Evaluation of Spatial Interpolation Techniques for Operational Climate Monitoring in the Philippines

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Abstract

To overcome the limitation of low network density and sparse distribution of meteorological stations, spatial interpolation is being performed for estimating meteorological variables that are not geographically covered by existing observation network. While there are several readily available spatial interpolation techniques, it is still difficult to determine which one best estimates actual observation. Considering the stimulus for disaster risk reduction, hydrological, agricultural, and other applications of interpolated data, this study compared six interpolation techniques (Inverse Distance Weighted (IDW), Completely Regularized Spline (CRS), Tension Spline (TS), Ordinary Kriging (OK), Universal Kriging (UK), and ANUSPLIN) that have been recommended in tropical maritime region. Validation results comparing historical monthly and interpolated rainfall data from 1981–2010 in 65 stations in the Philippines show that OK has the best performance among the aforementioned techniques followed by ANUSPLIN and TS. Ultimately, this study is a contribution to the existing inadequate literatures that have documented and evaluated interpolation techniques that can be used in archipelagic regions with prominent climate variability.


1. Introduction

To overcome the limitation of low network density and sparse distribution of meteorological stations, spatial interpolation is being performed for estimating meteorological variables (e.g. rainfall, air temperature, humidity, etc.) that are not geographically covered by existing observation network. While there are several spatial interpolation techniques that can be readily used, it is still difficult to determine which one best estimates the actual observations. Essentially, this is because each technique depends on the characteristics of the data set: a technique may be suitable for some variables but may not work for others.

The Philippine Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA) regularly employs spatial interpolation in its operational climatology to perform (1) monitoring of rainfall and provide (2) seasonal and monthly climate outlook, (3) climate projections, (4) tropical cyclone associated rainfall, and (5) other localized climate information. There has been no analysis done to assess and compare various techniques on spatial interpolation of point data measurements versus actual observations in the Philippines. More interestingly, there is an apparent lack of literature that worked on evaluation of spatial interpolation techniques in tropical, maritime, and archipelagic regions, which directed this study to contribute to filling this knowledge gap.

In the Philippines, areal rainfall is typically provided at regional, provincial, river basin, and watershed levels and at different accumulation time interval (e.g. daily, monthly, seasonal, and annual). Climate advisories especially pertaining to drought and dry spell are based on spatially interpolated station data aggregated to provincial level primarily because this is the locus of local governance in the Philippines. It is, therefore, of paramount importance to evaluate and determine spatial interpolation techniques that best fit the Philippine setting.

In this study, six spatial interpolation techniques that are commonly used in tropical maritime countries and are supplemented by physiographic covariates that affect spatial patterns of climate (i.e. terrain and water bodies) were compared. These interpolation techniques include non-geostatistical (i.e. Inverse Distance Weighted (IDW), Completely Regularized Spline (CRS), and Tension Spline (TS)), and geostatistical approaches (Ordinary Kriging (OK), Universal Kriging (UK)), and ANUSPLIN. The first five techniques are readily available in ArcGIS (a geographic information system software) while the latter is performed using the ANUSPLIN platform. To date, TS is used in PAGASA’s climate advisories because of its simplicity and accessibility.

In addition, this study seeks to answer the following question: (1) is there seasonality in the performance of the spatial interpolation techniques? (2) If yes, which technique has the best performance?

1.1 Significance to disaster risk reduction

To demonstrate the differences in the output of each interpolation technique and to iterate the significance of choosing the best interpolation technique, Fig. 1 shows drought and dry spell assessment in May 2015 aggregated to provincial level. Each interpolation technique produced varying results not just in the southern part of the Philippines but also in other provinces in Luzon and Visayas. Drought (or meteorological drought) is defined as a prolonged deficiency in rainfall and dry spell is less severe condition than drought.

In the same month, several provinces declared state of emergencies due to prevalent dry condition and PAGASA assessed that 60% of the country were under either drought or dry spell. The El Niño Southern Oscillation was in its strong warm phase (El Niño) during this time. El Niño is generally associated with widespread reduction of rainfall in the Philippines. In January 2016, the United Nations Office Coordination for Humanitarian Affairs published a projected 50% losses in rice and corn production, and chronic food insecurity in Mindanao due to rainfall deficiency (UN-OCHA 2015). In addition, de los Reyes and David (2009) reported that during the dry season for the period 1970–2005, strong El Niño episodes have contributed to 22% decrease in annual Philippine rice production.

Had a different interpolation technique been used in May 2015, intervention and mitigation measures would have been different due to a different dry condition assessment. Clearly, spatial
Interpolation has significant roles in the quality of information provided to end-users as stimulus for disaster risk reduction, hydrological, ecological or agricultural applications.

1.2 Climatology

According to the Köppen-Geiger Climate Classification, the Philippines is generally considered a tropical monsoon (Am) and tropical rainforest (Af) with some areas that fall under tropical savannah (Aw), subtropical highland (Cwb), and temperate oceanic climate (Cfb). Typically, the Philippine climate can be described as (1) humid equatorial marked by high air temperatures that have little diurnal and seasonal variability between maximum and minimum values and (2) tropical maritime climate with uneven annual rainfall distribution. For these reasons, this study used rainfall only because it mostly defines the variability in Philippine climatology.

Locally, the PAGASA Modified Coronas Climate Classification System (Fig. 2a) is used to categorize the Philippine climate into four climate types (Coronas 1920). Climate Type 1 (CT1) has dry climate from November to April and wet during the rest of the year mainly due to the southwest monsoon. CT2 has no distinct dry season with maximum rainy period from November to April associated with the northeast monsoon. CT3 has short dry season from January to March and otherwise rainy for the rest of the year. Lastly, CT4 is characterized by an evenly distributed annual rainfall.

2. Spatial Interpolation

With attempts to be exhaustive, this study was not able to locate works on the comparison of interpolation techniques in the Philippines. Alternatively, a review of existing works was done to identify techniques recommended for tropical maritime regions that are similar to the Philippines. While there are a number of studies that already provide historical gridded rainfall like APHRODITE (Yatagai et al. 2012), they cannot be necessarily used regularly for operations as interpolation algorithms are not provided. These studies are summarized in Table 1.

2.1 IDW

Banking on the idea that the correlation between two points decreases with distance (local neighbourhood approach), IDW predicts values that are within the input maximum search radius...
2.2 CRS and TS

CRS and TS are a form of spline interpolation that employs a mathematical function to predict values by fitting them in a smooth and minimal-curvature surface (variational approach). CRS results to interpolated values that may be different from the input range while the smoothness and curvature of the output results in TS are defined by the range of the input data.

Because of its availability in ArcGIS without the need for additional extension toolset, TS is currently being used in generating PAGASA climate advisories.

2.3 UK and OK

Kriging is a geostatistical approach that operates under the principle of spatial correlation (autocorrelation) between sample data points based on their distance from each other to predict nearby values. The autocorrelation in paired sample data points is called semivariogram. While UK and OK seem similar in terms of model form, UK differs in having varying mean modeled using second-order polynomial surface while OK uses a constant mean.

2.4 ANUSPLIN

The ANUSPLIN is a software package developed by the Australian National University that uses thin plate spline as an interpolation technique, which also incorporates independent variables like elevation (Hutchinson and Xu 2013). Thin plate spline is a technique that determines the degree of smoothness of an output surface from the sample data points through generalized cross validation (in the case of ANUSPLIN). The smoothness is a function of measured predicted errors from multi-variate linear regression. More details of the ANUSPLIN package can be found in the ANU website (http://fennerschool.anu.edu.au/research/products/anusplin-vrsn-44).

In consideration of the effects of topography to rainfall, ANUSPLIN was used in this work. While Taesombat et al. (2009) recommended that it is preferable to have as many as rainfall stations as possible especially in mountainous regions with fewer data and where the values may significantly change over short distances (Collins 1996), there are only two synoptic stations located in mountainous areas in the Philippines: Baguio (1500 masl) and Malaybalay (627 masl) (Fig. 2b).

3. Methods and data

This study used 65 PAGASA meteorological stations with quality-controlled monthly rainfall data from 1981−2010 with less missing data. Stations in CT1 have the densest and lowest stations spacing compared to other CTS.

Six interpolation techniques were considered in this study: IDW, CRS, TS, UK, OK, and ANUSPLIN. The first five models used a maximum search radius of 70 km with 12 nearest points based on average station spacing of 63 km in the entire country. In ANUSPLIN version 4.4, the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) at 90 meter horizontal resolution and aggregated to 1 square kilometer (km²) was utilized to represent topographic features. For all techniques, the output horizontal resolution is 1 km². While the literatures reviewed in this study (Table 1) suggest that interpolation is sensitive to external parameters like search radius and surface resolution, this study remains limited to the aforementioned estimated parameters given the existing number, spacing, and location of stations.

A monthly climatological variogram was computed for UK and OK to determine the kriging parameters (i.e. sill, nugget, and range) from January to December. As it could be quite difficult to conduct semivariogram modelling for all rainfall events such as daily and hourly intervals, Bastin et al. (1984) argues that in areas with evenly distributed annual rainfall, a single climatological variogram can be applied for kriging. Since the Philippines has prominent seasonal rainfall, the work of Lebel et al. (1987) can be applied which articulates that in regions where there is a pronounced climate variability, a single climatological variogram
can be used but only in seasons or time intervals with identical conditions.

### 3.2 Statistical measures

Through leave-one-cross-out validation, four statistical measures were computed: R-squared ($R^2$), Ratio of Variance (RV), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). This technique uses the entire sample as training set while leaving one station as validation point. Exhaustively, the process is reiterated for all 65 stations.

$R^2$ is the squared value of Pearson’s Product Moment Correlation Coefficient where it provides a measure of statistical linear correspondence between observed and predicted values. RV is a measure of the ratio in variances between observed and predicted values where 1 is the perfect score. It is computed as the quotient of square of standard deviation of observed values (dividend) and square of standard deviation of predicted values (divisor).

To measure the differences or the error between observed and predicted values, this study used RMSE and MAE. MAE is the absolute error between the observed and predicted values with 0 being the perfect score. RMSE indicates the influence of large predicted errors weighted according to the average magnitude of errors.

### 4. Results and discussion

Figure 3 confirms that the spacing, density, and geographic location of stations significantly affect the results of interpolation process because the stations in central to southern Luzon have the highest $R^2$ while those stations in Mindanao have lower values. There are more stations in Luzon with an average station spacing of 41 km while Mindanao has 90 km. Meanwhile, all interpolation techniques except CRS have resulted to practically similar $R^2$. This means that even using simple and straightforward interpolation techniques like TS, it could still successfully capture historical monthly rainfall and yield results comparable to OK, UK, and ANUSPLIN.

Figure 2a shows the location of Angat and Talaguio, and Maputi Stations, where the latter is located upstream northeast of the first two stations (the circle in Fig. 2a shows the location but not the actual watershed boundaries). Angat and Talaguio Stations belong to CT1 (dry condition from November to April) while Maputi falls under CT2 (peak rainfall: November to April). With station spacing that is < 30 km, there seems to be large differences in the performance of spatial interpolation techniques (Figs. 3a, 3b, 3c, 3d, 3e, and 3f). It appears that in clustered stations in mountainous regions and in areas lying in different climate types or with large differences in rainfall amount, low station spacing does not necessarily result to better interpolation because predicted values may significantly change over short distance. Establishment of more stations in areas with high rainfall variability is recommended to improve climate monitoring.

#### 4.1 Seasonality

Figure 4 shows the average scores of all stations using different techniques on a monthly interval and results produced weak performance in wet months (May to December). This weakening of interpolation performance is more prominent in IDW, CRS, TS than OK, UK, and ANUSPLIN where they yield consistent good results throughout the year. In Fig. 4b, RV is below 1.0 in December to April and above 1.0 from May to November, which signifies that the interpolation processes tend to under-predict rainfall during dry months and over-predict during wet months. This suggests that interpolation tends to be less effective in months where there is strong variance in rainfall especially in smaller time scales. RMSE and MAE have the same patterns with most prominent errors from May to December (Figs. 4c and 4d), which indicate that stations in CT1 and CT3 have more effects in the interpolation process since they have the most number of stations and least station spacing.
4.2 Statistical error

To determine whether RMSE has indeed high variability during dry and wet months, four stations were selected to represent each CT (Fig. 5). These stations are Baguio (CT1), Borongan (CT2), Tuguegarao (CT3), and Malaybalay (CT4). The graph shows that the highest RMSE corresponds to maximum rainy period of each CT but more interestingly, OK, UK, and ANUSPLIN have the lowest values in all CTs except in CT1. Since CT1 has more stations, non-geostatistical approaches could match the results of geostatistical approaches (i.e. OK and UK), and ANUSPLIN which confirm that station density and location affect the quality of interpolated data.

4.3 Probability Distribution Function (PDF)

A comparison of PDF curve was done for each interpolation technique in the selected representative stations in each climate type (Fig. 6) to determine the degree of overlap between the observed and predicted dataset. As expected, interpolated values in Baguio (Fig. 6a) have high kurtosis relative to the observed values indicating high frequency of outliers in the interpolated values. Compared with surrounding stations, Baguio has higher rainfall because of its location and with the absence of closer stations to higher elevation, interpolation overestimates rainfall surrounding Baguio. Both Figs. 6a and 6d show that ANUSPLIN-predicted values are shifted to left indicating occurrences of outliers relative to the observed values (and other interpolation techniques) because of the effects of topography on rainfall.

5. Conclusion

There is a general consistency that OK and ANUSPLIN have better performance compared with non-geostatistical approaches. In choosing a specific technique, considerations should be accounted based on the spacing, density, and geographic location of stations as they would greatly affect the results of interpolation. ANUSPLIN may seem to produce good validation results but with the lack of other stations in mountainous regions, relationship between elevation and rainfall may become spurious. As shown in Fig. 1f, ANUSPLIN may not necessarily represent ground truth. Because of this, non-geostatistical approaches specifically TS can be alternatively employed as it also provided good results. In clustered stations located in different climate types, it is recommended to establish more stations as interpolation may not capture large differences in rainfall patterns. This study also confirms that in regions where there is high rainfall variability (e.g. tropical maritime climate), climatological variograms can be utilized at monthly time scale. However, further investigation on the usefulness of climatological variograms and validation of the results of this study in smaller time interval should still be pursued. Lastly, this work notes that the performance of interpolation processes varies according to the seasonality of rainfall where lowest scores are observed during peak rainfall periods.
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