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Aquatic Procedia 4 (2015) 1381 – 1388

Aquatic Procedia

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INTERNATIONAL CONFERENCE ON WATER RESOURCES, COASTAL AND OCEAN ENGINEERING (ICWRCOE 2015)

Prediction of Land Surface Temperature under Cloudy Conditions using Microwave Remote Sensing and ANN

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Abstract

Land surface temperature (LST) is an important variable in climate, hydrologic, ecological, biophysical and biochemical studies (Mildrexler et al., 2011). The most effective way to obtain LST measurements is through satellites. Presently, LST from moderate resolution imaging spectroradiometer (MODIS) sensor is applied in various fields due to its high spatial and temporal availability over the globe, but quite difficult to provide observations in cloudy conditions. This study evolves of prediction of LST under clear and cloudy conditions using microwave vegetation indices (MVIs), elevation, latitude, longitude and Julian day as inputs employing an artificial neural network (ANN) model. MVIs can be obtained even under cloudy condition, since microwave radiation has an ability to penetrate through clouds. In this study LST and MVIs data of the year 2010 for the Cauvery basin on a daily basis were obtained from MODIS and advanced microwave scanning radiometer (AMSR-E) sensors of aqua satellite respectively. Separate ANN models were trained and tested for the grid cells for which both LST and MVI were available. The performance of the models was evaluated based on standard evaluation measures. The best performing model was used to predict LST where MVIs were available. Results revealed that predictions of LST using ANN are in good agreement with the observed values. The ANN approach presented in this study promises to be useful for predicting LST using satellite observations even in cloudy conditions.

Peer-review under responsibility of organizing committee of ICWRCOE 2015

Keywords: LST; MVI; MODIS; AMSRE; ANN.

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Peer-review under responsibility of organizing committee of ICWRCOE 2015
doi:10.1016/j.aqpro.2015.02.179

1. Introduction

Land Surface Temperature (LST) is the thermodynamic temperature of the uppermost layer of the Earth's surface commonly measured using the thermal radiance obtained from the thermal infrared sensors over clear sky conditions (Holmes et al., 2009). It is one of the key parameters in the field of climate research, weather forecast, land-surface interaction studies and it is a crucial parameter in global and regional models. The most commonly used infrared sensors available for the LST measurement are advanced very high radiometric resolution (AVHRR), moderate resolution imaging spectroradiometer (MODIS) which provide good spatial and temporal resolutions. Usually, LST obtained from the infrared measurements are derived using generalized split window algorithm, day and night algorithm or three channel LST algorithm (Li et al., 2013). Nevertheless, there are many factors which affect the derivation of LST from the infrared sensors such as atmospheric absorption due to clouds and water vapor, which results in unavailability of LST data from the infrared sensors. This creates a lot of gaps in the LST data, which hinders their application in many fields. Many researchers have worked to overcome the effect of cloud in the measured radiance to reduce uncertainty of infrared thermal determinations (Rossow and Gardner 1993, Prigent et al., 2003). However, due to cloud cover lots of missing values can be noticed in the currently available LST data.

LST can also be measured from the microwave radiometers, which can be used as complement to the available infrared LST measurements. These microwave measurements can penetrate through non precipitating clouds and are less affected by the atmospheric absorption, due to which LST can also be derived over nearly all sky conditions which is an advantage over infrared measurements. But the LST obtained from the microwave measurements are of coarse resolutions, resulting in more uncertainty than the infrared LST. Many researchers had successfully derived LST from the microwave measurements over clear and cloudy conditions. Basist et al. 1997 developed a methodology to estimate LST from the brightness temperatures of seven channels of SSM/I satellite. Aries et al. 2004 proposed methodology to reconstruct daily surface skin temperature diurnal cycle over the globe from moderate LST inferences for both clear and cloudy conditions based on principle component analysis (PCA) /iterative approach. L. Lu et al. 2011 suggested a methodology to rebuild the diurnal cycle of LST obtained from MSG/SEVIRI by temporal neighboring-pixel approach. Homles et al. 2009 estimated LST from 37GHz passive microwave observations using simple linear relationship. All these methods were tested either continentally or globally, but very few studies are available at a regional scale.

Vegetation is one of the most influencing interferences, which effects a proper LST estimation by satellite sensors. LST measurements of the non vegetated surfaces generally represent the temperature of the bare soil, whereas for the vegetated surfaces, the measurements represent the canopy temperature (Goward et al., 2002). Thermal response of vegetation depends on the biophysical properties of the vegetation itself (Quattrochi and Ridd, 1998). Hong et al. 2007 analyzed the relationship between LST and biophysical properties of the vegetation for three different regions and found a negative relationship between NVegWC (normalized vegetation water content) and Normalized difference vegetation index (NDVI) and between LST and NDVI. The negative exponential relationship between NVegWC and NDVI was found based on regression between them, which explains the dependency of vegetation on the water condition. Many researchers have used the relationship between LST and NDVI, an optical vegetation index which is mainly dependent on the chlorophyll content of the vegetation cover in the estimation of evapotranspiration, air temperature, disaggregation of LST etc. (Jiang and Islam, 2001; Prihodko and Goward, 1997; Kustas et al., 2003). Since NDVI is sensitive to clouds, it will be unable to get data under cloudy conditions. A major limitation of the NDVI is that, it represents uppermost part of the canopy and cannot provide information on woody biomass, while vegetation indices derived from the microwave measurements are sensitive to vegetation properties of relatively thick layer and these data available for day and night under all sky conditions (J. Shi et al., 2008). To cover this lacuna, we used the relationship between MVIs and LST to predict LST under all sky conditions. The objective of this study, is to propose a methodology to derive LST under clear and cloudy conditions using the microwave vegetation indices along with the digital topographical and geographical data using an artificial neural network model over Cauvery basin in India.

2. Study area and Data

2.1. Study area

Cauvery River basin selected as the study area is displayed in Fig. 1. The basin lies between latitudes 10^0 05' N and 13^0 30' N and longitudes 75^0 30' E and 79^0 45' E. The total length of the river from source to its outfall into the Bay of Bengal is about 800 km. The Cauvery basin extends over an area of 81,155 km^2. The basin lies in the States of Karnataka, Kerala, Tamil Nadu and Pondicherry of India. Cauvery basin experiences a tropical climate. The recorded maximum and minimum temperatures are 44°C and 18°C respectively. It is bounded on the west by the Western Ghats, on the east and south by the Eastern Ghats and on the north by the ridges separating it from the Tungabhadra (Krishna) and Pennar basins. Physiographically, the basin can be divided into three parts: the Western Ghat area, the Plateau of Mysore and the Delta. The delta area is the most fertile tract in the basin.

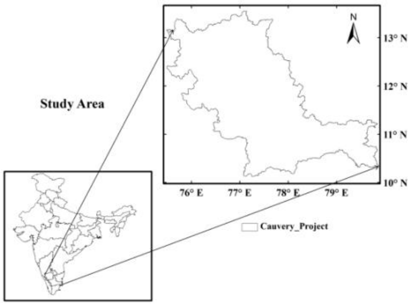

Fig. 1. Description of the study area.

2.2. Data Set

The data required for the analysis, obtained for the year 2010 are summarized in Table 1. MODIS and AMSR-E are sensors of Aqua satellite, which passes from south to north at about 1:30 pm and 1:30 am local solar time each day in sun synchronous orbit. The land use land cover (LULC) and elevation maps are shown in Fig. 2. MODIS LULC product has five classification schemes, out of which we have used the International Geosphere Biosphere Program (IGBP) classification scheme.

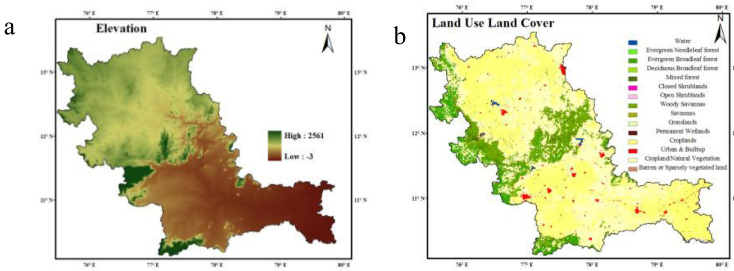

Fig. 2. (a) Elevation; (b) Land Use Land Cover.

Table 1. Details of the data set used.

Sensor/Satellite	Parameter	Product Name	Spatial Resolution	Purpose
MODIS/Aqua	LST	MYD11A1	1km	As target variable in ANN model and for prediction of LST
AMSR-E/Aqua	Tb at 18.7V, H and	AE-L2A	25km	Derivation of MVI_A and MVI_B

	36.5V, H GHz			
MODIS/Aqua	LULC	MCD12Q1	500m	Input variable in ANN model
SRTM	Elevation		90m	Input variable in ANN model

Where, V = vertical polarization, H = horizontal polarization, LULC = land use land cover

3. Methodology

3.1. Data Preprocessing

The LST and LULC data acquired from the MODIS sensor were in sinusoidal projection with the spatial resolution of 1km, while Tb of AMSR-E sensor data were at 25km and were in different projections. To make all the data to be consistent with each other sinusoidal projection of MODIS datasets were changed to AMSR-E geographical projection using the MODIS reprojection tool (provided by NASA) by a nearest neighbor method. For the analysis all MODIS datasets were aggregated to 25km spatial resolution. LULC and elevation data were also upscaled to 25km.

3.2. Prediction of LST over clear and cloudy conditions

LST can be derived from the microwave brightness temperature of vertical polarization at 37GHz channel (Tb37V), because of the strong and linear relationship between them. But for the low vegetated surfaces, Holmes et al.2009 found that small variations in the soil water content may result in high bias. So In this context, we used microwave vegetation indices along with digital topographical and geographical data in the ANN model to predict LST under clear as well as cloudy conditions, because microwave vegetation indices used here are sensitive to short vegetated surfaces. J. Shi et al. 2008 developed a new set of MVIs using AMSR-E observations. The concept behind is that bare surface emission signals of two adjacent AMSR-E frequencies are highly correlated and coefficients of the linear function are dependent only on the frequency pair and are polarization independent. This leads to the assumption that two adjacent frequencies of microwave sensors in vegetated surfaces can be described as a linear function by minimizing soil emission signals and other atmospheric effects. The intercept (MVI_A) and slope (MVI_B) in the linear function are called microwave vegetation indices. MVI_A parameter is effected by vegetation parameters and as well as the surface temperature, whereas, MVI_B is effected only by vegetation parameters. Expressions for MVI_A and MVI_B are given as

$$MVI\_A\,(f_1, f_2) = \frac{1}{2}\left[T_{bv}(f_2) + T_{bh}(f_2) - B(f_1, f_2) * \left(T_{bv}(f_1) + T_{bh}(f_1)\right)\right] \quad (1)$$

$$MVI\_B(f_1, f_2) = \frac{T_{bv}(f_2) - T_{bh}(f_2)}{T_{bv}(f_1) - T_{bh}(f_1)} \quad (2)$$

where, f_1 = lower frequency channel (18.65 GHz)
f_2 = higher frequency channel (36.7 GHz)
T_{bv} = brightness temperature of vertical polarization
T_{bh} = brightness temperature of horizontal polarization

In this study, we have used MVI_A, MVI_B, elevation, LULC, latitude, longitude and Julian day as input variables to get a nonlinear relationship with the LST, which is the target variable incorporated in the ANN model, which is given as

$$LST\_u_{ij} = f(\,MVI\_A_{ij}, MVI\_B_{ij}\,, Elevation_i, LULC_i, Latitude_i, Longitude_i, j\,) \quad (3)$$

where, LST_u_{ij} = LST at 25km resolution of the pixel i on the day j. Inputs required for the model were selected based on the availability of the corresponding LST_u. For training the network, data was selected in such a way that, LST data used in this process should contain all ranges of LST_u. To achieve this we used stratified random sampling method to choose LST_u. Firstly, we arranged the LST_u in ascending order and then divided the data arranged into 10 bins. After this, from each bin 70% of the data were selected for training the network and remaining 30% for validation. Later, using 70% data from each bin we have employed Feed-forward neural networks with five algorithms, namely, sequence of Levenberg Marquardt, resilient back propagation, scaled conjugate gradient algorithm, bfgs quasi neuton algorithm and conjugate gradient algorithm with fletcher reeve restarts. Trial and error process was applied to select optimized architecture. Best network was selected based on the correlation coefficient, root mean squared error and Nash Sutcliffe evaluation measures. Furthermore, to predict LST under cloudy conditions, all seven inputs (present in the cloudy conditions) were applied in the selected best network with the assumption that the selected network obtained from the relationship between LST and seven inputs for clear pixels would also be valid for the cloudy pixels.

3.3. Evaluation of predicted LST

Pearson correlation coefficient (r), Nash Sutcliffe (NSE) and Root mean squared error (RMSE) evaluation measures were selected to evaluate the predicted LST with the available LST_u images over clear sky conditions

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})\,(y_i - \bar{y}).}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \,.\, \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}}$$

where, x_i = observed values
$\bar{x}$= mean of the observed values
y_i = predicted values
n = number of observations

4. Results and Discussions

The best trained network was used to predict LST under clear as well as cloudy conditions. Since MODIS LST data are available only under clear sky conditions, these were used to evaluate the predicted LST. The statistical analysis was done separately for the four seasons, i.e. winter, summer, rainy and post monsoon seasons. Since most of the data for rainy were missing, it is desired to know for which seasons the model performs better. Results for different seasons are given in the Fig. 3.1. For the winter and summer seasons, the model has performed better than for the other two seasons, because most of the data were taken from these two seasons to get the relationship between LST_u and another seven inputs. The relationship between MODIS LST and Tb of vertical polarization at 37 GHz channel were checked for all the seasons shown in Fig. 3.2. For the winter seasons, strong correlation was found between them compared to other seasons. Due to this less linear relationship between Tb37V and MODIS LST we used microwave vegetation indices in the prediction of LST and also we checked the results by adding Tb37V values in the ANN modeling which slight improvements were achieved for all the seasons.

Further, to check the potentiality of an ANN model we removed the 2nd Feb, 7th March, 4th June and 20th November of the year 2010 datasets one after the other for the respective winter, summer, rainy and post monsoon seasons and repeated the procedure to predict LST as mentioned in section 3.2. Then these were evaluated with the available corresponding MODIS LST. Spatial distribution of MODIS LST, predicted LST and filled LST (combining MODIS LST over clear sky conditions and predicted LST over cloudy conditions) for these selected days are shown in Fig. 4. The initial visual interpretation revealed that the spatial distributions of predicted LST are similar to the corresponding MODIS LST for all the seasons, Furthermore, the results of the statistical analysis for the considered days revealed that during the 7th of march the ANN model has performed better than other days with the correlation coefficient of 0.846, RMSE of 2.6 K and NSE of 0.69. The scatter plots between predicted LST and MODIS LST for the same days of the year 2010 are displayed in Fig. 4. The most part of the Cauvery basin is covered by the croplands. In the rainy season these were usually filled up with the water, this may affect the microwave measurements because these measurements are very sensitive to water content.

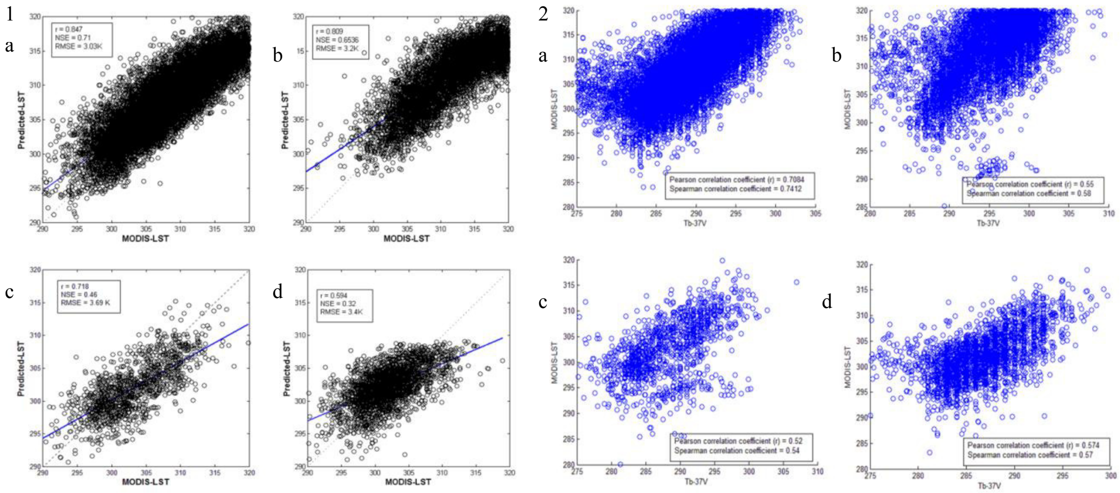

Fig. 3. (1) Scatter plots between MODIS LST (K) and predicted LST (K); (2) Scatter plots between MODIS LST (K) and Tb37V (K) for (a) winter (b) summer (c) rainy (d) post monsoon seasons.

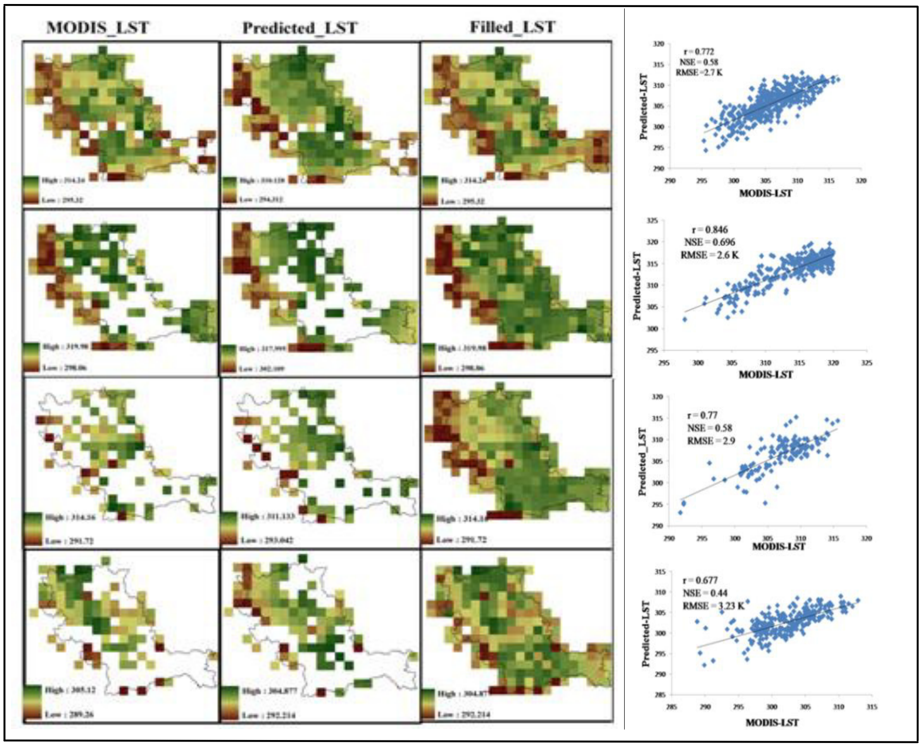

Fig. 4. Spatial distribution of MODIS LST, Predicted LST, Filled LST and scatter plot between MODIS LST(K) and Predicted LST (K) for the days (a) Feb 2nd; (b) March 7th; (c) June 4th; (d) November 20th of the year 2010.

The variability of the predicted LST for different land use covers is also checked. For the forest region, as expected, the model performed well with the correlation coefficient of 0.859, NSE of 0.73 and RMSE of 3.06K . Even for Croplands and Grasslands the errors are within the limits displayed in Fig. 5. Microwave vegetation indices can improve the results in the prediction of LST because, these indices are sensitive to vegetation parameters, with less soil background and atmospheric effect when compared to traditional NDVI optical vegetation index.

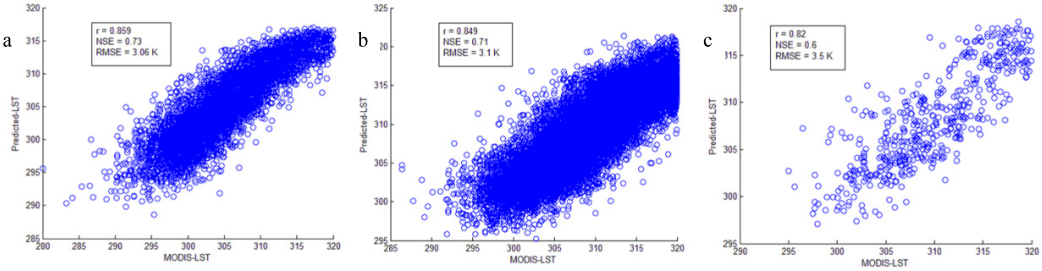

Fig.5. Scatter plots between MODIS LST (K) and predicted LST (K) for (a) Forest ; (b) Croplands ; (c) Grasslands.

4. Conclusions

In this study, we used microwave vegetation indices (MVI_A and MVI_B) with digital topographical, geographical data and Julian day to predict LST under cloudy as well as clear sky conditions. Availability of MODIS LST for the clear sky pixels enabled us to evaluate the predicted LST. Results revealed that microwave vegetation indices can be applied for all the seasons to predict LST under cloudy conditions using an ANN model. Nevertheless, predicted LST from the microwave vegetation indices has its limitation of coarse spatial resolution.

Acknowledgements

We would like to thank NASA Land Process Distributed Active Archive Center for providing MODIS LST and LULC data and NSIDC Distributed Active Archive Center (DAAC) for AMSR-E data.

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