SPATIOLTEMPORAL MODELING THE IMPACT OF SURFACE CHARACTERISTICS VARIATIONS ON LAND SURFACE TEMPERATURE VARIATIONS: A CASE STUDY OF SAMALGHAN VALLY

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ABSTRACT:

Spatiotemporal mapping and modeling of Land Surface Temperature (LST) variations and characterization of parameters affecting these variations are of great importance in various environmental studies. The aim of this study is a spatiotemporal modeling the impact of surface characteristics variations on LST variations for the studied area in Samalghan Valley. For this purpose, a set of satellite imagery and meteorological data measured at the synoptic station during 1988-2018, were used. First, single-channel algorithm, Tasseled Cap Transformation (TCT) and Biophysical Composition Index (BCI) were employed to estimate LST and surface biophysical parameters including brightness, greenness and wetness and BCI. Also, spatial modeling was used to modeling of terrain parameters including slope, aspect and local incident angle based on DEM. Finally, the principal component analysis (PCA) and the Partial Least Squares Regression (PLSR) were used to modeling and investigate the impact of surface characteristics variations on LST variations. The results indicated that surface characteristics vary significantly for case study in spatial and temporal dimensions. The correlation coefficient between the PC1 of LST and PC1s of brightness, greenness, wetness, BCI, DEM, and solar local incident angle were 0.65, −0.67, −0.56, 0.72, −0.43 and 0.53, respectively. Furthermore, the coefficient coefficient and RMSE between the observed LST variation and modelled LST variation based on PC1s of brightness, greenness, wetness, BCI, DEM, and local incident angle were 0.83 and 0.14, respectively. The results of study indicated the LST variation is a function of s terrain and surface biophysical parameters variations.

1. INTRODUCTION

Land surface temperature (LST) is considered as controller parameter of surface energy exchanges top of land surface (Anderson et al. 2008; Prata et al. 1995; Weng et al. 2019). The role of land surface temperature (LST) in the energy exchanges between land surface and atmosphere is significant. Currently, using from satellite-based thermal infrared (TIR) remote sensing data in physical and quantitative models a popular method to obtain LST maps at different spatiotemporal scales (Zhao et al. 2019).

LST is extremely changeable and affected by various parameters in both spatial and temporal dimensions (Guo et al. 2015). These parameters include temporal characteristics, geographic coordinates, topographic factors, thermal surface properties, biophysical parameters, soil texture, meteorological parameters and sub-surface features (geothermal, hydrothermal and volcanic areas) (Weng et al. 2019).

Considering of LST variations is among the most effective factors on the surface energy balance components (Weng et al. 2019), surface soil moisture (Jiang and Weng 2017), climate change (Weng 2009), drought (Son et al. 2012), evapotranspiration (Jiang and Weng 2017), global warming (Xie et al. 2010), Urban Heat Island Intensity (UHII) (Firozjaei et al. 2018; Weng et al. 2018), energy consumption (Giridharan and Emmanuel 2018), thermal comfort (Van Hove et al. 2015). Therefore, study of LST variations and the parameters affecting these changes is important (Karimi Firozjaei et al. 2018; Weng et al. 2019).

In many previous studies, the impact of land use and land cover changes on LST were investigated (Jiang and Tian 2010; Xiao and Weng 2007). In some studies the impact of surface biophysical parameters on LST using of fundamental surface descriptors such as Normalized Difference Vegetation Index (NDVI) (Weng et al. 2004), Normalized Difference Built up Index (NDBI) (Li et al. 2009) and surface topography (Zhao et al. 2019) were investigated. Zhan et al. (2013) provided an overview of multiple indices, which used to model the LST spatial changes (Zhan et al. 2013). Hutengs and Vohland (2016) studied about modeling of LST with considering of digital elevation data, surface reflectance, and land cover maps (Hutengs and Vohland 2016). Sismanidis et al. (2017) selected NDVI data, DEM, albedo and land surface emissivity data as the effective factors for modeling of LST (Sismanidis et al. 2016). He et al. (2018) provided a systematic analysis about the impact of the environmental parameter which effect on LST and presented the effective factors that influence LST (He et al. 2018).

In most studies, to determine the impact of surface biophysical parameters on the LST, regression techniques were employed (Sattari et al. 2018; Yang et al. 2017). Also, in these studies, the relationship between surface characteristics and LST variations were investigated in the spatial dimension (Sattari et al. 2018; Yang et al. 2017). One of the drawbacks of previous studies is the lack of examining the impact of surface characteristics variations on LST in both spatial and temporal dimensions under an integrated model.

The aim of this study is to introduce a method to model the impact of surface characteristics variations on LST variations for the studied area in Samalghan Valley. For this purpose, two basic steps were taken: (1) Using of principal component analysis (PCA) to determine the LST and surface characteristics variations in the temporal dimension; (2) using of Partial Least

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Squares Regression (PLSR) to investigate the impact of surface characteristics variations on LST variations. Surface biophysical characteristics including brightness, greenness, wetness and Biophysical Composition Index (BCI) and terrain parameters including DEM and local incident angle were considered as main effective factors on LST in this study.

2. PROPOSED METHOD

2.1 Studied area

The study area included Samalghan Valley and its suburbs with an approximate area of 2471 Km2. Geographically, case study locates from 56° 36' 29" and 57° 14' 36" E longitude and from 37° 21' 37" and 37° 45' 21" N latitude. The region is distanced 262 km from the Caspian Sea, 90 km from the Hyrcanian forests, and 33 km from the Bojnord (capital city of North Khorasan province, Iran). The average height of this city is about 1111 meters above sea level. The climatic conditions of the studied area are moderate and dry. The location of the study area is shown in Figure 1.

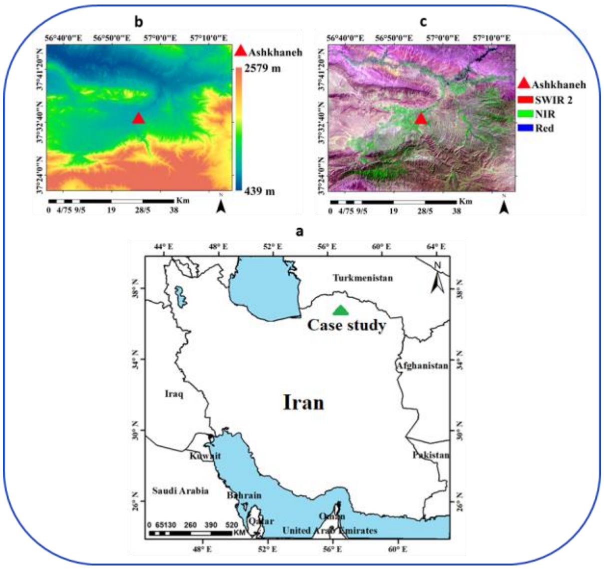

Figure 1. The study area

2.2 Data

Landsat imagery of the studied area for 20/07/1988, 15/07/1992, 13/07/1997, 25/06/2002, 27/07/2008, 12/07/2014 and 07/07/2018 were used to derive surface biophysical characteristics. These images were georeferenced in UTM coordinate system and located in zone 40N. The downloaded data from the USGS included the highest quality Level-1 Precision Terrain (L1TP) data which were considered suitable for time-series analysis. The geo-registration was consistent and the root mean square error (RMSE) less than 12 meters (≤0.5 pixel) (Weng et al. 2019). The Moderate Resolution Imaging Spectroradiometer (MODIS) Atmospheric Profiles products (MOD07), were exploited to complete the input parameters, and estimation of LST maps from Landsat images. Also, The ASTER Digital Elevation Model (GDEM) was used to derive various topographical parameters including elevation, slope, aspect and the solar local incidence angle. The air temperature and relative humidity data for the days which related to the images date for free by the meteorological organization of Northern Khorassan ("www.nkhmet.ir") were used.

2.3 Method

The methodologies were applied to achieve the current study objectives are presented in Figure 2. In the first step, the preprocessing of utilized satellite images has been done including atmospheric corrections, radiometric corrections and subset of the studied area. In the second step, from spatial modeling, single-channel algorithm (Jiménez-Muñoz et al. 2014; Sobrino et al. 2004), Tasseled Cap Transformation (TCT) (Baig et al. 2014) and BCI (Deng and Wu 2012) based on reflective and thermal bands of Landsat imagery, GDEM, MODIS product and meteorological data the LST, brightness, greenness, wetness, BCI, and local incident angle were extracted for the period from 1988 to 2018. In the next step, the PCA (Jolliffe 2011) was employed to determine the degree of variation of the LST and surface characteristics in the temporal dimension at pixel scale. The PCA is one of the techniques for determining variations of environmental parameters in the temporal dimension (Dalal et al. 2010). The variations of environmental parameters in the temporal dimension can be examined on a pixel scale using PCA (Vázquez-Jiménez et al. 2017). To model the variations of each particular parameter over a given time interval, the PCA model applied to its specific values over a time scale at a scale of each pixel (de Almeida et al. 2015; Gaitani et al. 2017; Hirosawa et al. 1996; Wang et al. 2010). PC1 output contains negative and positive values. The higher and more positive value of a pixel in PC1 indicates that the values of this pixel have been large and unchanged over time. But, the lower and more negative value of a pixel in PC1 indicates that the values of that pixel have been low and unchanged over time. The value of PC1 which closer to zero indicates that changes in the values of pixel have been high over time. Finally, the PLSR (Farifteh et al. 2007) was used to investigate the impact of surface characteristics variations on LST variations.

Figure 2. The analytical procedures of the study

3. RESULTS

The results indicated that the mean LST for the studied area is changing over the study period (Figure 3).

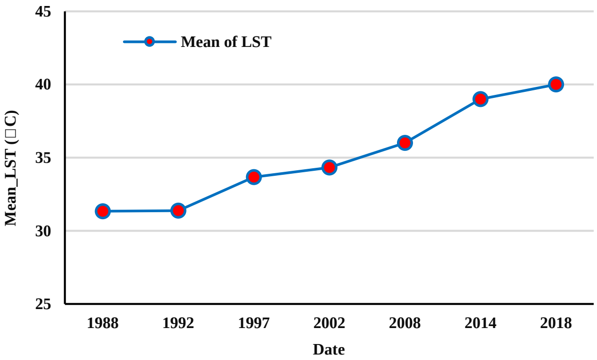

Figure 3. The mean LST of the studied region for 1988 to 2018 (°C).

Previous studies have shown that the LST response is specified by surface characteristics such as the surface moisture, vegetation cover and impervious surface and topographical parameters (Deng and Wu 2013; Xunqiang et al. 2011; Yang et al. 2017). Surface biophysical and topographical parameters are the most important factors influencing on spatial-temporal variations of LST is variations between the other factors.

The PCA was applied for the deeper analysis of the LST variations and each of the surface characteristics at the pixel scale from 1988 to 2018 (Figure 4). The PC1 output contains negative and positive values. The higher and more positive value of a pixel in PC1 indicates that the values of this pixel have been large and unchanged over time. But, the lower and more negative value of a pixel in PC1 indicates that the values of that pixel have been low and unchanged over time. The value of PC1 which closer to zero indicates that changes in the values of pixel have been high over time (Figure 4).

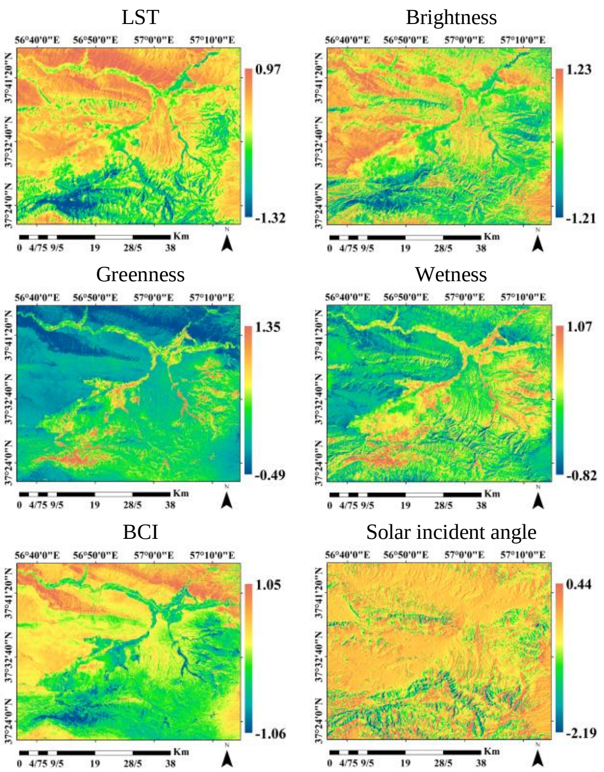

Figure 4. The PC1 maps of LST and various surface characteristics.

The relationship between the PC1 of LST and the PC1 of each surface characteristics were investigated using PLSR (Table 1).

Based on regional approach, among the various surface characteristics, BCI variations showed the highest impact on the LST variations. In general, for study area, the effect of surface biophysical characteristics on LST variation was greater than the effect of topographical parameters (Table 1). The value of LST decreases with increasing surface brightness and reduced vegetation and moisture of surface, and vice versa (Choudhury et al. 2018; Sattari et al. 2018). A negative relationship between vegetation and moisture indices and LST is due to the effect of surface thermal inertia and evapotranspiration (Zhao et al. 2019). On the study of spatial and temporal LST variations in the case study, due to extensive areas and heterogeneous topography, the impacts of topographic effect such as lapse rate and downward solar radiation to the surface were considered (Table 1).

Surface parameters	Solar incidence angle	DEM	Greenness	Wetness	Brightness	BCI
R^2	0.53	-0.43	-0.67	-0.56	0.65	0.72

Table 1. Relationship between the PC1 of LST and the PC1 of each surface biophysical parameters using PLSR with regional approach.

Using the multivariate PLSR, it is possible to consider the influence of several dependent parameters on an independent parameter. In this study, through the simultaneous consideration of the PC1 of the surface characteristics and the PC1 of the LST, the impact of a set of surface characteristics (BCI, Solar incidence angle, and DEM) on LST variation was investigated (Figure 5).

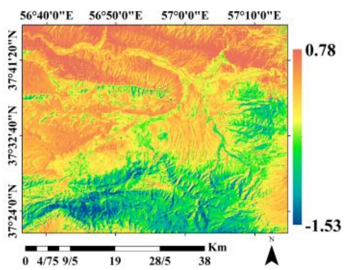

Figure 5. Modeled LST variations based on BCI, Solar incidence angle, and DEM variations using multivariate PLSR.

The results assessment of the relationship between the surface characteristics variations and the LST variations are shown in Table 2. The results assessment indicated that the LST variations can be modeled with the high precision considering the surface characteristics variations such as the BCI, Solar incidence angle, and DEM.

Parameters	***Regional approach***
R	0.83
RMSE	0.14

Table 2. Assessment of the relationship between the surface characteristics variations and the LST variations.

Simultaneous investigation of the relationship between the variations in surface characteristics and LST variations is of great importance (Karimi Firozjaei and Kiavarz 2018; Zhao et al. 2019).

4. CONCLUSIONS

Variations of LST is among the most effective factors on the surface energy balance components, surface soil moisture, climate change, drought, evapotranspiration, global warming, Urban Heat Island Intensity (UHII), energy consumption, thermal comfort. Therefore, study of LST variations and parameters affecting on it is important.

In this study, two models of PCA and PLSR were used to determine the LST and surface characteristics variations in the temporal dimension at pixel scale and investigate the impact of surface characteristics variations on LST variations. The variations of LST and surface characteristics in the temporal dimension can be examined on a pixel scale using PCA. The results of study indicated the LST variations is a function of surface parameters variations. The correlation coefficient and RMSE between the modeled LST based on based on BCI, Solar incidence angle, and DEM variations using multivariate PLSR and the observed LST were 0.81 and 0.14, respectively. Using the integrated PCA-PLSR model is useful for modeling of various environmental parameters changes and identifying the effecting factors that it.

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