All the measurement points underwent this process. Statistics that show how well the anticipated data matches the actual data observed had to be used. It is possible to determine the differences between the fore- casts made using various interpolation techniques and the actual data recorded at the rain gauges by various statistical analyses. The accuracy of interpolation techniques is summarized by the RMSE and R.

The outcomes of deterministic theoretical model by using IDW interpolation method is shown in Table 2.

Model	Power /Semivariogram	RMSE Value	R value
	function		
IDW	1	25.68	0.54
IDW	2	28.63	0.36
IDW	3	18.57	0.61

Table 2: Spatial Interpolation data by IDW method.

In this cross validation IDW with power 3 semi-variogram per-formed well with RMSE (18.57) and R (0.61) The R value of power 2 semi variogram model appears insignificantly lesser as compared to power 1, and RMSE value being significantly higher. Similarly, Power 3 variogram model has also higher correlation and lower RMSE. Thus, power 3 semi-variogram can be regarded as best-fit model for IDW. This semivariogram model, thus, can be considered to better represent for study area using IDW interpolation.

4.3.2 Cross validation of deterministic model using RBF

RBF minimizes the surface's overall curvature while fitting a surface through the measured sample values. RBF can anticipate values beyond the maximum and below the minimum measured values, whereas IDW can never do so. For smoothly variable surfaces like height, RBF can deliver good results. RBF, however, is ineffective when the surface values dramatically shift over a short distance. For, further interpolation in this study, RBF model with a completely regularized spline (CRS) semivariogram was used. The outcomes of deterministic theoretical model by using RBF interpolation method is shown in Table 3.

Table 3:	Spatial	Interpolation	by RBF method.	

Model	Power	/	Semivariogram	RMSE value	R value
	Function				
RBF	CRS			29.38	0.67

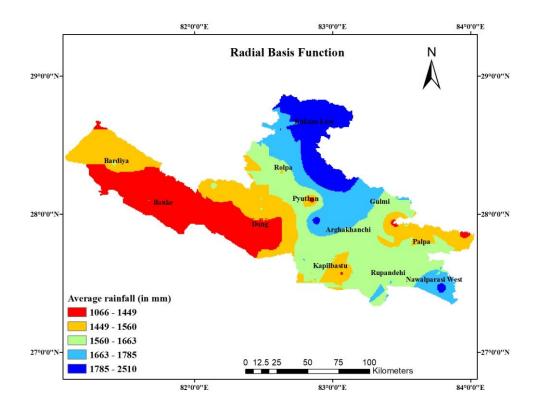


Figure 5: Spatial Interpolation map by RBF.

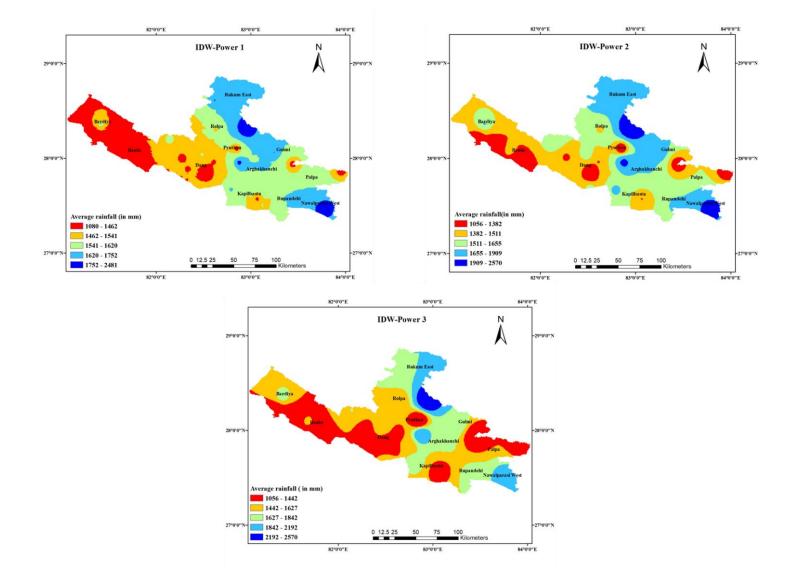


Figure 6: Spatial Interpolation using IDW

4.3.2 Cross validation of Stochastic models using Ordinary and Simple Kriging

In case of OK, exponential semi-variogram performed well with RMSE (17.32) and R (0.71). The R value of Gaussian semivarogram model appears insignificantly lesser as compared to exponential, and nugget effect is significantly less in OK exponential. Thus, exponential semi-variogram can be regarded as best fit model for OK. In case of SK gaussian semi-variogram performed well with highest R (0.68) and lowest RMSE (25.62). This semi- variogram model, thus, can be considered to better represent for study area among the OK and SK. The nugget to sill ratio is

about 0.39. It shows the rainfall data is moderately correlated as stated in the study over the New Delhi, India (Adhikary and Dash, 2014). Spatial variation of rainfall is affected by natural factors like air temperature, moisture bearing winds, oceanic currents, distance inland from the coast, mountain range etc. The spatial rainfall over the present area is also expected to be greatly affected by the above factors as reflected by the moderate correlation of data.

 Table 4 Comparison of semivariogram parameters of OK method for the selection of best

 - fitted theoretical model.

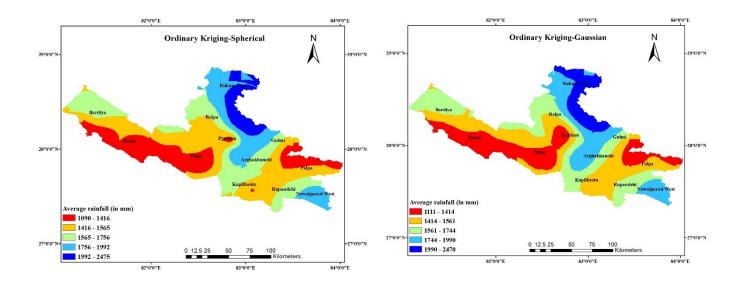
Model	Nugget	Sill	Nugget / Sill	R	RMSE
Spherical	14.41	33.5	0.43	0.49	29.25
Exponential	16.81	52.83	0.31	0.71	17.32
Gaussian	15.63	41.26	0.37	0.56	28.68

 Table 5 Comparison of semivariogram parameters of SK method for the selection of best

 - fitted theoretical model.

Model	Nugget	Sill	Nugget / Sill	R	RMSE
Spherical	19.48	37.53	0.51	0.51	30.86
Exponential	16.82	40.59	0.41	0.58	35.52
Gaussian	16.98	43.24	0.39	0.68	25.62

The interpolated maps by using ordinary and simple kriging using different models have been shown below in Figure 7 and Figure 8 respectively.



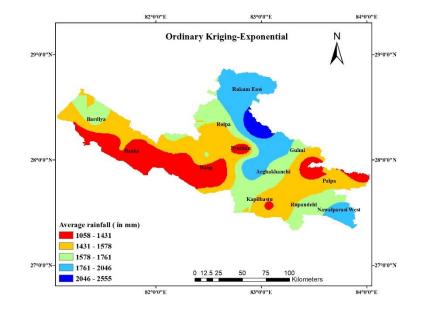
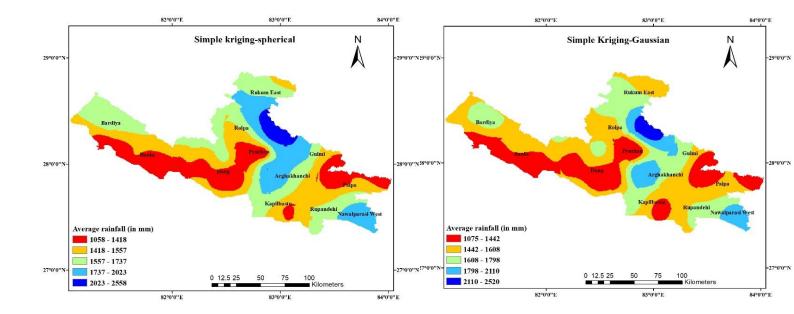


Figure 7: Spatial Interpolation map of Ordinary kriging



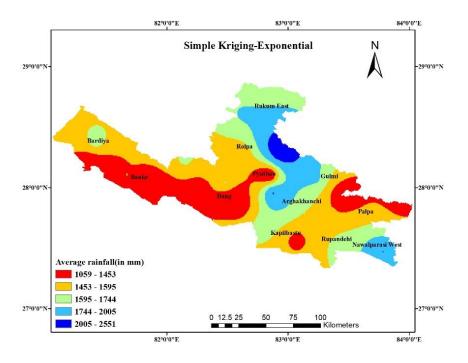


Figure 8: Spatial Interpolation map of Simple Kriging

4.4 Validation

From the cross - validation result, we found that the power 3 function of IDW, CRS model of RBF, Exponential model of OK and Gaussian model of SK resulted in highest *R* and lowest *RMSE amongst* all the applied models of the respective methods. So, these 4 models were applied to the validation datasets (25% of

whole datasets) in order to find the best optimal method for the mapping of spatial distribution of rainfall in the study area. *Rand RMSE* were then calculated for the 4 methods. The values of these parameters are shown in Table 4.5 for IDW, RBF, OK, SK methods. With the highest value of *R* and lowest value of *RMSE* Ordinary kriging was found to be the best optimal method for the prediction of rainfall spatial distribution of rainfall in the study area.

Table 6 The R and RMSE statistics of OK, SK, IDW and RBF obtained from orthogonal validation.

Model	Power / Semivariogram function	R	RMSE
ОК	Exponential	0.68	17.32
SK	Gaussian	0.59	25.62
IDW	Power 3	0.52	18.57
RBF	CRS	0.55	29.38

4.5 Visualization of prediction

As the Ordinary kriging method has given the best prediction of rainfall distribution, the spatial distribution of the predicted rainfall distribution was visualized from the interpolated surface map using the Ordinary kriging method. The interpolated map of ordinary kriging using Exponential model indicate that there is comparatively least rainfall at lower terai regions than midhills. About maximum up to 2600mm of average rainfall has been predicted between 22 years at uphill. The minimum average rainfall ranges between 1058-1431 mm and it is in terai regions like Dang and Banke.

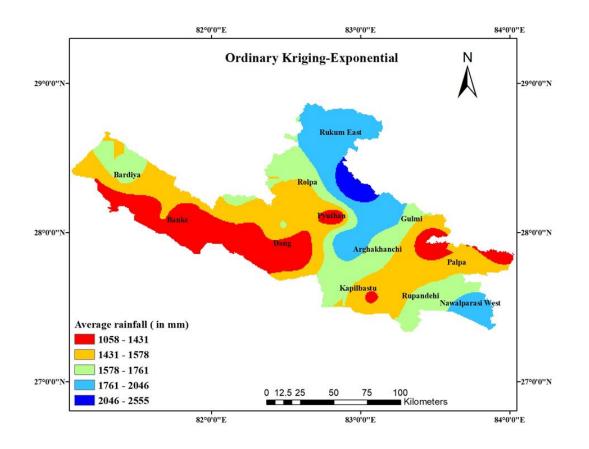


Figure 9: Observed Spatial Interpolation map of rainfall over high and low land of Lumbini Province by using optimal interpolation method.

4.6 Seasonal Distribution of Rainfall Using Optimal Interpolation Method

Comparing the results above and using the best interpolation technique. Now, over a period of 22 years, we have displayed the seasonal distribution of rainfall in the province of Lumbini using that best interpolation. The distribution of rainfall for the four seasons of winter, pre monsoon, summer monsoon, and post monsoon is shown in the figures below.

4.6.1 Winter Rainfall Distribution

Generally, the three months from December to February are recognized as winter season. Average precipitation over 22 years ranges from (44-89) mm. The precipitation is high in the northeast and gradually decreases towards the Southern and southwestern part.

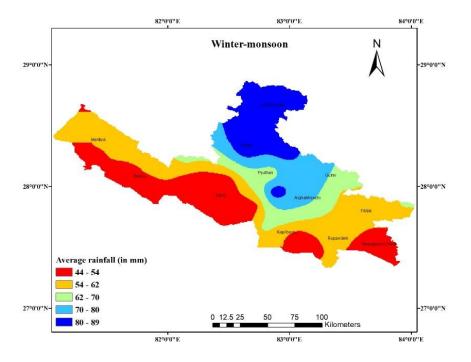


Figure 10: Spatial Interpolation map of winter season.

4.6.2 Pre monsoon Rainfall Distribution

In Nepal, the pre-monsoon season lasts from March to May (MAM). During the months of March to May, the nation is dominated by a dry westerly wind. Late afternoon thunderstorms and gusty winds are caused by the emergence of local convective clouds. The average rainfall over 22 years ranges between (78-339) mm. The precipitation is higher over the province's northward side and gradually decreases toward southern and southwestern parts of province.

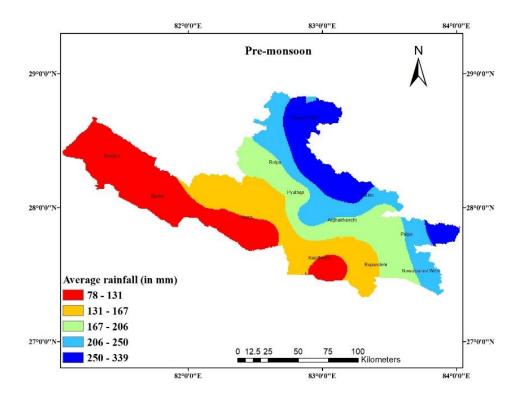


Figure 11: Interpolated map of Pre monsoon season

4.6.3 Summer Season Rainfall Distribution

Monsoon season in Nepal typically lasts from June to September (JJAS). This season is regarded as one of the most essential in Nepal since it contributes the highest percentage of rainfall, accounting for 80% of yearly rainfall. During this season average rainfall over 22 years ranges between 886 to 2052 mm.

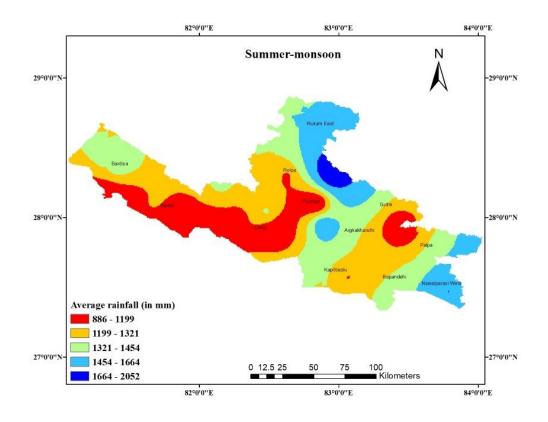


Figure 12 Interpolated map of Summer Monsoon season

4.6.4 Post monsoon Rainfall Distribution

Post-monsoon season in Nepal, which runs from October to November (ON). Occasionally, the country receives precipitation from cyclonic storms that form in the Bay of Bengal and Arabian Sea. Post monsoon (October-November) is the driest season, 22 years of average rainfall ranges from (3-87) mm, distribution is quite discrete over the territory.

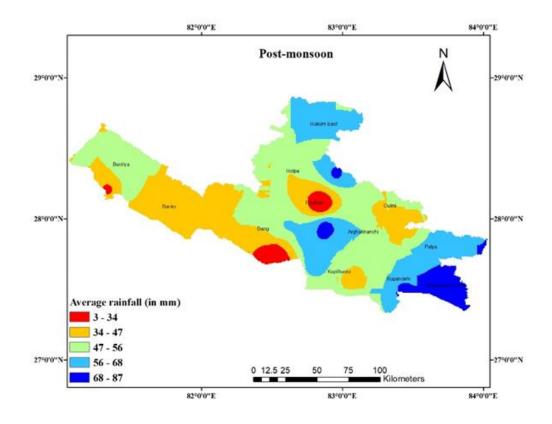


Figure 13: Interpolated map of Post monsoon rainfall.

4.7 Discussion

The study evaluated the performance of two deterministic interpolation methods (IDW and RBF) and two stochastic interpolation methods (Ordinary Kriging and Simple Kriging). The interpolation results were compared using the principle of covariance and error indicator R and RMSE respectively. The result of the indicator are presented in Table (4.1, 4.2, 4.3*and*4.4) in addition with the Figure (4.3, 4.4*and*4.5) show the distribution of mean rainfall over Lumbini province using data from 39 stations on the period of 2000 - 2021, with the highest value of R and lowest value of RMSE. Ordinary Kriging was found to be the optimal interpolation method for the prediction of rainfall in the study area.Earlier studies have also noted the performance of interpolation method which is in agreement with our study as well. For example, For the new climatic classification of Nepal, Kriging interpolation methods is best to interpolate missing climatic parameters (Karki et al., 2015). Kriging is an advanced geostatistical method for interpolation as this research

has similar results as our study predicts. Similarly, Using High correlation and low RMSE our study comes in agreement with the study by Piazaa in Italy, which is the study of rainfall estimates on comparing interpolation methods (Piazza et al., 2011). The spatial distribution of predicted rainfall distribution was then visualized from the interpolation map using ordinary Kriging which indicates lower rainfall in terai region than midhills. Seasonal distribution of rainfall is observed using kriging interpolation method and figure demonstrates the scatter plot of four different seasonal rainfall distribution.

Chapter 5

Conclusion and Future Prospects

5.1 Conclusion

To analyze the spatial distribution of rainfall, the research is based on the Arc GIS Geostatistical module and several semivariogram function models. This work examines the simulation accuracy and prediction impacts of both deterministic and stochastic interpolators. With ArcGIS, various interpolation modules are accessible. These modules each offer distinct advantages and disadvantages, and one may perform better than the other de-pending on the circumstance or field. We looked at the results of various deterministic (IDW, RBF) and stochastic (OK, SK) models. The OK modules outperformed the other three interpolation and validation sets showed that OK performed better than other modules in cross - validation datasets (i.e., 75% of whole datasets), also OK performed the best in validation with testing datasets (i.e., 25% of whole datasets). Taking into consideration the performance of OK in validation datasets, it becomes reasonable to consider OK as the better method of interpolation in the study area. However, no method is found to be significantly superior to other.

Spatial rainfall distribution in Lumbini province from 2000 to 2021 was found to have moderate spatial dependence form which it can be inferred that the rainfall distribution was not stronglyspatially correlated in the study area. Interpolation with Ordi-nary Kriging method in the study area northeastern part of the provincehas got high rainfall distribution with average rainfall about (2046-2555) mm, almost in many areas of Dang and Banke with some areas of Palpa and Rupandehi has a minimal count of average rainfall distribution over 22 years i.e., rainfall ranging from (1058-1431) mm. However, almost many parts of the Lumbini province has accounts moderate rainfall around (1431- 2046) mm from year 2000 to 2021.

Using optimal interpolation that is OK the seasonal rainfall distribution has also been calculated. The total amount of average rainfall in winter, over a 22-year period,

ranges between (44- 89) mm. Precipitation is heavier in the north and gradually lessens in the south and southwest. Pre-monsoon generally starts from march and ends in May. The average rainfall for 22 years ranges from (78-339) mm. Precipitation is heavier in the north and progressively gets lighter in the south and southwest. Typically, the monsoon season begins in June and ends in October. Precipitation totals for this season range from (886-2052) mm.

Monsoon impact is greater in the northern part and gradually decreases at southern and some parts of southeastern. Post- monsoon is regarded as the driest season i.e. (October–November), with an average rainfall distributed range from (3-87) mm for the period of 22 years interval.

5.2 Future Prospectus

Accurate rainfall distribution has significance in meteorology, hydrology, agriculture, and water resource projects.

From this study, the provincial government's knowledge of rainfall patterns over Lumbini province can have important applications on decision making programs as well as various resource management inquiries.

Furthermore, because the current study only evaluates annual rainfall data over a 22-year period, the year-by-year seasonal geographic variance is unknown. To build a realistic distribution map over the area, a long-term study with extensive field measurements using scientific equipment is significantly sought. By combining these types of interpolation with others such as Universal Kriging, Thiesson Polygon, Bayseian Kriging, and others, rainfall estimation would be more dependable not just in the Lumbini province but also throughout the country.

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