Spatial Patterns of Climatic Factors using PRISM in Korea

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Abstract

Most of interpolated climatic factors are affected by topographical environments such as elevation and distance from observation site. While Korea is not large in the land area, topography is complex. Thereby, Korea shows great variability on spatial and temporal patterns of climatic factors. PRISM(Precipitaton elevation Regressions on Independent Slope Model) uses a DEM and brings a combination of climatological and statistical concept.

The aim of this study WAS to prepare a high resolution temperature and precipitation data using PRISM. This study applied PRISM and used monthly cumulative precipitation and temperature data from 1977 to 2006 for preparing climatic data map in Korea. We also compared interpolation techniques such as PRISM, IDW and Kriging. Consequently, PRISM was proven to be suitable for preparing dataset with consideration of the topographical environment in Korea.

Key words: Climatic factors, PRISM, GIS, IDW, Kriging

1 INTRODUCTION

PRISM(Parameter-Elevation Regressions on Independent Slopes Model) was developed by descriptions of associated algorithms with climate-elevation regression function, the station weighting approach, topographic facets, coastal proximity in USA(Daly et al., 1994).

Korea shows great variability in topography and climatic factors such as temperature and precipitation. Considering land area of Korea, we need to high resolution climate dataset within limited area. Climate dataset for whole Korea can be prepared with Inverse Distance Weighted (IDW) interpolation process, employing elevation and distance from observation stations. In addition, Kring takes into consideration the spatial structure of the parameter and Ordinary Kriging is the most commonly used type of Kriging. To apply PRISM on Korea topography, it is required to build input datasets, which was provided by Korea Meteorological Administration (KMA) and DEM (Digital Elevation Model) through GIS method. The implemented datasets provide monthly precipitation and temperature values around 5km resolution.

2 MATERIAL AND METHODS

2.1 Elevation dataset

Elevation is the most important factor for running PRISM(Daly et al., 2002), because regression function between climate and elevation serves as the main predictive equation in the model. We used climate data form 72 observation station including Jeju island. DEM with 5kmX5km was used to derive elevation regression function as follows(Daly et al., 1994):

$$Y = \beta_0 + \beta_1 Z \tag{1}$$

Where, Y is the predicted climate element, β_1 and β_0 are the regression slope and intercept, respectively, Z is the elevation at the target grid cell. Moreover, the calculation of the elevation weight as follows(Daly et al., 1994, Hong et al., 2007):

$$W(z) = 1, \quad \Delta z \leq \Delta z_m$$

$$W(z) = \frac{100}{(\Delta z - \Delta z_m)^b} \quad \Delta z_m < \Delta z < \Delta z_x \tag{2}$$

$$W(z) = 0, \quad \Delta z \geq \Delta z_x$$

$\triangle z_m$ is the minimum elevation difference, $\triangle z_x$ is the maximum elevation difference, b is typically set to 1.0, which is equivalent to a 1-dimension inverse distance weighting function.

2.2 Topographic Facets

Facet assigns a slope orientation to each DEM cell at column i, row j by first calculating elevation gradients across the cell from west to east and south to north and 8 point compass(Daly et al., 1994).The facet weight for station is calculated as follows(Daly et al., 1994, Hong et al., 2007):

$$W(f)=1 \quad , \quad \triangle f \leq 1 \text{ and } B=0$$
$$W(f) = \frac{1}{(\triangle f+B)^c} , \quad \triangle f > 1 \text{ or } B > 0$$

(3)

Where, $\triangle f$ is the absolute orientation difference between the station and target grid cell, B is the number of intervening barrier cells with an orientation significantly different than that of the target grid cell. C is the facet weighting exponent (Daly et al., 2002).
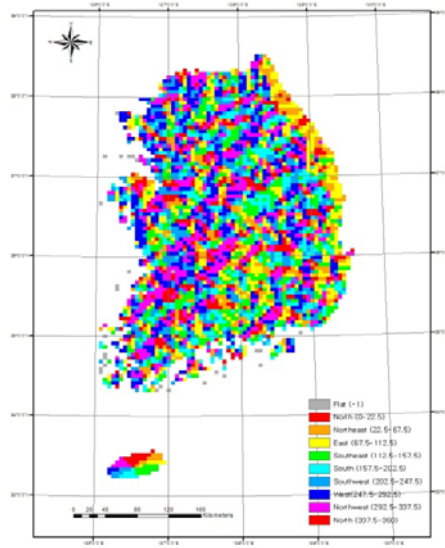

Figure 1. Map of topographic facet in Korea

2.3 Costal proximity

For analyzing climatic variation in relatively small area, minimum 5 stations were decided as number of observing stations within the radius, which is range from 40km to 100km (**Figure 2**).
Costal proximity grids have been developed estimating the proximity of each grid cell to major water bodies (Daly et al., 2002). The coastal proximity weight for a station is calculated as follows (Daly et al., 1994, Hong et al., 2007):

$$W(p)=1, \quad \triangle p=0$$

$$W(p)=0, \quad \triangle p > p_x$$

(4)

$$W(p)= \frac{1}{\triangle p^v} , \quad 0 < \triangle p \leq p_x$$

$\triangle p$ is the absolute difference between the station and target grid cell costal proximity index, v is the costal proximity weighting exponent, and p_x is the maximum proximity difference.
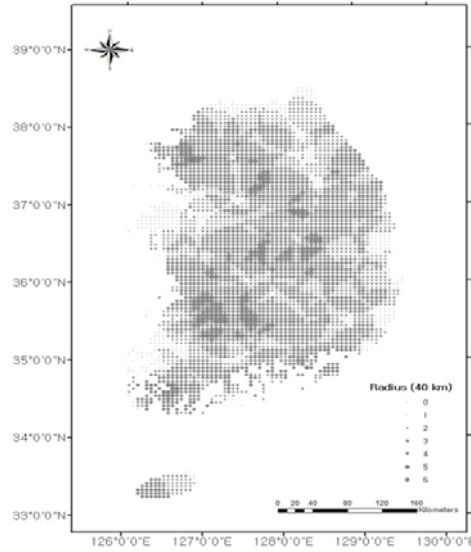
Figure 2. Number of observation stations within the radius of 40km.

2.4 *Distance influence on climate*

A station's influence in the regression function is assumed to decrease as its distance from the target grid cell increase(Daly et al., 2002). The distance weighting is given as follows(Daly et al., 1994, Hong et al., 2007):

$$W(d)=1, \quad d\leq 1 \tag{5}$$

$$W(d)= \frac{1}{d^a}, d>1, (if\ W(d)>1, and \quad then \quad W(d)=1)$$

Where, d is the horizontal distance between the station and the target grid cell and a is the distance weighting exponent.

2.5 Weighting for regression function
Each station is assigned a weight that is based on several factors. The combined weight, W, of a station is given as follows (Daly et al., 1994):

$$W= [F_d\,W(d)^2 + F_z\,W(z)^2]^{1/2}\,W(f)\,W(p) \tag{6}$$

Where, W(d), W(z), W(f), and W(p) are the distance, elevation, topographic facet, costal proximity, respectively.

2.5 Interpolation Techniques

A deterministic interpolation method [the inverse distance-weighted (IDW) method; Watson and Philip, 1985] was implemented to specifically assign fraction values to missing locations based on the surrounding measured values. IDW, although lacking in optimality criteria, is in general recognized as more appropriate than the classic nearest-neighbor method (Thiessen, 1911), which in turn introduces discontinuous surfaces and is traditionally used for large-area hydrological assessments. For a given estimation point, the IDW Technique provides a set of weights that sum to unity and that are inversely related to the distance to the data points(Luzio et al., 2008).

$$W = \frac{\sum \frac{W_i}{d}}{\sum \frac{1}{d}}$$ (7)

Where, W is estimated climatic value in unobserved point, W_i is observed climatic value in point i and d(km) is distance between certain observed point and point i.

$$|T'| = 0.00688 + 0.0013 \cos\{0.0172(i - 60)\}$$ (8)

Where, $|T'|$ is absolute temperature lapse rate by day number, i stands for day numbers in year. This absolute temperature lapse rate is applied on(Yun et al., 2001).

$$T = \frac{\sum \frac{T_i}{d_i}}{\sum \frac{1}{d_i}} + \left[z - \frac{\sum \frac{z_i}{d_i}}{\sum \frac{1}{d_i}}\right]T'$$ (9)

Where, T is estimated temperature at the object point, T_i is observed temperature at the observatory i, d_i is the distance from the object point to the observatory, z is the elevation at the object point, and z_i is the elevation at the observatory i (Nalder and Wein, 1998).

Kriging is a geostatistical approach (Matheron, 1971) that has gained acceptance as a tool for the interpolation of many types of data, including precipitation (Chua and Bras, 1982, Dingman et al., 1988; Phillips et al. 1992). Ordinary Kriging is a method for predicting the value of a random process at a specific location in a region, given a dataset consisting of measurements of the random process at a specific location inn a region, given a dataset consisting of measurements of the random process at a variety of locations in the region (Ronald and Jay, 2009).

$$Z^*(u) = \sum_{\alpha=1}^{n(u)} \lambda_\alpha(u)z(u_\alpha) + \left[1 - \sum_{\alpha=1}^{n(u)} \lambda_\alpha(u)\right]m$$ (10)

Where, $Z^*(u)$ is the ordinary kriging estimate at spatial location u, $n(u)$ is the number of data used at the known locations given a neighborhood, $Z(u_\alpha)$ are the n measured data at locations u_α located close to u, m is mean of distribution, $\lambda_\alpha(u)$ is weights for location computed from the spatial covariance matrix based on the spatial continuity(variogram) model (Suman, 2007).

3 RESULTS AND DISCUSSION

3.1 Interpolating Temperature and precipitation Using PRISM

The spatial patterns of high resolution gridded temperature and precipitation was produced by PRISM and depicted in F**igure 3** and **4**. There exists spatial variation both in temperature and precipitation Southern coastal area including Jeju island, shows high relatively temperature and precipitation. Temperature gradually decrease from south to north and from west to east. Central eastern part, which has relatively high elevation, shows lower temperature than that of other western low area. In particular, precipitation was high at east and south coast
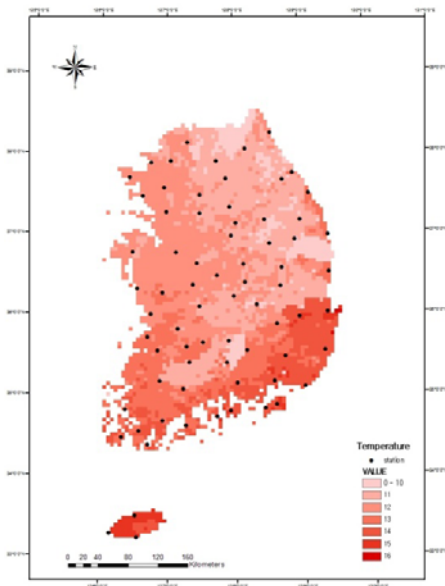
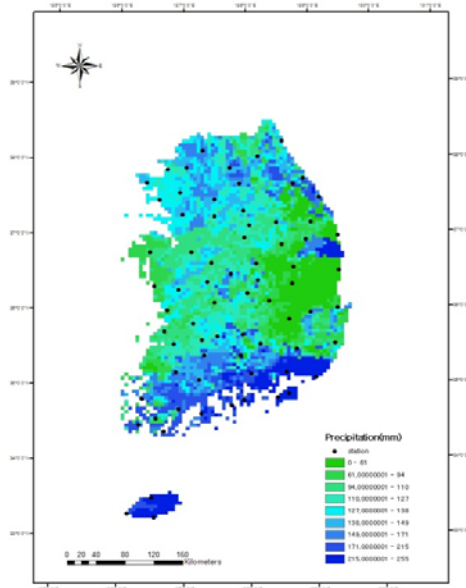***Figure 3****. Map of mean monthly temperature for 30 years.*   ***Figure 4****. Map of mean monthly precipitation for 30 years*

The interpolation result by PRISM was compared with those by Kriging and IDW(**Figure 5 and 6**). PRISM was proven to interpolate the temperature and precipitation in more detailed patterns. And Kriging make temperature and precipitation map which has gradual and smoothing change, while temperature and precipitation map produced by IDW shows less detail and irregular change.
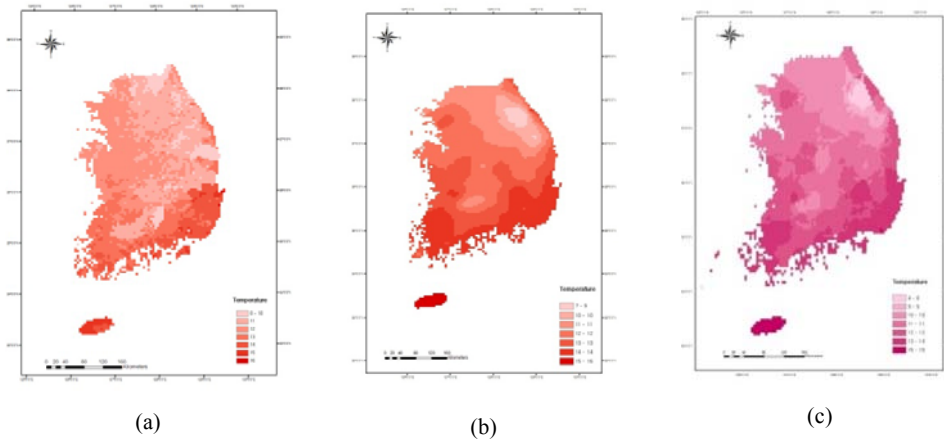

(a)   (b)   (c)

Figure 5*. Comparison Interpolations of temperature by (a) PRISM, (b) Kriging ,(c) IDW*
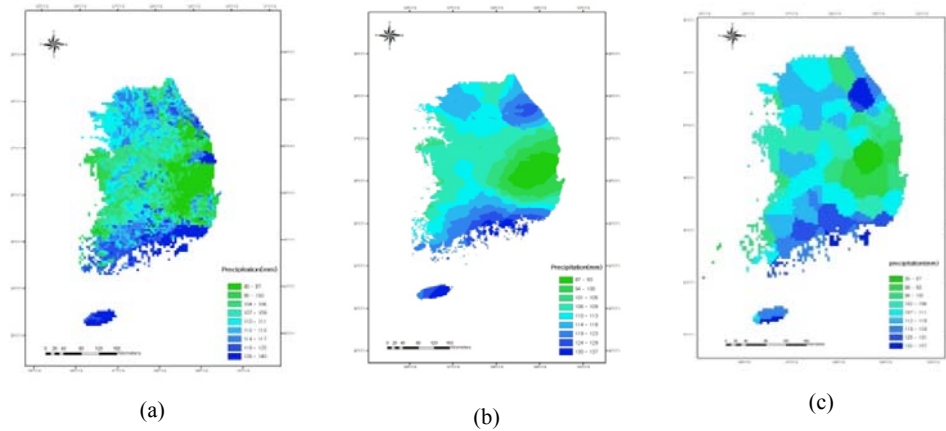
Figure 6. Comparison Interpolations of precipitation by *(a) PRISM, (b) Kriging ,(c) IDW*

3.2 Validation of Model

In this study, The performance of PRISM was evaluated by quantitative ways using the observations and grid data. PRISM cross validation was done using the "Jacknife" procedure(Daly et al., 1994, Daly et al., 2002) which each of station temperature and precipitation values were omitted from the dataset, predicted in its absence, and then returned to the dataset. In this paper, The model validated with mean absolute error(MAE), mean square error(MSE), and bias (predicted-observed). In case of temperature, MAE ranged from 0.14 to 1.35, MSE ranged from 0.01 to 4.61, and bias ranged from -0.005 to 0.764. Especially, The MAE and bias increased in orographic terrain such as mountain of Taebaek, Jiri, Seodae, and Dedun. On the other hand, In case of precipitation, MAE ranged from 2.18 to 18.37, MSE ranged from 38.66 to 680, bias ranged from -12.09 to 10.88. Particularly, Precipitation distribution in Korea is strongly influenced by topography. Precipitation pattern was high in mountain range at east coast and along the south coast, largely.

In particular, PRISM exhibited the lowest cross-validation errors, followed by Kriging and IDW method. Moreover, The spatial patterns of temperature derived by PRISM were more closely linked to topography facet and coastal proximity than IDW and Kriging.

We had been also "changed factors" for optimal variable condition appropriated in topographic of Korea (**Table 1**). As a result, 0.8 of Fd and 0.2 of Fz were presented adequately as optimal condition in station weighting function.

Table 1**.** The Factors of value at the station weighting function

Function	$W=[F_dW(d)^2+F_zW(z)^2]^{1/2}W(f)W(p)$			
Precipitation	Factor	MAE	MSE	Bias
$F_{d,}\,F_z$	0.7, 0.3	8.8973	227.4875	0.5141
$F_{d,}\,F_z$	0.8, 0.2	8.8388	224.7827	0.5838
$F_{d,}\,F_z$	0.6, 0.4	8.9001	226.5803	0.4523
Temperature				
$F_{d,}\,F_z$	0.7, 0.3	0.4253	0.5060	-0.0056
$F_{d,}\,F_z$	0.8, 0.2	0.4210	0.4987	-0.0011
$F_{d,}\,F_z$	0.6, 0.4	0.4257	0.5023	-0.0094

Consequently, PRISM was proven to be suitable for preparing dataset with consideration of topographical environment in Korea. However, bias was rapidly increased when the number of station was not relatively

sufficient around coastal fields and mountainous regions within radius. Temporal and spatial change was affected on radiation at land cover and vegetation patterns in forest. However, we did not considered its factors in this study. In order to have high resolution climatic dataset, it should be improved through diverse climatic factors and various statistical methods.

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