International Journal of Ecology and Environmental Sciences 50: 533-541, 2024
ISSN: 2320-5199 (Online); https://doi.org/10.55863/ijees.2024.0062

Estimation of the Relationship between Vegetation Pattern and Land Surface Temperature in Asansol Municipal Corporation

SOUGATA MAJI[1*,3] AND DRUHEEN CHAKRABORTTY[2]
[1]*Bankura University, Bankura, West Bengal, India*
[2]*Bankura Christian College, Bankura, West Bengal, India*
[3]*Present address: State Aided College Teacher,Bidhan Chandra College, Asansol, West Bengal, India*
E-mail: majisougata14@gmail.com, druheengeobcc@gmail.com
***Corresponding author**

ABSTRACT
Changing built-up area is the obvious reason for the fluctuation of land surface temperature phenomena that leads to a distressing urban environment. Urban vegetation has the potential to minimize the land surface temperature intensity. The present study investigated the relationship between land surface temperature (LST) and vegetation patterns in Asansol Municipal Corporation. Landsat 5 TM and Landsat 8 OLI satellite images for the years 1991 and 2021 were used for analysis of landscape metrics viz., class area, patch density, edge density, and mean shape index. Correlation techniques were applied to depict the association between the variables. The study concludes that vegetation configuration has no significant relationship with LST during the study period. However, the vegetation composition is slightly associated with LST which suggests that vegetation composition may play a crucial role in mitigating the LST phenomenon. However, the relationship is very complex and varies spatially and scale-wise.

Key words: Landscape Metrics, LST, Urbanization, Vegetation composition

INTRODUCTION

Urban environment research focused on the difference in air temperature between city area and their surrounding rural areas is called Urban Heat Island (UHI) phenomenon (Landsberg 1981, Weng et al. 2004). Now it has been considered one of the major environmental challenges to city planners (Taha 1997, Zhibin et al. 2014). Rapid urbanization through the extension of urban sprawl is continuously modifying the land use land cover (LULC), ecological diversity, and energy flow (Naeem et al. 2018), which sharply deteriorates environmental quality. Therefore, minimizing the Land Surface Temperature (LST) through afforestation which can reduce the temperature intensity by evaporative cooling and providing shades (Shashua-Bar and Hoffman 2000) should be promoted. Previous studies have established the relationship between LST and vegetation amount using the Normalized Difference Vegetation Index (NDVI) (Weng et al. 2004, Chen et al. 2006, Raynolds et al. 2008, Guha and Govil 2020, Maroni et al. 2021). Studies also showed how the LULC can bring an impact on LST (Barakat et al. 2019, Zhang et al. 2017, Sun et al. 2012). Zhang et al. (2009) highlighted the association between vegetation patches and the LST phenomenon. However, very few studies have paid attention to the quantitative analysis of the influence of vegetation configuration and composition on the LST phenomenon (Li et al. 2012, Zhibin et al. 2014, Naeem et al. 2018). According to Turner (1990), landscape spatial pattern has a vital role in ecological functioning. Therefore, vegetation composition and configuration can influence the energy and material flows (Zhang et al. 2009), which has an impact on LST (Weng et al. 2007). Previous studies have shown mixed results. (Zhibin et al. 2014) and a good correlation between vegetation patterns with LST but (LI et al. (2012) and Naeem et al. (2018), have shown no significant relationship between vegetation pattern and LST. Some studies suggest the ecological process varies according to scale (Turner et al. 1989, Hess et al. 2006, Zhibin et al. 2014). Therefore, it can be expected that the determination of the relationship between the LST and the vegetation patterns is very complex and full of anomalies. The present study has been carried out in Asansol Municipal Corporation (AMC) which is being considered one of the fastest urbanizing areas to assess the relationship between changing land use land cover and LST. Generally, remote sensing data from satellite images are used in UHI studies to drive LST and temporal changes of LULC in any area. The present study also used GIS techniques along with landscape metrics to examine the correlation between vegetation pattern and LST.

STUDY AREA

Asansol city is the second largest city in West Bengal after the capital city Kolkata. The amplification of Asansol city due to industrial and mining expansion and the continuation of population growth lead to its promotion into Asansol Municipal Corporation (AMC) in the period of 1991-2001 (Ghoshdastidar 2011). AMC is located on the western side of the Paschim Bardhaman District where the Domadar River is flowing on the southern side along the border of the AMC. In 1994, the former Asansol Municipality, the Burnpur Notified Area, and some colliery areas were combined to establish the Asansol Municipal Corporation. The municipal areas of Kulti, Raniganj, and Jamuria were added to the Asansol Municipal Corporation's purview on June 29, 2015. AMC is now having 106 wards engulfing an area of 326.48 km^2 (Anonymous 2017) sheltering 563917 people (2011 census). Presently, the latitudinal and longitudinal extension of the new entity is from 86°48'E- 87°10'E and 23°35'N-23°47'N (Fig. 1). The region belongs to tropical savannah climate symbolized by AW, where the average temperature is 32°C in summer and in winter it goes down below 10°C. The area receives more than 1400 mm of the average annual rainfall, occurring mainly from June to September (Chatterjee et al. 2014) due to south-west monsoon winds (Das 2018). Physiographically, the urban area is part of the Chottanagpur fringe area and has a general slope from north-west to south-east direction (Das 2018), covered by alluvial soil (Chakravarti 1998). The predominant red and yellow soil found in the western part of the area is formed by intense weathering. The soil is coarser, deficit in nitrogen, calcium, and phosphate, and has low water retention capacity. Therefore the soil is not suitable for agriculture (Das 2018). The vegetation is mainly moist deciduous and mixed-type forests where Sal, Asan, Palas, Simul, and Arjun are the dominant tree species (Anonymous 2015).

MATERIAL AND METHODS

Data Sources

The satellite image of Landsat TM 5 in 1991 and Landsat 8 OLI in 2021 obtained from the website of USGS Earth Explorer (https://earthexplorer.usgs.gov) and used for the analysis. (Table1). Different pre-processing steps including atmospheric correction, sun elevation correction have been performed before the analysis.

Land use land cover (LULC) classification

The land use land cover has been classified for the years 1991 and 2021 by a supervised classified technique using the maximum likelihood method of image analysis in ArcGIS 10.1. Band, 1-5 and 7 of Landsat 5 TM and Band 2-7 of Landsat 8 OLI has been considered for LULC classification. To prepare the map first a composite band has been prepared for each image through image analysis tools. The training samples have been taken randomly for six classes including vegetation, agricultural land, settlement, barren land, water body and industry and mining from both images through the training sample manager. Accuracy assessment has been done through the confusion matrix method.

LST retrieval

Land surface temperature (LST) computation is usually done by the thermal image of each temporal

Table 1. Specification of satellite data

Satellite	Sensor	Path/Row	Date	Spectral mode	Resolution (m)
Landsat 5	Thematic Mapper (TM)	139/44	30/04/1991	MultispectralThermal Infrared	30120
Landsat 8	Operational Land Imager (OLI),Thermal Infrared Sensor (TIRS)	139/44	18/05/2021	Multispectral PanchromaticThermal Infrared	3015100

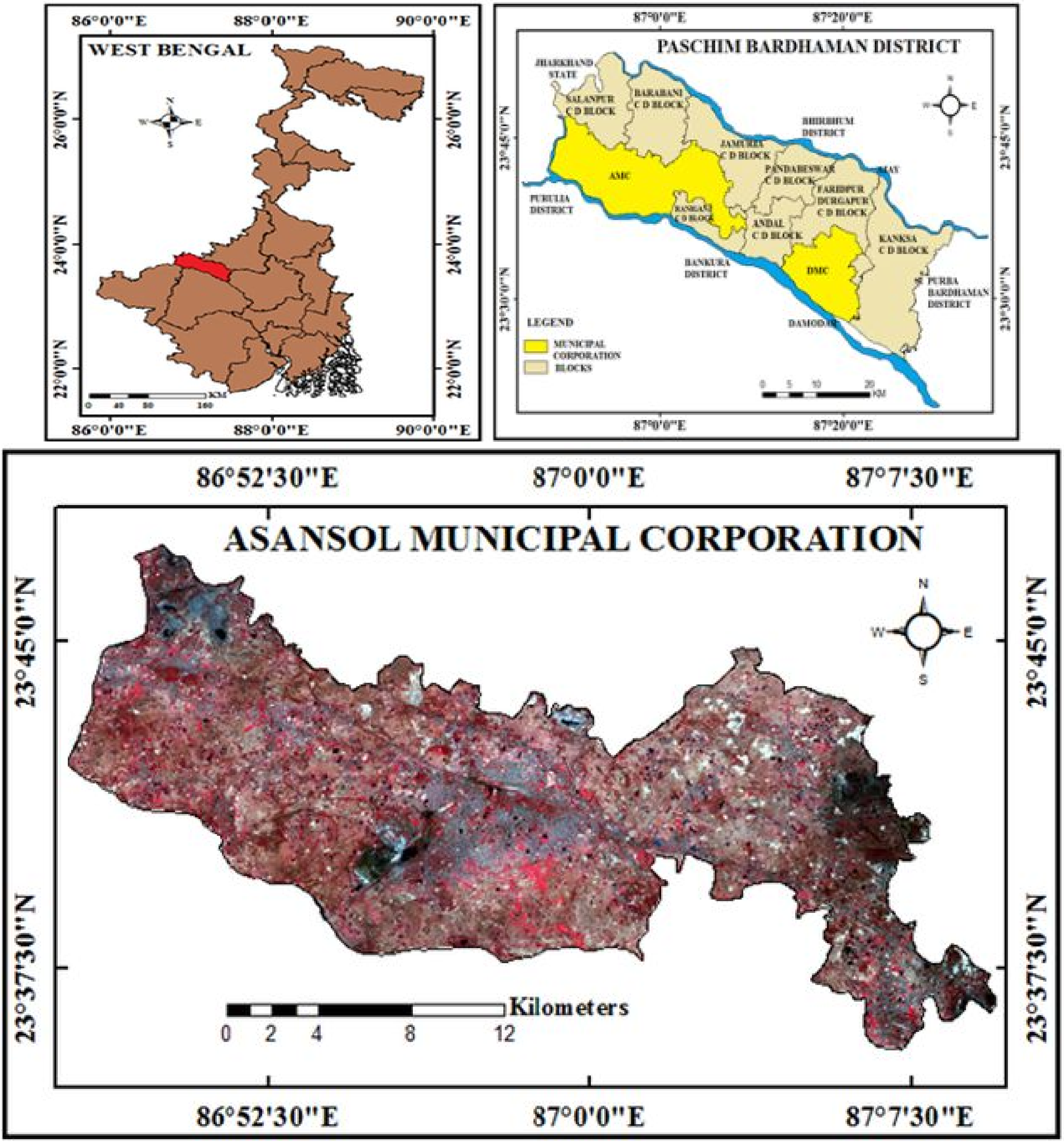


Figure 1. Location map of the study area

satellite image. In the present study Band 6 from Landsat 5 TM in 1991 and Band 10 from and Landsat 8 OLI in 2021 were used for the retrieval of LST as per the procedures suggested by Maroni et al. (2021) (Fig. 2). In order to demarcate the LST zones in the study area for both years, the inverse distance weighted (IDW) interpolation technique has been applied. The temperature distribution has been classified into five equal classes for both images, and green and red colours have been used to represent the lowest and highest temperature of the images, respectively.

Urban green space characteristics

The four landscape metrics viz., class area (CA), mean shape index (MSI), patch density (PD), and edge density (ED) were used to determine the vegetation composition and configuration and to correlate with LST to identify whether vegetation characteristics influence LST. Vegetation

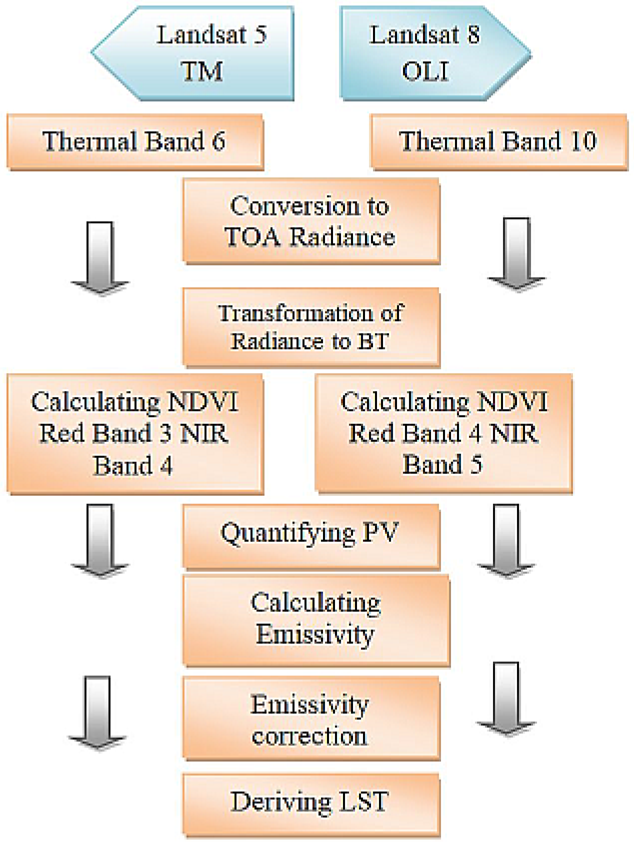


Figure 2. Flow chart of LST retrieval

composition describes the diversity and relative abundances (Wu 2013) that include CA while configuration denotes shape, size, and spatial arrangement of landscape elements (Wu 2013) that include PD, ED, and MSI. These metrics have been selected for sharing expletive information about vegetation configuration and composition and are easy to understand (Naeem et al. 2018). The metrics were derived at the class level by the patch analyst tool in ArcGIS 10.1.

Correlation analysis

The main intention of the study is to identify the extent of the relationship having between land surface temperature and vegetation composition and configuration. In order to find out the relationship the scatter diagram is drawn between LST and CA, LST and PD, LST and ED, and LST and MSI to show the nature of the relationship and Pearson's Correlation Coefficient (r) is computed to measure the degree of association between the variables.

RESULTS

The LULC maps have been prepared for the years 1991 and 2021 as seen in Figure 3. The present study focuses on six land use classes viz., agricultural land, barren land, industry and mining, settlement, vegetation, and water body. The LULC map for 1991 indicates that agricultural land covers the highest area, occupying 162.84 km^2 (49%). This is followed by vegetation, which covers 89.87 km^2 (27%), and settlements, which covers 41.03 km^2 (12%). Besides industry and mining, barren land and water body occupy 20.75 km^2 (6%), 13.98 km^2 (4%), and 2.12 km^2 (1%), respectively. In 2021, agricultural land remains the highest occupied area, covering 148.24 km^2 (45%). The sharp increase has been seen for settlement area i.e. 91.48 km^2 (28%) whereas vegetation area decreased to 41.36 km^2 (13%) in 2021. The remaining classes including industry and mining, barren land and water bodies occupy 20.19 km^2 (6%), 25.36 km^2 (8%), and 3.99 km^2 (1%), respectively. The overall accuracy for both images is 86.93 and 85.58% in 1991 and 2021, respectively.

In 1991, the NDVI ranged between -0.344 (low) and 0.595 (high), with an average value of 0.125. In 2021, the NDVI value ranged from -0.100 (low) to -0.560 (high) with an average value of 0.23. The NDVI images (Fig.4) show that green colour represents vegetative areas, while red colour represents non-vegetative areas.

Figure 5 shows the spatial distribution of land surface temperature. The temperature range for the year 1991 was between 23.82-31.92°C, with an average temperature of 27.87°C. The highest temperature was concentrated in the southern part, while the eastern part experienced the lowest temperature. In 2021, the surface temperature range was between 24.26-29.74°C, with an average temperature of 27°C. The highest temperature was observed in the northern part, while the western part possessed the lowest temperature.

Figure 6 displays flat scatter plots with a coefficient of determination (R^2) value of less than 0.1 in all calculations. This indicates that there is no statistically significant relationship between the land surface temperature and green space composition and configuration during the study period. The coefficient of determination (R^2) also indicates that there is no

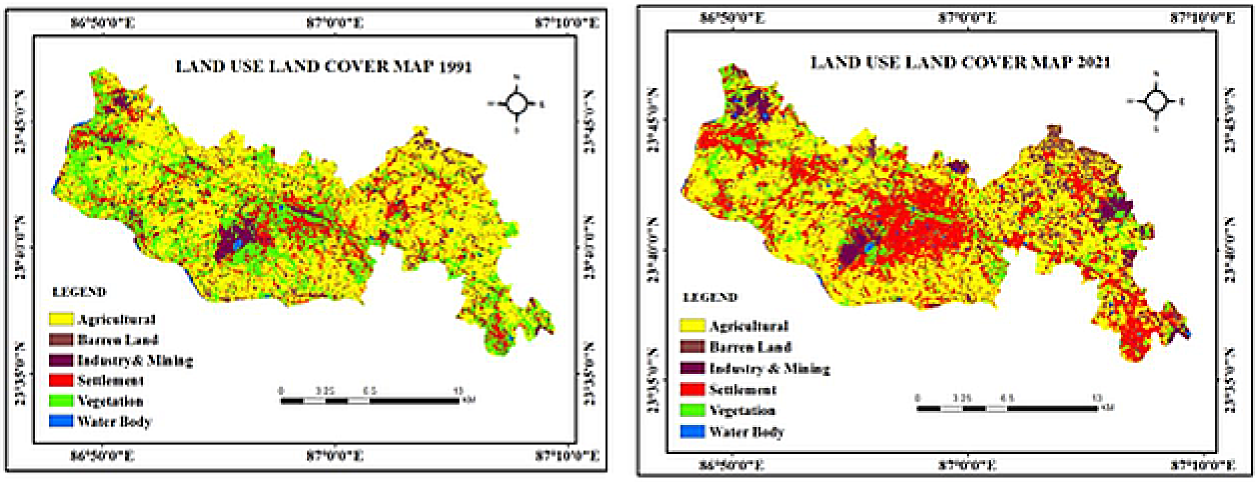


Figure 3. LULC map of AMC

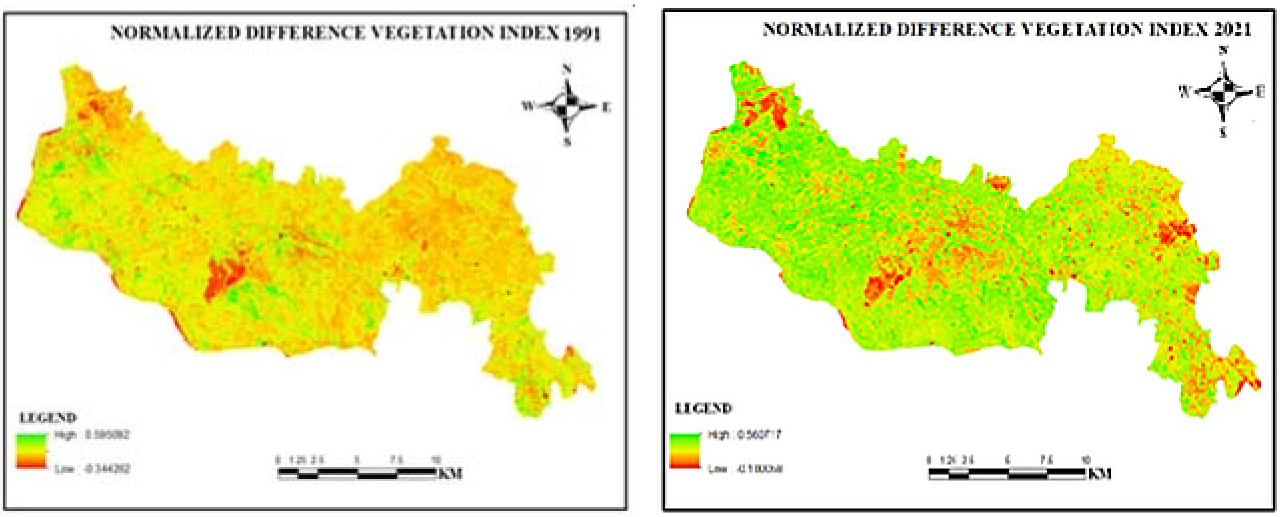


Figure 4. NDVI map of AMC

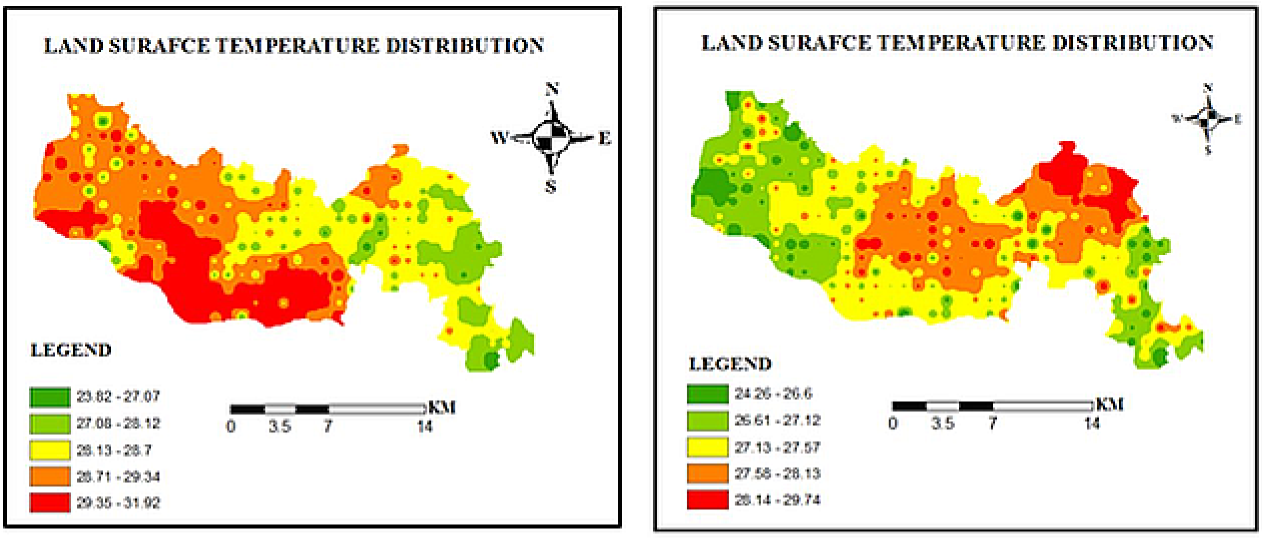


Figure 5. LST distribution map of AMC

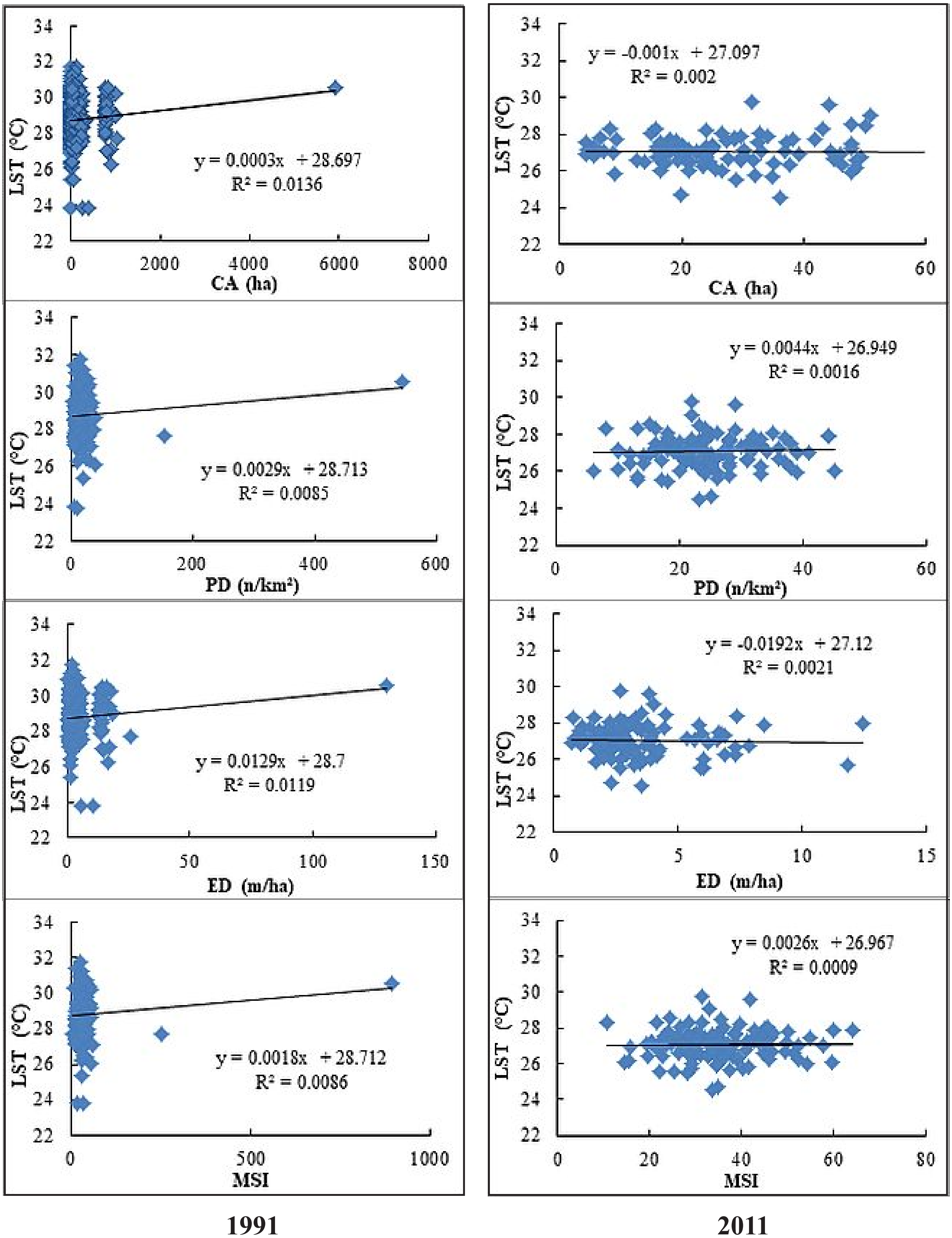


Figure 6. Correlations between landscape metrics and LST

trend between vegetation composition and configuration with LST.

Pearson's Coefficient (r) shows the degree of association among the variables (Table2). In 1991, the landscape metrics including PD and MSI were not correlated with LST. However, CA and ED had slightly higher values of 0.12 and 0.11 respectively, compared to earlier matrices which indicate a weak positive correlation. In contrast, in 2021, CA, PD, ED, and MSI were not correlated with LST.

Table 2. Pearson's correlation between landscape metrics and LST

Landscape metrics	1991	2021
CA	0.12	-0.05
PD	0.09	0.04
ED	0.11	-0.05
MSI	0.09	0.03

Relationship between NDVI and LST

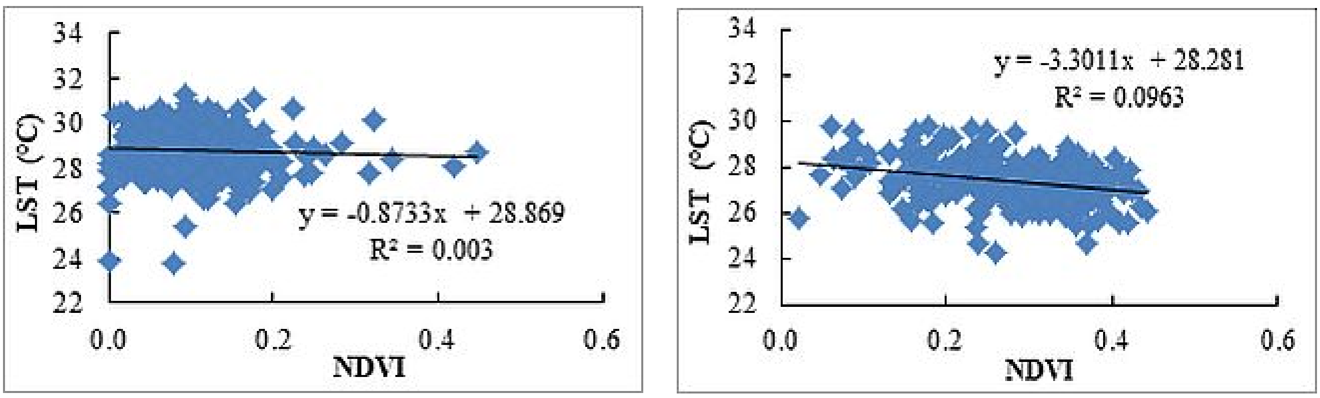
A scatter plot is also used to illustrate the relationship between LST and NDVI for two years (Fig. 7). In 1991 the scatter plot was flat, with a Pearson's Coefficient (r) value of -0.054. Therefore, in 1991, there was no correlation between the variables. However, in 2021 the scatter plot showed a slightly trending pattern and Pearson's correlation coefficient (r) was -0.309. It indicates that NDVI and LST have a weak negative correlation.

DISCUSSION

LULC change is the immediate result of rapid urbanization. The industrial policy of 1948 from 1951-1971, the formation of Eastern Coalfields Limited (E.C.L) from 1971-1991 and The Liberalization Policy of the Indian Government from 1991-2001 periods were the collective reasons for the birth of new towns and the set-up of industries that led to the huge influx of people towards the study area from the neighbouring states. The process is still going on that encounters urbanization process. The LULC maps of two dates support the above statement. While the settlement area increased by 16% between 1991 and 2021, vegetation area decreased by 14% during the same period. Barren land also increased by 4% during that period**.** The industrial and mining activities, construction of asphalt roads, extension of residential areas, and decreasing vegetation area are the combined reasons for the intense land surface temperature (Zareie et al. 2016).

The study has used four landscape metrics to identify the influence of green space patterns on land surface temperature. For these various correlation statistics have been applied to explicit the relationship between two variables. The result has shown us that vegetation composition may have a greater effect in comparison to vegetation configuration. This result is the similar to the previous study (Naeem et al. 2018). It can be said Pearson's Correlation explicates the relationship in a better way compared to two-dimensional scatter plots (Naeem et al. 2018) though both methods are compatible in correlation analysis.

Class area (CA) is a compositional element of landscape metrics that denotes the quantity of vegetation. Pearson's Correlation Coefficient (r) has shown mixed results in the stipulated period. In 1991



1991 **2011**

Figure 7. Correlations between NDVI and LST

CA was positively correlated and had a slightly higher value compared to others. It can be said vegetation quantity may bring down the intensity of land surface temperature and it is consistent with previous studies (Weng et al. 2004, Li et al. 2012), it may be due to evapotranspiration (Givoni 1994) and provides shades (Shashua-Bar and Hoffman 2000) but in 2021 there was no relationship between the two variables. Another important metric is edge density (ED) which denotes the configuration of green spaces. It depends on the availability of patches. ED and LST had a weak positive correlation in 1991 and no correlation in 2021. The positive correlation may affect LST to a certain extent. The previous study (Naeem et al. 2018) has suggested that equal distribution of plantations in a certain order can minimize the surface thermal effect. Generally, patch density (PD) and LST have a positive correlation (Zhibin et al. 2014). Patch density indicates fragmentation of landscape which means increases patch number decreases mean patch size that contributes to land surface temperature. In the study, there is no relationship between PD and LST in both cases which is not similar to previous studies (Zhibin et al. 2014, Zhang et al. 2009, Yokohari et al. 1997). Landscape shape index (LSI) denotes the complexity of the landscape. Complexity increases the surface temperature (Zhibin et al. 2014, Naeem et al. 2018). The result of the present study has shown no relationship with LST. The LST and NDVI relationship has been portrayed widely. The principal reason to use NDVI in LST calculation is to presume the vegetation condition (Weng et al. 2004). However, some earlier studies decline the facts. They have stated that NDVI does not have the proper ability to quantify vegetation amount (Small 2001) because NDVI depends on the reflectance of the visible and near infrared bands. Therefore same spectra including soil, background, and shadow can influence the variability of NDVI (Yang et al. 1997, Jasinski 1990). However, in 2021 the NDVI average value indicated the overall vegetation is shrub and grassland type. The dense vegetation has no place due to the urbanization process while in 1991 the average value was unable to detect the vegetation type.

CONCLUSIONS

The vegetation quantity has a vital role to mitigate the surface temperature effect. The correlation between NDVI and LST and CA and LST has indicated that it may be an effective measure to reduce the surface temperature intensity. The other landscape metrics including the complex shape of vegetation with increasing patch Density help to increase the surface temperature where a large size patch reduces temperature intensity. Asansol Municipal Corporation is less studied from the perspective of green space composition and configuration analysis. Though in the aforesaid period, there is no significant relationship has been found but changing the scale might affect the relationship. However, the analysis will be helpful for urban landscape designers' to think of the city in the future from this perspective.

Authors' contributions: Both the authors contributed equally

Conflict of Interest: The authors have no conflict of interest.

REFERENCES

Akbar, T.A., Hassan, Q.K., Ishaq, S., Batool, M., Butt, H.J. and Jabbar, H. 2019. Investigative spatial distribution and modelling of existing and future urban land changes and its impact on urbanization and economy. Remote Sensing, 11(2), 105. https://doi.org/10.3390/rs11020105

Amanollahi, J., Abdullah, A.H., Ramli, M.F. and Pirasteh, S. 2012. Land surface temperature assessment in semi-arid residential area of Tehran, Iran using Landsat imagery. World Applied Sciences Journal, 20(2), 319-326. https://doi.org/10.5829/idosi.wasj.2012.20.02.3661

Anonymous. 2015. Land-Use Development and Control Plan Vision 2025 for Asansol Subdivision: Final Report. Asansol Durgapur Development Authority, Government of West Bengal, Asansol.

Anonymous. 2017. About Asansol Municipal Corporation. https://web.archive.org/web/20170312080951/http://asansolmunicipalcorporation.org/over_view.php

Barakat, A., Ouargaf, Z., Khellouk, R.J., El Jazouli, A. and Touhami, F. 2019. Land use/land cover change and environmental impact assessment in BeniMellal district (Morocco) using remote sensing and GIS. Earth Systems and Environment, 3, 113-125. https://doi.org/10.1007/s41748-019-00088-y

Chakravarti, J. 1998. Evolution of Asansol Durgapur Industrial Complex and its Impact on Regional Economy. Doctoral dissertation, University of Calcutta, Kolkata

Chatterjee, S., Bisai, D. and Khan, A. 2014. Detection of approximate potential trend turning points in temperature time series (1941-2010) for Asansol weather observation station, West Bengal, India. Atmospheric and Climate Sciences, 4, 64-69. https://doi.org/10.4236/acs.2014.41009

Chen, X., Zhao, H., Li, P. and Yin, Z. 2006. Remote sensing image-based analysis of the relationship between urban heat island and land use/cover changes. Remote Sensing of Environment, 104(2), 133-146. https://doi.org/10.1016/j.rse.2005.11.016

Das, N., Mondal, P., Sutradhar, S. and Ghosh, R. 2020. Assessment of variation of land use/land cover and its impact on land surface temperature of Asansol subdivision. The Egyptian Journal of Remote Sensing and Space Sciences, 24(1), 131-149. https://doi.org/10.1016/j.ejrs. 2020.05.001

Das, S. 2018. Impact of Industrialization & Urbanization on the Environment of Asansol Durgapur planning Area. Doctoral dissertation Department of Geography, University of Calcutta.

Ghoshdastidar, M. 2011. An Interaction between Spatial and Economic Changes in a City: A Case Study of Asansol. Doctoral dissertation, University of Calcutta, Kolkata.

Givoni, B. 1994. Urban design for hot humid region. Renewable Energy, 5, 1047-1053. https://doi.org/10.1016/0960-1481(94)90132-5

Guha, S. and Govil, H. 2020. An assessment on the relationship between land surface temperature and normalized difference vegetation index. Environment, Development and Sustainability, 23, 1944-1963. https://doi.org/10.1007/s10668-020-00657-6

Hess, G.R., Bartel, R.A., Leidner, A.K. and Rosenfeld, K.M. 2006. Effectiveness of biodiversity indicators varies with extent, grain, and region. Biological Conservation, 132(4), 448-457. https://doi.org/10.1016/j.biocon.2006.04.037

Jasinski, M.F. 1990. Sensitivity of the normalized difference vegetation index to subpixel canopy cover, soil albedo, and pixel scale. Remote Sensing of Environment, 32, 169-187. https://doi.org/10.1016/0034-4257(90)90016-F

Landsberg, H.E. 1981. The Urban Climate. Academic Press, New York.

Li, X., Zhou, W. and Ouyang, Z. 2012. Spatial pattern of green space affects land surface temperature: evidence from the heavily urbanized Beijing metropolitan area, China. Landscape Ecology, 27, 887-898. https://doi.org/10.1007/s10980-012-9731-6

Maroni, D., Cardoso, G.T., Neckel, A., Maculan, L.S., Oliveria, M.L.S., Bodah, E.T., Bodah, B.W. and Santosh, M. 2021. Land surface temperature and vegetation index as a proxy to microclimate. Journal of Environmental Chemical Engineering, 9(4), 105796. https://doi.org/10.1016/j.jece.2021.105796

Naeem, S., Cao, C., Qazi, W.A., Zamani, M., Wei, C., Acharya, B.K. and Rehman, A.U. 2018. Studying the association between green space characteristics and land surface temperature for sustainable urban environments: An analysis of Beijing and Islamabad. International Journal of Geo-Information, 7, 38. https://doi.org/10.3390/ijgi7020038

Raynolds, M.K., Comiso, J.C., Walker, D.A. and Verbyla, D. 2008. Relationship between satellite-derived land surface temperatures, arctic vegetation types, and NDVI. Remote Sensing of Environment, 112, 1884-1894. https://doi.org/10.1016/j.rse.2007.09.008

Shashua-Bar, L. and Hoffman, M.E. 2000. Vegetation as a climatic component in the design of an urban street-an empirical model for predicting the cooling effect of urban green areas with trees. Energy and Building, 31, 221-235. https://doi.org/10.1016/S0378-7788(99)00018-3

Small, C. 2001. Estimation of urban vegetation abundance by spectral mixture analysis. International Journal of Remote Sensing, 22, 1305-1334. https://doi.org/10.1080/01431160151144369

Sun, Q., Wu, Z. and Tan, J. 2012. The relationship between land surface temperature and land use/land cover in Guangzhou, China. Environment and Earth Sciences, 65, 1687-1694. https://doi.org/10.1007/s12665-011-1145-2

Taha, H. 1997. Urban climates and heat islands: albedo, evapotranspiration, and anthropogenic heat. Energy and Building, 25, 99-103. https://doi.org/10.1016/S0378-7788(96)00999-1

Turner, M.G., Robert, V. and O'Neill, R.H. 1989. Effects of changing spatial scale on the analysis of landscape pattern. Landscape Ecology, 3, 153-162. https://doi.org/10.1007/BF00131534

Turner, M.G. 1990. Spatial and temporal analysis of landscape patterns. Landscape Ecology, 4(1), 21-30. https://doi.org/10.1007/BF02573948

Weng, Q., Lu, D. and Schubring, J. 2004. Estimation of land surface temperature–vegetation abundance relationship for urban heat island studies. Remote Sensing of Environment, 89, 467-483. https://doi.org/10.1016/j.rse.2003.11.005

Weng, Q., Liu, H. and Lu, D. 2007. Assessing the effects of land use and land cover patterns on thermal conditions using landscape metrics in city of Indianapolis, United States. Urban Ecosystem, 10(2), 203-219. https://doi.org/10.1007/s11252-007-0020-0

Wu, J. 2013. Landscape sustainability science: Ecosystem services and human well-being in changing landscapes. Landscape Ecology, 28, 999-1023. https://doi.org/10.1007/s10980-013-9894-9

Yang, W., Yang, L. and Merchnat, J.W. 1997. An analysis of AVHRR/NDVI-ecoclimatological relations in Nebraska, USA. International Journal of Remote Sensing, 18, 2161-2180. https://doi.org/10.1080/014311697217819

Yokohari, M., Brown, R., Kato, Y. and Moriyama, H. 1997. Effects of paddy fields on summertime air and surface temperatures in urban fringe areas of Tokyo, Japan. Landscape and Urban Planning, 38(1-2), 1-11. https://doi.org/10.1016/S0169-2046(97)00010-8

Zareie, S., Khosrav, H., Nasiri, A. and Dastoran, M. 2016. Using Landsat Thematic Mapper (TM) sensor to detect change in land surface temperature in relation to land use change in Yazd, Iran. Solid Earth, 7, 1551-1564. https://doi.org/10.5194/se-7-1551-2016

Zhang, F., Kung, H., Johnson V.C., LaGrone, B.L. and Wang, J. 2017. Change detection of land surface temperature (LST) and some related parameters using Landsat image: A case study of the Ebinur lake watershed, Xinjiang, China. Wetlands, 38, 65-80. https://doi.org/10.1007/s13157-017-0957-6

Zhang, X., Zhong, T., Feng, X. and Wang, K. 2009. Estimation of the relationship between vegetation patches and urban land surface temperature with remote sensing. International Journal of Remote Sensing, 30(8), 2105-2118. https://doi.org/10.1080/01431160802549252

Zhibin, R., Haifeng, Z., Xingyuan, H., Dan, Z. and Xingyang, Y. 2014. Estimation of the relationship between urban vegetation configuration and land surface temperature with remote sensing. Journal of the Indian Society of Remote Sensing, 43(1), 89-100. https://doi.org/10.1007/s12524-014-0373-9

Received:12th December 2023
Accepted:29th March 2024