J Inf Process Syst, Vol.11, No.4, pp.556~572, December 2015
http://dx.doi.org/10.3745/JIPS.02.0030

ISSN 1976-913X (Print)
ISSN 2092-805X (Electronic)

JOURNAL OF INFORMATION PROCESSING SYSTEMS JIPS

Spatial Interpolation and Assimilation Methods for Satellite and Ground Meteorological Data in Vietnam

Khac Phong Do*, Ba Tung Nguyen*, Xuan Thanh Nguyen*, Quang Hung Bui*, Nguyen Le Tran*, Thi Nhat Thanh Nguyen*, Van Quynh Vuong**, Huy Lai Nguyen***, and Thanh Ha Le*

Abstract

This paper presents the applications of spatial interpolation and assimilation methods for satellite and ground meteorological data, including temperature, relative humidity, and precipitation in regions of Vietnam. In this work, Universal Kriging is used for spatially interpolating ground data and its interpolated results are assimilated with corresponding satellite data to anticipate better gridded data. The input meteorological data was collected from 98 ground weather stations located all over Vietnam; whereas, the satellite data consists of the MODIS Atmospheric Profiles product (MOD07), the ASTER Global Digital Elevation Map (ASTER DEM), and the Tropical Rainfall Measuring Mission (TRMM) in six years. The outputs are gridded fields of temperature, relative humidity, and precipitation. The empirical results were evaluated by using the Root mean square error (RMSE) and the mean percent error (MPE), which illustrate that Universal Kriging interpolation obtains higher accuracy than other forms of Kriging; whereas, the assimilation for precipitation gradually reduces RMSE and significantly MPE. It also reveals that the accuracy of temperature and humidity when employing assimilation that is not significantly improved because of low MODIS retrieval due to cloud contamination.

Keywords

Assimilation, Interpolation, Meteorological Variables, Kriging, Vietnam

1. Introduction

There are increasingly more demands for distributed high-resolution surface meteorological data to stimulate advances in assessing forest fire risk, water resources, soil sciences, agricultural and ecological studies [1-4]. The meteorological data required by these applications is usually measured at meteorological stations, and the data is only valid for the points where it is measured. Spatial interpolation can be used to estimate meteorological variables at other locations. In addition, the low accuracy of interpolated data at locations far away from stations can be improved by assimilating with corresponding satellite data.

Various statistical methods have been studied in the literature on climate data interpolation and have been assimilated to create full-gridded, high-resolution data. The aim is to anticipate values for miss-

Manuscript received May 26, 2015; accepted June 17, 2015; onlinefirst December 7, 2015.
Corresponding Author: Khac Phong Do (phongdk@fimo.edu.vn)
* Field Monitoring Center, University of Engineering and Technology, Vietnam National University, Hanoi, Vietnam ({phongdk, tungnb, thanhnx, hungbq, letn, thanhntn, halt}@fimo.edu.vn)
** Institute for Forest Ecology and Environment, Vietnam Forestry University, Hanoi, Vietnam (quynhxm_2005@yahoo.com)
*** Faculty of Environmental Engineering and Management, School of Environment and Resources Development, Asian Institute of Technology (AIT), Pathumthani, Thailand (lainguyenhuy@gmail.com)

data locations from a limited amount of sample data points which are associated with some possible ancillary variables. For the purpose of interpolation Kriging has been evaluated as a better interpolation method with high accuracy and low bias, in comparison to other methods [5,6]. Some work conducting research Kriging interpolation in their country-level data were reported [7-9]. A total of 922 meteorological stations in the U.S. were interpolated using residual Kriging associated with elevation data and 12 direction models [6]. In Finland [10], Kriging is applied with external drift (e.g., mean elevation, sea levels, and lake percentage) on station-based temperature and precipitation. In the northwest region of Vietnam, some researchers have applied Kriging interpolation to frost and low temperature data from stations to construct and continuously update a high-resolution, 100 m × 100 m warning map of frost and low temperatures in some provinces [11,12]. Some optimistic results were reported in our previous work [13], in which Universal Kriging (UnK) interpolation was employed for temperature and humidity variables. In this research, we have expanded UnK interpolation for precipitation variables and have applied an assimilation technique to three meteorological variables, including temperature, relative humidity, and precipitation, using the MODIS Atmospheric Profiles product (MOD07) and Tropical Rainfall Measuring Mission (TRMM). This ten-fold cross validation was used to evaluate the accuracy of our proposed interpolation and assimilation methods with 6-year worth of meteorological data from 2008 to 2013. In addition, we also compared our results with those from the Weather Research and Forecasting (WRF) model in August and December 2010.

This paper consists of four main sections: the introduction, datasets and methodology, results, and conclusion.

2. Datasets and Methodology

2.1 Study Area

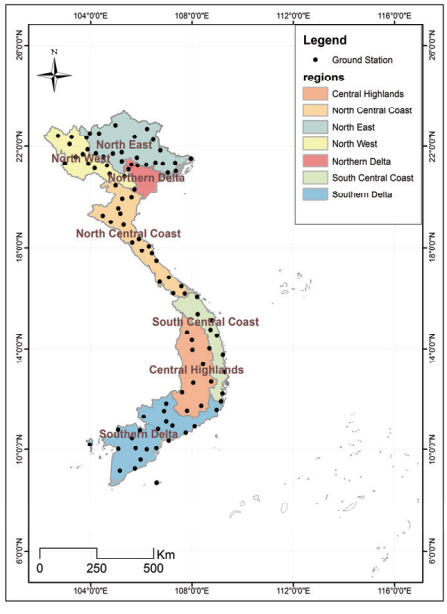


Fig. 1. Meteorological station map in Vietnam.

The study area for this research is in Vietnam, which is located at approximately 8°N to 23°N and 100°E to 120°E. Vietnam is a tropical country and spans a land area of almost 33 million ha, including 5 main terrain groups: mountains, karts, valleys and mountainous hollows, sedimentary deltas, and coasts. Mountains and sedimentary deltas are the most important terrains. Based on geographical conditions, Vietnam is divided into seven climate regions: Northwest, Northeast, Red River Delta, North-Central Coast, South-Central Coast, Central Highlands, and South, as shown in Fig. 1.

In the northern regions, the average temperature ranges from 22°C–27.5°C in the summer and from 15°C–20°C in the winter, whereas, the southern areas have more stable average temperatures that range from 26°C–27°C and 28°C–29°C throughout the year. The annual rainfall in Vietnam ranges from 700–5,000 mm, and the most common numeric precipitation quantity recorded is about 1,400–2,400 mm in which the North customarily receives more rainfall than the South. Moreover, the mountain systems play a vital role in the distribution of annual rainfall. In high mountainous areas with high rainfall, the annual average relative humidity peaks up to 86%–87%, whilst it is in range of 80%–85% in other northern areas. However, in the South or Central Highlands, the index of relative humidity only drops to 77%–78%. The rain mechanism exerts profound impacts on the annual oscillogram of relative humidity. In the first half of winter, the relative humidity is quite low in the Northeast and North Delta. It increases during the remaining winter period due to heavy, drizzly rains and then decreases. It increases again in the summer months. In the North Central and South Central, the relative humidity is low in the summer and quite high in the winter. Meanwhile, the humidity is quite low in the middle and end of winter and quite high during the summer in the North West, Central Highlands, and South.

2.2 Datasets

There are five types of data that we collected and used in this study, which are as described below.

Ground station data: all meteorological data was collected from the National Centre for Hydro Meteorological Forecasting (NCHMF) from 2008 to 2013. Every day, the temperature (GR TEMP) and relative humidity (GR RH) were measured at 13:00, and precipitation (GR PRECIP) was accumulated and measured at 13:00 and 24:00 (Vietnam time zone) from 98 stations spread around Vietnam (Fig. 1). In addition, spatial information, including the location and altitude (GRA), of these ground stations are also included in the data set. The ground station data was employed to interpolate a full-gridded map of Vietnam for each meteorological data set.

Satellite atmospheric variables: the MODIS Atmospheric Profile product (MOD07_L2) produces data during the day and night at 5×5 1-km spatial resolution. MOD07_L2 includes the surface temperature (MOD TEMP) and moisture (MOD RH) at 20 different levels ranging from the surface of the earth to the top of the atmosphere under cloud-free conditions [14]. MOD TEMP and MOD RH were assimilated with the interpolation fields of temperature and humidity, respectively, to obtain better results.

Tropical Rainfall Measuring Mission (TRMM): The TRMM 3B42RT (V7) used in this study is a global product with $0.25^{\circ} \times 0.25^{\circ}$ spatial resolution [15]. This data set is acquired every three hours and distributed for free by NASA Goddard Earth Sciences Data and Information Services (GESDISC) [16]. TRMM data was assimilated with the interpolation field of rainfall to achieve better results.

Satellite Digital Elevation Map (DEM): The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) is a medium-to-high spatial resolution, multispectral imaging system

flying onboard the Terra satellite. The imaging system acquires a stereoscopic image at 15 m spatial resolution for creating the DEM. As a result, the ASTER DEM is a 30-m-elevation dataset created by stereo-correlating automated techniques [17]. ASTER DEM was used as ancillary data in order to eliminate the elevation effect of temperature data.

Weather Research and Forecasting model data: The Asian Institute of Technology (AIT) provides model-based meteorological gridded data (temperature, relative humidity, and rainfall) at a resolution of 12 km × 12 km in two months (August and December 2010). In the northern part of Vietnam, the peak of rainfall is customarily in August, while the dry season occurs in December in the southern regions. This data was used to examine the correlation efficient with ground station data and our results.

2.3 Methodology

2.3.1 Kriging spatial interpolation for meteorological data

Interpolation techniques anticipate values for miss-data locations from the curb of a number of sample data points. There are various statistical methods that have been developed for climate data interpolation. Some research indicates that Kriging-based interpolation methods have higher accuracy and lower bias than other geo-statistical methods [18,19]. These methods are a linear combination of weights determined by the spatial variation structure. In our previous study [13], we applied UnK to interpolate temperature and relative humidity data based on the outstanding estimation.

The spatial processes record surface trends and drift, which is a variety of the attributes depending on other variables. The temperature decrease coincides with the altitude increase at nearly 6.5°C per km [20], whereas, the latitude and longitude impacts temperature according to linear regression [21]. Furthermore, the rainfall is also influenced in orographic regions [22,23]. In addition, according to the research conducted in [24], the method of decomposing the observation into a surface trend and a residual value is better than interpolating directly onto the observed data, especially when applying it to a wide spatial area. Therefore, the UnK algorithm is carried out through three main steps. First, the data trend is identified and removed from observed meteorological data so that the residual will be more stationary. Specifically, the trend is estimated by a regression model and the meteorological data in order. Second, the variogram model can be constructed by using the spatial correlation of the residuals in order to calculate the weight of the neighbors. Finally, the trend is compensated back to the estimated residuals to gain the final results.

2.3.2 Assimilation methodology

Data assimilation is a set of technologies for merging model predictions and monitoring data. The technique's main target is to obtain a more accurate model from a variety of data sources [25]. Normally, there are two fundamental approaches for data assimilation, namely sequential assimilation and retrospective assimilation (non-sequential). Clearly, sequential assimilation only considers an observation made in the past until the time of analysis, while non-sequential assimilation can utilize an observation from the future. In the 1950s, Cressman proposed the inadequacy of the observation to modify the assimilated value at a location where we already know its meteorological value, which can be gained by interpolation. At the grid location j, the assimilated value A_j is calculated within a radius R as:

$$A_j = G_j + \frac{\sum_{i=1}^{n} \omega(i,j)(S_i - G_i)}{\sum_{i=1}^{n} \omega(i,j)} \tag{1}$$

where, G_i, G_j are interpolated values from the ground station data at locations i, j, respectively; S_i is the observation from the satellite at location i; and $\omega(i,j)$ is the weight of S_i at location j. The weights are prescribed as:

$$\omega(i,j) = \begin{cases} \frac{R^2 - r(i,j)^2}{R^2 + r(i,j)^2} & if\ r(i,j) \le R \\ 0 & if\ r(i,j) > R \end{cases} \tag{2}$$

where, $r(i,j)$ is the distance between the location i and j. However, this method exerts some detrimental impacts. For example, all of the observations are processed identically without considering their quality; or if an interpolated value has good quality, it is not necessary to take the place of this value by poor quality observations.

To deal with the drawbacks of the Cressman method, we carried out a simple statistical method, along with a direct computation of the best linear unbiased estimation (BLUE). Suppose that each meteorological value observed at the same position from each source can be presented as: $Y_i = x + e_i$, where, x is the actual value and e_i is the error ($i = 1,2$ for the data station and data satellite, respectively). Their errors satisfy the following hypotheses:

- $E(e_i) = 0$, unbiased measurements.
- $Var(e_i) = \sigma_i^2$, the accuracy is known.
- $Cov(e_1, e_2) = 0$, $E(e_1 e_2) = 0$, errors are independent.

Kriging products contain an interpolated Kriging value (KV) field and a Kriging error (KE) field, while the observation field (MV) was gained directly from satellite data (MODIS MOD07 and TRMM) and the observation error field (ME) is achieved by calculating the covariance between the station data and satellite data. Note that, it is essential to correct the MV for the ground station data before assimilating it by the linear regression function of $f(x)$: $MV \xrightarrow{f(x)} MV'$ (described in the next subsection), in order to assure unbiased measurement.

We combined two data resources in order to discover an estimator $\bar{X}$, which is:

- Linear: $\bar{X} = \propto_1 Y_1 + \propto_2 Y_2$, with $\propto_1 + \propto_2 = 1$.
- Unbiased: $E(\bar{X}) = x$.
- Minimal variance: $Var(\bar{X})$ is mininal.

To compute the weight $\propto_i$, we used the unbiased hypothesis:

$$\begin{aligned} E(\bar{x}) &= (\propto_1 + \propto_2)x + \propto_1 E(e_1) + \propto_2 E(e_2) \\ &= (\propto_1 + \propto_2)x \end{aligned} \tag{3}$$

The variance of $\bar{x}$ is calculated as the following equations:

$$\begin{aligned} Var(\bar{x}) &= E((\bar{x} - x)^2) \\ &= E((\propto_1 e_1 + \propto_2 e_2)^2) \\ &= \propto_1^2 E(e_1^2) + \propto_2^2 E(e_2^2) \\ &+ 2 \propto_1 \propto_2 E(e_1 e_2) \\ &= \propto_1^2 \sigma_1^2 + \propto_2^2 \sigma_2^2 \\ &= \propto_1^2 \sigma_1^2 + (1 - \propto_1)^2 \sigma_2^2 \\ &= (\sigma_1^2 + \sigma_2^2) \propto_1^2 - 2\sigma_2^2 \propto_1 + \sigma_2^2 \end{aligned} \tag{4}$$

Estimator $\bar{x}$ has to minimize this variance, which is a function of $\propto_1$. That estimator is the minimum where its derivative with respect to $\propto_1$ is zero, so that:

$$\propto_1 = \frac{\sigma_2^2}{\sigma_1^2+\sigma_2^2} \tag{5}$$

Finally, the value of $\bar{x}$ is:

$$\bar{x} = \frac{\sigma_2^2}{\sigma_1^2+\sigma_2^2} Y_1 + \frac{\sigma_1^2}{\sigma_1^2+\sigma_2^2} Y_2 \tag{6}$$

According to Eq. (13), the calculation to assimilate the meteorological value at location s is shown below as:

$$DA_s = \frac{KE_s}{KE_s+ME_s} MV'_s + \frac{ME_s}{KE_s+ME_s} KV_s \tag{7}$$

where, DA_s, MV'_s *and* KV_s stand for data assimilation, corrected satellite data and the KV at location s, respectively. ME_s, KE_s are the satellite data errors and the KE at location s.

2.3.3 Meteorological satellite data correction

The fact remains that the biases and errors between satellite and ground meteorological data must be estimated before assimilation. Particularly, each satellite dataset X has been corrected to its corresponding meteorological ground data Y using linear regression function $y = f(x): X \xrightarrow{y=\alpha x+\beta} Y$, where α and β are regression parameters. Every day, we acquired k pairs of each meteorological data $(x_1y_1), (x_2y_2), \dots, (x_ky_k)$ at k ground station positions from two sources of the satellite and ground station, respectively. The estimation of two parameters, α and β, is to minimize the sum:

$$Q(\alpha, b) = \sum_{i=1}^{k} (y_i - \alpha x_i - \beta)^2 \tag{8}$$

Using the least mean square minimization to solve (8) we obtained:

$$\alpha = \frac{k\sum_{i=1}^{k} x_i y_i - \left(\sum_{i=1}^{k} x_i\right)\left(\sum_{i=1}^{k} y_i\right)}{k\sum_{i=1}^{k} x_i^2 - \left(\sum_{i=1}^{k} x_i\right)^2} \tag{9}$$

and:

$$\beta = \bar{y} - \alpha\bar{x} = \frac{\sum_{i=1}^{k} y_i - \alpha\sum_{i=1}^{k} x_i}{k} \tag{10}$$

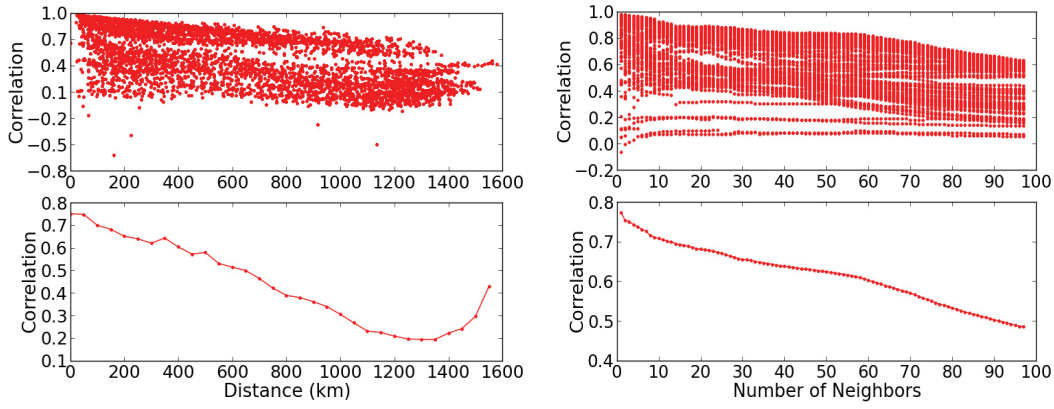
2.3.4 Ten-fold cross validation

Ten-fold cross validation is applied to assess and choose the best interpolation and assimilation methods for each meteorological variable. In detail, 98 ground stations were randomly partitioned into ten subsets equally, where nine subsets were used as interpolation data and the remainder was preserved as the validation data for testing. The cross-validation process was then repeated ten times, called fold, to ensure that each of the ten subsets were used exactly once as the validation data. The ultimate estimation was averaged ten results of ten folds. The relative precision of these models was compared with respect to the root mean square error (RMSE) and mean percent error (MPE).

3. Results and Discussions

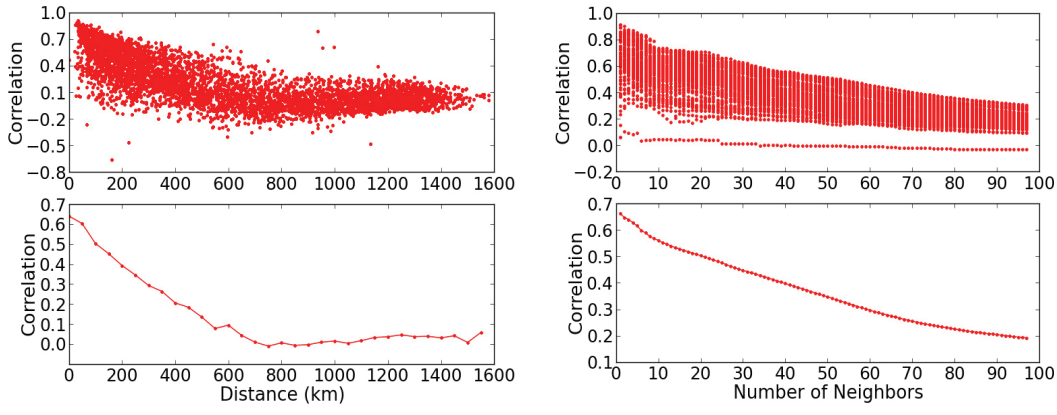
3.1 Spatial Correlation and Variogram Modeling

Overall, the spatial correlation coefficient of precipitation is much lower than temperature and humidity variables and this coefficient decreases more sharply in the case of further distance and more surrounding stations. Fig. 2(a) shows the spatial correlation for temperature in terms of distance, in which the correlation coefficient R within 50 km reaches about 0.8. These coefficients for humidity and precipitation are lower than the temperature, at around 0.6 and 0.35, as seen in Figs. 3(a) and 4(a), respectively. Similarly, Fig. 2(b) shows the spatial correlation for temperature in terms of the number of neighbors in which the correlation coefficient R with the ten nearest neighbors stands at approximately 0.7. In contrast, humidity and rainfall have quite a low correlation coefficient R if calculated with the ten nearest neighbors, at only 0.55 and 0.3, respectively, as shown in Figs. 3(b) and 4(b).



(a) (b)

Fig. 2. Spatial correlation coefficient of temperature with respect to distance (a) and to number of neighbor ground stations (b).



(a) (b)

Fig. 3. Spatial correlation coefficient of humidity with respect to distance (a) and to number of neighbor ground stations (b).

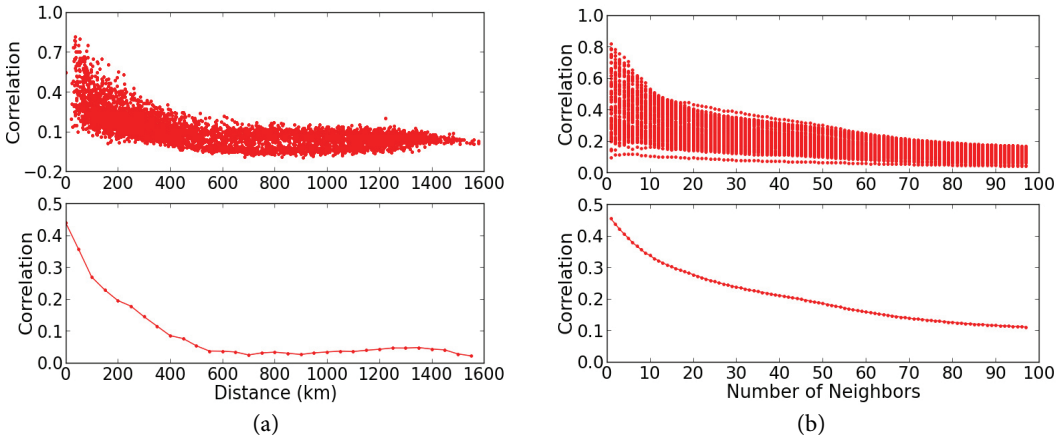


Fig. 4. Spatial correlation coefficient of precipitation with respect to distance (a) and to number of neighbor ground stations (b).

These differences suggest the distinction in the number of neighbors when constructing the variogram and selecting its practical range. In this research, we used 10 ($R \approx 0.7$), 7 ($R \approx 0.6$), and 5 ($R \approx 0.4$) neighbor ground stations for interpolating temperature, humidity, and precipitation variables, respectively. Meanwhile, the practical range was within 600 km for temperature ($R \approx 0.5$), 300 km for humidity ($R \approx 0.3$), and 100 km for precipitation ($R \approx 0.28$). The results also suggested that the Spherical model would definitely be the best suited to the variogram for all of the meteorological variables.

3.2 Satellite Data Correction

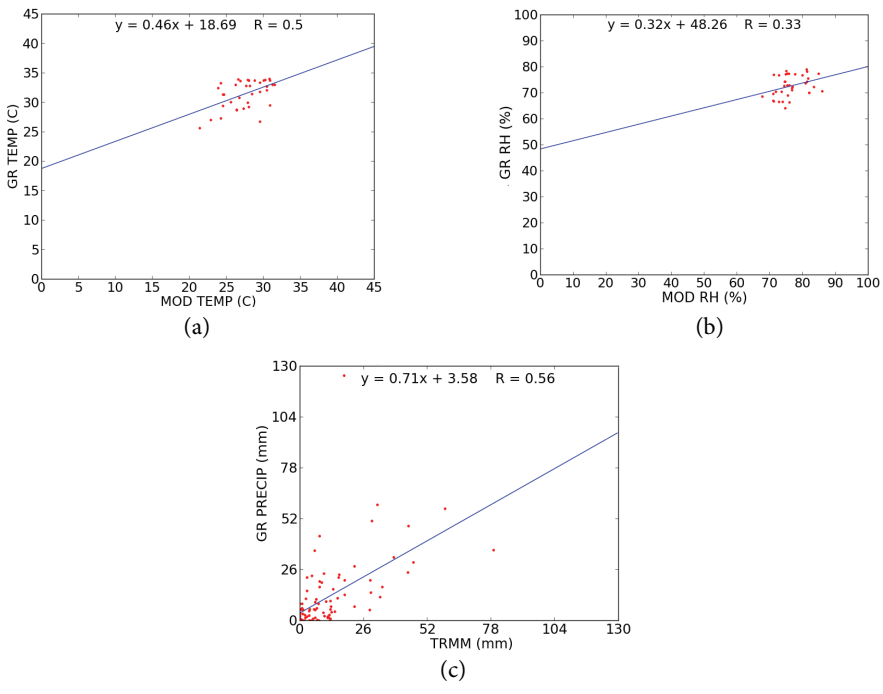


Fig. 5. Correlation of temperature (a), humidity (b), precipitation (c) in August 10, 2010.

Data correction aims at improving satellite data quality before the data assimilation step. Based on the amount of matching between satellite- and ground-meteorological variables and their correlation coefficient, it was then decided whether or not to apply the data correction step. We propose two strict conditions for these parameters, which will be applied on each daily dataset. First, the number of pairs for each meteorological data were equal to or greater than 30 according to the statistical theory ($k \geq 30$). Second, the correlation coefficient between satellite- and ground-based data was high enough ($R = 0.4$ and $R = 0.3$ for temperature, precipitation, and humidity, respectively).

The correlation coefficient on August 10, 2010 between the MOD TEMP and GR TEMP was about 0.50, between GR RH and MOD RH it was 0.33, and between the GR PRECIP and TRMM it was 0.56. In this case, the average number of observed data at each station position per day for MOD RH was 37, but for MOD TEMP it was 38 because of cloud cover. TRMM is a global product with full data at any position, so every day, there were 98 pairs of precipitation variables. Data assimilation was applied to all meteorological variables for this case.

3.3 Interpolation and Assimilation Results

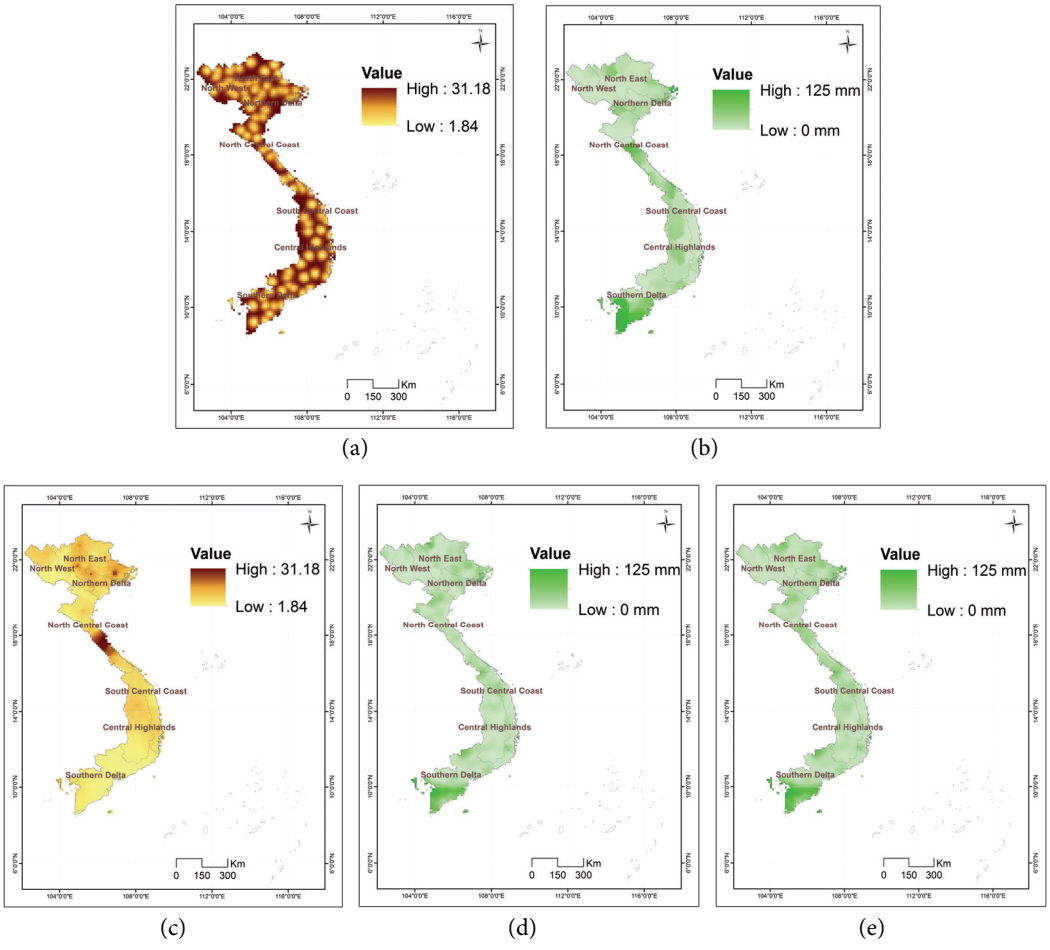
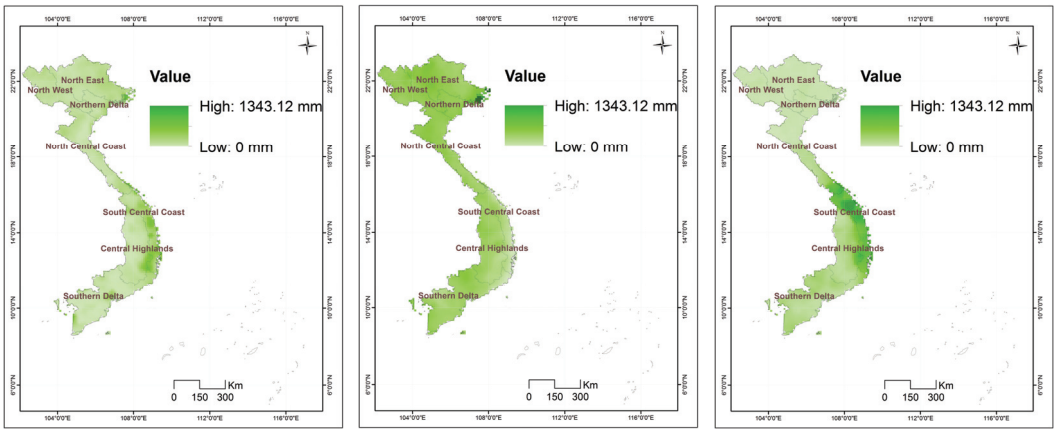


Fig. 6. Interpolated error map (a), Interpolated GR_PRECIP (b), TRMM error map (c), corrected TRMM (d), and assimilated precipitation (e) in Vietnam, August 10, 2010.

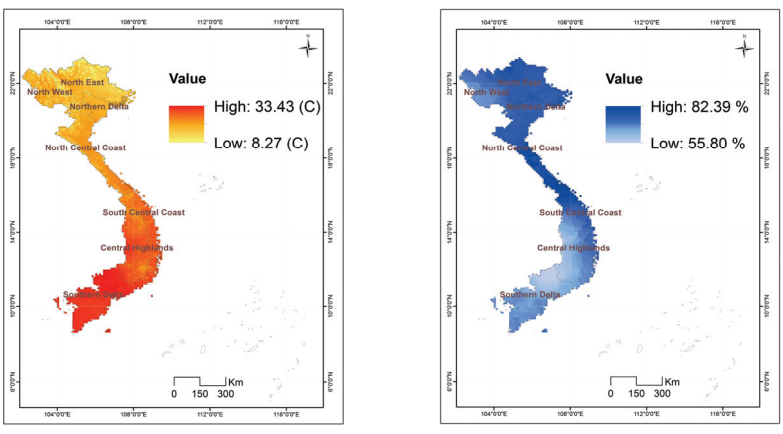
Fig. 6 illustrates the interpolation and assimilation results on a dataset recorded on August 10, 2010. The KE map and interpolated map of ground precipitation measurements at 0.1° × 0.1° are shown in Fig. 6(a) and (b). Meanwhile, the TRMM error map and corrected TRMM map that were calculated from the satellite TRMM and online ground precipitation measurements are presented in Fig. 6(c) and (d). The data assimilation technique mentioned in Section 2 is based on four maps to create the final precipitation result, as shown in Fig. 6(e).

In Vietnam, the rainy seasons in the seven climate regions vary. The biggest drought period is from January to March in all regions of Vietnam, as shown in Fig. 7(a). Otherwise, high rainfalls occur in the north of Vietnam in August (see Fig. 7(b)), and for the North Central Coast they happen in November (see Fig. 7(c)). The replication of rainfall behaviors from assimilated data was confirmed by real seasonal and regional characteristics. Similarly, temperature and humidity data were processed in the same way for procedure maps at (0.1° × 0.1°). Fig. 8 presents the average temperature and humidity throughout Vietnam in January. Cold weather and high humidity occurred in the winter months in the north and hot temperatures and dry conditions dominated in the south.



(a) (b) (c)

Fig. 7. Total precipitation in (a) January, (b) August, and (c) November in Vietnam.



(a) (b)

Fig. 8. Average temperature (a) and humidity (b) in January over Vietnam.

3.4 Ten-Fold Cross Verification Results

In order to evaluate the effectiveness of the interpolation and assimilation methods, we used the RMSE, which is defined as follows:

$$RMSE = \frac{1}{T} \cdot \sum_{t=1}^{T} \left(sqrt \left(\frac{1}{M} \cdot \sum_{i=1}^{M} \left(Z_{s_i} - \bar{Z}_{s_i} \right)^2 \right) \right) \tag{11}$$

and the MPE is defined as:

$$MPE = \frac{1}{T} \cdot \sum_{t=1}^{T} \left(\frac{1}{M} \cdot \sum_{i=1}^{M} \frac{\left| Z_{s_i} - \bar{Z}_{s_i} \right|}{Z_{s_i}} \cdot 100\% \right) \tag{12}$$

where, M is the number of testing stations; T is the number of tests in a ten-fold estimation; Z_{s_i} and $\bar{Z}_{s_i}$ are the observed meteorological variables and their interpolated values, respectively.

Validation for the proposed assimilation techniques were carried out on a dataset collected over the course of six years. As a result, the number of temperature, humidity, and precipitation images were 526, 120, and 771 days, respectively.

The validation results of different techniques for temperature, relative humidity, and precipitation are presented in Tables 1–3, respectively. Regarding temperature and humidity, the assimilation technique (UnK+DEM+Assim / UnK+Assim) did not improve interpolation results. When temperature interpolation with DEM correction was applied, the RMSE was 1.97K and MPE was 0.532%. Assimilation slightly increased RMSE and MPE up to 2.056K and 0.569% (Table 1). Similarly, the assimilation for humidity increased RMSE and MPE from 6.61% and 7.73% to 8.89% and 10.36%, respectively (Table 2). Due to there being less variant characteristics in space of both temperature and humidity variables and the low quality of corresponding satellite products, UnK gained better results than the assimilation techniques could.

Table 1. Temperature models validation results

Model	RMSE (K)	MPE (%)
UnK+DEM	1.97	0.532
UnK+DEM+Assim	**2.056**	**0.569**

Table 2. Relative humidity models validation results

Model	RMSE (%)	MPE (%)
UnK	6.61	7.73
UnK+Assim	**8.89**	**10.36**

Table 3. Precipitation models validation results

Model	RMSE (mm)	MPE (%)
UnK	15.21	88.40
UnK+Assim	**14.12**	**66.58**

Table 3 illustrates the evaluation results of precipitation interpolation between the two methods of UnK and UnK+Assim. The error estimation of MPE in the UnK+Assim model decreased considerably to 66.58%, compared to 88.40% in UnK. The value of RMSE also indicates that the integration of ground and satellite precipitation produced better accuracy than only ground data did. The proposed assimilated technique has shown the strongest effect on precipitation variables, which can be explained by their large variants in the space of rainfall variables in comparison with temperature and humidity.

3.5 The WRF Assessment

We used temperature, humidity, and precipitation maps in August and December 2010 that were produced by using the WRF model as the third party to assess the quality of our products. Fig. 9 shows the correlation coefficient between the WRF's products and our results. Temperature gains strong correlation in both December and August, which can be explained by the good quality of the temperature products (see Table 1). Humidity just shows a high relation in December but in August. Rainfall has the lowest correlation coefficient in both months due to the lower quality of precipitation products. The trend of correlation coefficients between the WRF and assimilation products can be explained via relation of the WRF and ground station measurements (Fig. 10).

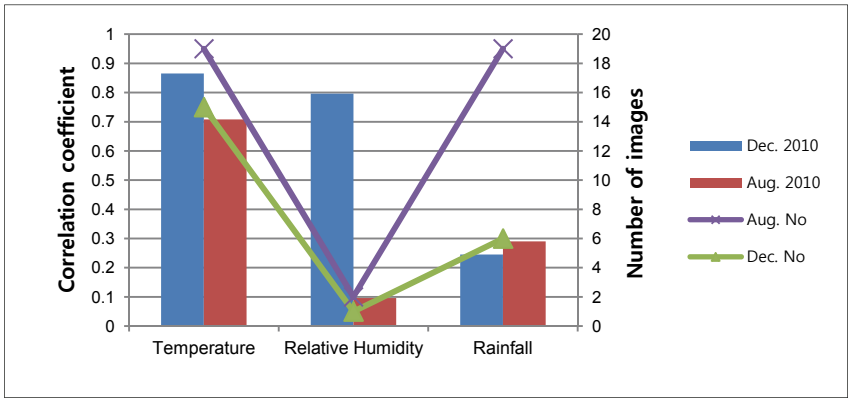


Fig. 9. The Weather Research and Forecasting's products vs. assimilated products.

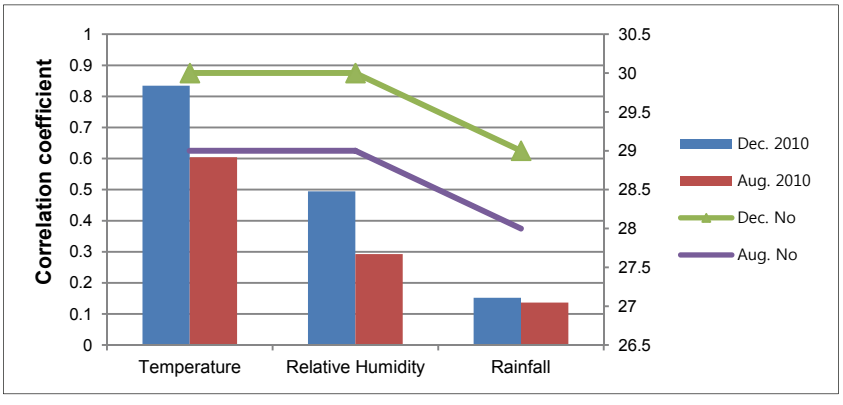
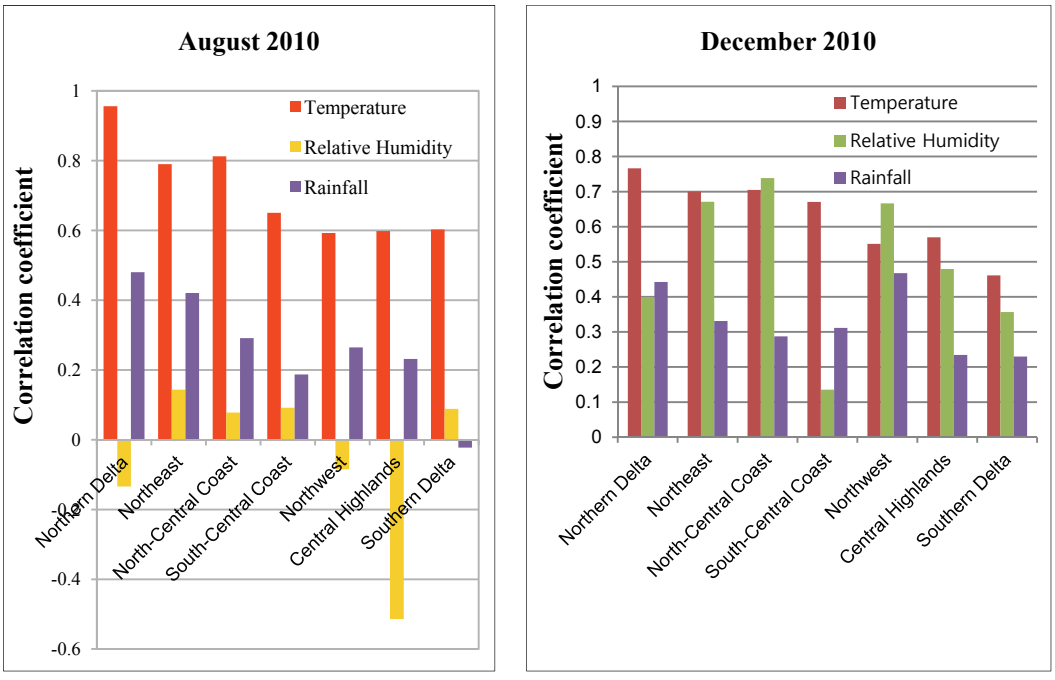


Fig. 10. The Weather Research and Forecasting's products vs. ground station.

Fig. 11 illustrates the comparison results between the WRF model and our approach in more detail. Overall, in two months, the high correlation in terms of temperature occurred in all seven climate regions, with the number for the Northern Delta being the highest ($R \approx 0.95$ in August and $R \approx 0.75$ in December). However, the rainfall correlation in the northern regions was higher than the southern ones, especially in the Southern Delta, which had a negative correlation. As can be seen in Fig. 11(a), there were some variations in relative humidity correlation in August and all of them were quite low. The Northeast had the highest humidity correlation at only 1.5; whereas, the negative humidity correlation occurred in the Northern Delta, Northwest, and Central Highlands ($R \approx -0.5$). In contrast, the relative humidity in December was high in the Northeast, North-Central Coast, and Northwest ($R \approx 0.7$) and this number for the South-Central Coast was just over 0.1.



(a) (b)

Fig. 11. Correlation coefficient between the Weather Research and Forecasting and assimilation products in 7 climate regions.

4. Conclusion

We have presented the applications of spatial interpolation and assimilation methods for meteorological variables including temperature, relative humidity, and precipitation in the regions of Vietnam. The input meteorological data includes satellite data (MOD TEMP, DEM, TRMM) and ground data collected over the course of six years (2008–2013) from 98 ground weather stations located throughout Vietnam. The outputs were interpolated fields and assimilated fields of temperature, relative humidity and precipitation. Our results show that Kriging interpolation and assimilation with MODIS surface temperature outperforms when applied to temperature data with the support of a

digital elevation model. The assimilation of TRMM precipitation data improved the spatial prediction of ground precipitation.

Acknowledgement

The authors would like to thank the research projects, "Forest fire information system, QGTD.13.26" and "Air pollution monitoring and warning system, QGTD.13.27," from Vietnam National University, Hanoi for their financial support.

References

[1] M. B. Araujo and M. Luoto, "The importance of biotic interactions for modelling species distributions under climate change," *Global Ecology and Biogeography*, vol. 16, no. 6, pp. 743-753, 2007.

[2] J. Miller and J. Franklin, "Modeling the distribution of four vegetation alliances using generalized linear models and classification trees with spatial dependence," *Ecological Modelling*, vol. 157, no. 2, pp. 227-247, 2002.

[3] T. L. Liu, K. W. Juang, and D. Y. Lee, "Interpolating soil properties using kriging combined with categorical information of soil maps," *Soil Science Society of America Journal*, vol. 70, no. 4, pp. 1200-1209, 2006.

[4] R. K. Meentemeyer, N. J. Cunniffe, A. R. Cook, J. A. Filipe, R. D. Hunter, D. M. Rizzo, and C. A. Gilligan, "Epidemiological modeling of invasion in heterogeneous landscapes: spread of sudden oak death in California (1990-2030)," *Ecosphere*, vol. 2, no. 2, pp. 1-24, 2011.

[5] H. Apaydin, F. K. Sonmez, and Y. E. Yildirim, "Spatial interpolation techniques for climate data in the GAP region in Turkey," *Climate Research*, vol. 28, no. 1, pp. 31-40, 2004.

[6] T. Wu and Y. Li, "Spatial interpolation of temperature in the United States using residual kriging," *Applied Geography*, vol. 44, pp. 112-120, 2013.

[7] C. Daly, M. Halbleib, J. I. Smith, W. P. Gibson, M. K. Doggett, G. H. Taylor, J. Curtis, and P. P. Pasteris, "Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States," *International Journal of Climatology*, vol. 28, no. 15, pp. 2031-2064, 2008.

[8] R. Benavides, F. Montes, A. Rubio, and K. Osoro, "Geostatistical modelling of air temperature in a mountainous region of Northern Spain," *Agricultural and Forest Meteorology*, vol. 146, no. 3, pp. 173-188, 2007.

[9] S. P. Serbin and C. J. Kucharik, "Spatiotemporal mapping of temperature and precipitation for the development of a multidecadal climatic dataset for Wisconsin," *Journal of Applied Meteorology and Climatology*, vol. 48, no. 4, pp. 742-757, 2009.

[10] J. Aalto, P. Pirinen, J. Heikkinen, and A. Venalainen, "Spatial interpolation of monthly climate data for Finland: comparing the performance of kriging and generalized additive models," *Theoretical and Applied Climatology*, vol. 112, no. 1-2, pp. 99-111, 2013.

[11] V. K. Duong, D. C. Hoang, T. G. Ngo, H. S. Nguyen, and H. Q. Nguyen, "Study for building a frost and low temperature monitoring and warning model for north west region in Vietnam," in *Proceedings of National Scientific Conference on Meteorology and Hydrology, Environment and Climate Change*, 2012, pp. 161-167.

[12] V. K. Duong, T. T. Tran, H. Q. Nguyen, and H. S. Nguyen, "Method of zoning map of frost and low temperature in the north west of Vietnam," in *Proceedings of National Scientific Conference on Meteorology and Hydrology, Environment and Climate Change*, 2012, pp. 168-174.

[13] X. T. Nguyen, B. T. Nguyen, K. P. Do, Q. H. Bui, T. N. T. Nguyen, V. Q. Vuong, and T. H. Le, "Spatial interpolation of meteorologic variables in Vietnam using the Kriging method," *Journal of Information Processing Systems*, vol. 11, no. 1, pp. 134-147, 2015.

[14] J. C. Jimenez-Munoz, J. A. Sobrino, C. Mattar, and B. Franch, "Atmospheric correction of optical imagery from MODIS and reanalysis atmospheric products," *Remote Sensing of Environment*, vol. 114, no. 10, pp. 2195-2210, 2010.

[15] A. Shaban, C. Robinson, and F. El-Baz, "Using MODIS images and TRMM data to correlate rainfall peaks and water discharges from the Lebanese Coastal Rivers," *Journal of Water Resource and Protection*, vol. 1, no. 4, pp. 1-10, 2009.

[16] Z. Liu, "Comparison of precipitation estimates between Version 7 3-hourly TRMM Multi-Satellite Precipitation Analysis (TMPA) near-real-time and research products," *Atmospheric Research*, vol. 153, pp. 119-133, 2015.

[17] A. Hirano, R. Welch, and H. Lang, "Mapping from ASTER stereo image data: DEM validation and accuracy assessment," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 57, no. 5-6, pp. 356-370, 2003.

[18] X. Li, G. Cheng, and L. Lu, "Spatial analysis of air temperature in the Qinghai-Tibet Plateau," *Arctic, Antarctic, and Alpine Research*, vol. 37, no. 2, pp. 246-252, 2005.

[19] J. S. Yang, Y. Q. Wang, and P. V. August, "Estimation of land surface temperature using spatial interpolation and satellite-derived surface emissivity," *Journal of Environmental Informatics*, vol. 4, no. 1, pp. 37-44, 2004.

[20] C. Rolland, "Spatial and seasonal variations of air temperature lapse rates in Alpine regions," *Journal of Climate*, vol. 16, no. 7, pp. 1032-1046, 2003.

[21] C. Zhao, Z. Nan, and G. Cheng, "Methods for modelling of temporal and spatial distribution of air temperature at landscape scale in the southern Qilian mountains, China," *Ecological Modelling*, vol. 189, no. 1, pp. 209-220, 2005.

[22] S. H. Chua and R. L. Bras, "Optimal estimators of mean areal precipitation in regions of orographic influence," *Journal of Hydrology*, vol. 57, no. 1, pp. 23-48, 1982.

[23] S. L. Dingman, D. M. Seely-Reynolds, and R. C. Reynolds, "Application of kriging to estimating mean annual precipitation in a region of orographic influence," *Journal of the American Water Resources Association*, vol. 24, no. 2, pp. 329-339, 1988.

[24] H. Dobesch, P. Dumolard, and I. Dyras, *Spatial Interpolation for Climate Data: The Use of GIS in Climatology and Meteorology*. London: ISTE, 2007, pp. 87-96.

[25] M. Rodell, P. R. Houser, U. Jambor, J. Gottschalck, K. Mitchell, C. J. Meng, et al., "The global land data assimilation system," *Bulletin of the American Meteorological Society*, vol. 85, no. 3, pp. 381-394, 2004.

Khac Phong Do http://orcid.org/0000-0002-6487-3420

He received the B.S. degree in Computer Science from University of Engineering and Technology, Vietnam National University, Hanoi (UET–VNU) in 2014. At the moment, he is enrolling a Master course as a member of Field Monitoring Center at UET–VNUHN. His current research interests include Satellite Image Processing, Computer Vision and Meteorological Data Interpolation.

Ba Tung Nguyen http://orcid.org/0000-0002-3020-3058

He received the B.S. degree in Computer Science from University of Engineering and Technology (UET), VNU in 2013. After graduation, he works in Human-Machine Interaction Lab on a project about Human gestures recognition. And now he is undertaking a master course as a member of the Multidisciplinary Integrated Technologies Center For Field Monitoring at UET-VNU. His research interests include Human Gestures Recognition and Satellite Imagery Processing for Early Warning in Forest Fire.

Xuan Thanh Nguyen http://orcid.org/0000-0001-5464-0327

He received the B.S. in Computer Science from University of Engineering and Technology, Vietnam National University (UET, VNU), Hanoi, Vietnam in 2013. During 2013–2014, he studied first year of master program at UET, VNU and did research at Human Machine Interaction Laboratory, UET–VNU. Now, He is studying second year of master at Japan Advanced Institute of Science and Technology. His research interests include Computer Vision, Satellite Image Processing and Video Coding.

Quang Hung Bui http://orcid.org/0000-0001-5250-4719

He received his B.Sc. from Vietnam National University in 2001. He received M.E. and Ph.D. from Division of Systems Science and Applied Informatics, Graduate School of Engineering Science, Osaka University in 2005 and 2008, respectively. Currently he is Director of the Multidisciplinary Integrated Technologies Center for Field Monitoring, Vietnam National University of Engineering and Technology. His research interests are Spatial Databases, Spatial Data Infrastructure, Spatial Data Mining and Geographical Information Systems.

Nguyen Le Tran http://orcid.org/0000-0003-0336-9375

He received the B.S. degree in Computer Science from University of Engineering and Technology (UET), VNU in 2012. After graduation, he pursues his passion of research by enrolling a master course in Computer Science in UET–VNU and he will complete the master program in the end of 2015. His research interests include Image Processing and Computer Vision.

Thi Nhat Thanh Nguyen http://orcid.org/0000-0002-7253-3813

She received B.S. and M.S. degrees in Information Technology from the College of Technology, Vietnam National University, Hanoi in 2005. She received a Ph.D. at University of Ferrara, Italy in 2012. Her research interests are in Satellite Image Processing, Air Pollution, and Satellite Aerosol. She is now a lecturer and researcher in University of Engineering and Technology, Vietnam National University.

Van Quynh Vuong http://orcid.org/0000-0002-3375-3362

He received a Ph.D. degree in silviculture and forest fire management in 1991 at the Voronhezo Forestry University in the Republic of the Russian Federation. He has been a professor at Forestry University of Vietnam since 2012. His research interests are in the area of forest hydro-meteorology, forest fire management, environmental protection and disaster prevention. They include topics such as measures to use of forests to mitigate flooding and water resource stability, valuation of environmental services of forests, forest fire risk prediction, forest fire prevention, forest resources monitoring.

Huy Lai Nguyen http://orcid.org/0000-0003-1405-3456

He received the B.E. degree in Biotechnology from International University–Vietnam National University, Ho Chi Minh City in 2012. He received the M.E. degree in Environmental Engineering and Management (EEM)/School of Environment, Resources & Development (SERD) from Asian Institute of Technology (AIT), Thailand in 2015. Currently, he is the research associate in faculty of EEM/SERD, AIT. His research interests are anthropogenic and biogenic emission inventory development, meteorological/air quality modeling system.

Thanh Ha Le http://orcid.org/0000-0002-7288-0444

Thanh Ha Le received B.S. and M.S. degrees in Information Technology from the College of Technology, Vietnam National University, Hanoi in 2005. He received a Ph.D. at the Department of Electronics Engineering at Korea University. In 2010, he joined the Faculty of Information Technology, University of Engineering and Technology, Vietnam National University, Hanoi as a lecturer and researcher. His research interests are multimedia processing, coding satellite image processing and computer vision. He is now doing research on forest fire using remote sensing approach as well as high efficient and multiview video coding.