Influence of Dominant Land Cover on the Variability of Vegetation Indices, LST and Albedo: A Spatio-temporal Approach

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ABSTRACT: Changes in Land Use Land Cover (LULC) in the Doon valley of Uttarakhand, India situated between Himalaya in the North and Shivalik range in the south lead to changes in the land surface properties in the region. The LULC changes also influenced the dominant land cover characteristics which has a significant influence on Land Surface Temperature (LST). Monthly spatial variability of various vegetation indices pertaining to dominant land cover characteristics viz. Normalized Difference Vegetation Index (NDVI) and Modified Chlorophyll Absorption Ratio Index (MCARI) and the environmental parameters viz. LST and Albedo has been studied for 2018 w.r.t. dominant LULC (forest, agricultural land and built-up) by resampling it to 1 km grid. The LULC was prepared using cloud free satellite imagery of Sentinel-2 for Jan, Feb, Mar, Apr, May, Jun and Dec using SVM classifier. NDVI shows higher value for the grids built-up and agriculture as dominant class while grids constituting built-up as dominant and forest as second dominant class display lower values in summer season mainly due to dominance of deciduous forest in doon valley. It is to be noted that MCARI which indicate vegetation health and vigour show anomaly behavior (lower values) in the forest dominated grids primarily due to seasonal and anthropogenic pressures and forest fire) in summer season, whereas agriculture dominated grids show comparatively higher values. Forest fire during this season also leads to degradation of the vegetation/green cover and hence affecting the LST and albedo of the region. It has been noticed that urban area shows considerably high NDVI and MCARI values, because of the presence of avenue trees (validated through filed visit), hence regulating the albedo and LST in urban dominated grids in the study area. It can be concluded that the existing vegetation cover is not healthy in the study region which may be attributed to rapid increase in the built-up / urbanization and subsequent anthropogenic pressure which leads to decline in forest cover and natural vegetation. The study emphasizes the impact of the changes in the LULC and the associated environmental characteristics are responsible for increase in the LST which in turn effects the quality of life in the region.

1. INTRODUCTION

Land Use Land Cover (LULC) changes has significant impact on amount of solar radiation absorbed, evapo-transpiration, temperature and albedo. It is estimated that LULC change induced increase in surface temperature of the earth is expected to expose 69% of the world's population to the impact of global warming by 2050 (World Urbanization Prospects, 2014). Vegetation, which is one of the important land cover, absorb and emit energy which plays a major role in balancing Earth’s heat budget, acts as carbon sinks, drive the weather and helps in cloud formation. Plant leaves produces their own micro climate by controlling the humidity and temperature of their immediate surroundings through evapo-transpiration (Snyder et al., 2011). Even though evapotranspiration patterns are known to escalate with the higher temperature, other variables (like humidity, CO_2) also influence evapotranspiration (ET). The impact of vegetation cover on earth, which is around 20% of the terrestrial land cover, and the role it plays in influencing the climate is well studied and established science (Kanianska, 2016), however the impact of vegetation cover in the local level spatio-temporal temperature regimes is not well understood especially in the tropical regions.

Many research studies have established that barren surfaces and built-up area are predominantly responsible for increase in Land Surface Temperature (LST) (Ndossi & Avdan, 2016). In Indian landscape, only a few studies, mainly for some metropolises such as Mumbai (Grover & Singh, 2015), Chennai (Amirtham & Devadas, 2009), Jaipur (Jalan & Sharma, 2014) and Delhi (Grover & Singh, 2015; Mallick, Kant, & Bharath, 2008) has been accomplished in order to develop the understanding of built-up area's impact towards constantly increasing LST. Assessment of the change in LST w.r.t. LULC can help study the influence of the LULC change on increasing temperature and assist in identification of the threshold of deforestation for proper planning and sustainable development.

The vegetation indices identified for this study are: Normalized Difference Vegetation Index (NDVI) and Modified Chlorophyll Absorption Ratio Index (MCARI). Advantages of NDVI are that it highlights/enhances a particular class, also it helps in handling of temporal multispectral database and to minimize the shadow effect. MCARI shows the sensitivity towards the vegetation's chlorophyll content, therefore depicting the health of the vegetation. Quality of vegetation is determined by Chlorophyll content which is a reflection of health and vigor of vegetation (Hong, Lakshmi, & Small, 2007). Chlorophyll pigment present in vegetation, plays a crucial role in governing the visible region of electromagnetic spectrum for its spectral reflectance (Thomas & Gausman, 1977). Vegetation indices are being used at a quite large scale to study the relation between LULC and surface temperature. Many studies have been done by utilizing NDVI (Karnieli et al., 2010; Yuan & Bauer, 2007). However, vegetation indices focusing on the vegetation health are not been much studied.

The present work has been carried out to estimate the influence of dominant land use land cover over the spatial variability of identified vegetation indices, LST and Albedo, which will help in understanding the dependency of these parameters on dominant land cover (Dickinson, 1995). Hence, in this study influence of dominant LULC on vegetation indices, LST and Albedo in Doon valley of Uttarakhand, India has been studied by utilizing open source Earth Observation (EO) data.

2. STUDY AREA

Dehradun valley in Uttarakhand state of India has been taken up as the study area in this case study. Geogarphically, this area is situated at 30°18'59.3856"N latitude and 78°1'55.8768"E longitude. "In the north and northwest it borders the districts of Uttarkashi and Tehri Garhwal, in the east and southeast by Pauri Garhwal and Ganges River, in the west by Shimla and Sirmaur districts of Himachal Pradesh, Yamunanagar district of Haryana and the Tons and Yamuna river". The climate of Dehradun comes under moderate category as it is situated at the foothills of Himalayas, which is somewhat same as of other north Indian cities i.e., blazing summers, chill winters, rainy monsoon, and a mild spring.

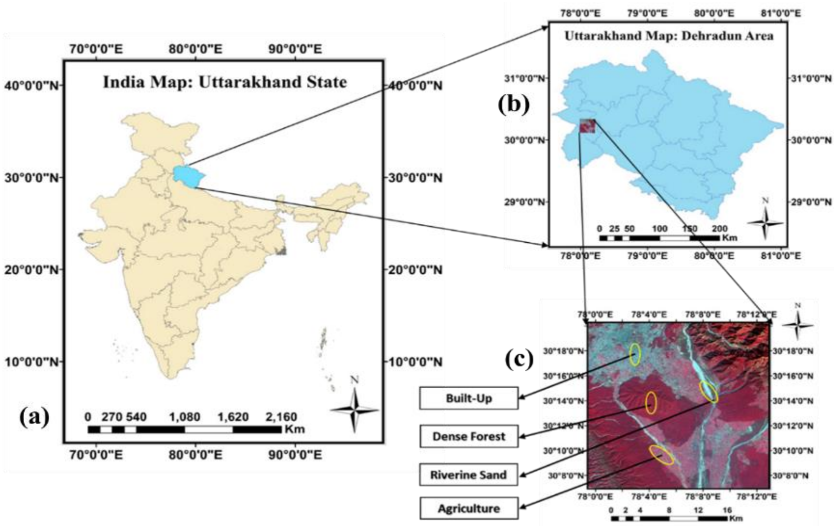

Figure 1 Study Area: (a) India Map; (b) Uttarakhand; (c) Site of Doon Valley

3. DATA USED & METHODS

3.1. Dataset Used

In this research work, multispectral temporal data of Landsat-8 (30m), Sentinel 2B (10m for B2, B3, B4 and B8; 20m for B11 & B12) and MODIS albedo (500m) have been used for Jan, Feb, Mar, Apr, May, Jun and Dec month of year 2018. Landsat-8 satellite images have been used for estimation of LST, whereas, Sentinel-2 has been used for calculating various vegetation indices corresponding to red edge and chlorophyll.

3.2. Methodology

Classification: Supervised (level1) classification by employing Support Vector Machine (SVM) classifier has been carried out with 6 major classes' viz., forest, built-up, agricultural land, barren area, water and others by utilizing Sentinel 2B data. Accuracy assessment has been performed for the classified data through field study as well as high resolution google earth images. The classified images of all the months were overlaid with the grids of 1km*1km. For this study, various combinations of major land cover type (forest, vegetation and built-up) were identified according to the total percentage of individual grid area covered by them. The combination of these land cover types was done by identifying first land cover type >60% as the "dominant class" and another land cover type in the same grid covering 20% and above area of the grid as "second dominant" land cover class. The final six combination of land cover type has been described in Table1.

LST Retrieval using Thermal band of Landsat data: Landsat 8 Thermal Infra-Red (TIR) and Operational Land Imager (OLI) have been utilized for estimation of LST according to the Planck's Equation (Table 2). There are several algorithms to calculate LST, but studies have shown that, this procedure generate better results when compared with others (Ndossi & Avdan, 2016). Following these steps, LST for Jan, Feb, Mar, Apr, May, Jun and Dec 2018 has been calculated. Jul, Aug, Sept, Oct and Nov were not selected because of absence of cloud free satellite image over the study area.

Land Surface Albedo: "Albedo of any geographic location depends on the predominant land cover type, the density and structure of that land cover, the spectral properties of the components composing a landscape, and the seasonality" (Gao et al., 2005). For the calculation of albedo following formula has been used:

$$\text{Albedo} = \frac{SW_{in} - SW_{net}}{SW_{in}} \quad \text{Eq (1)}$$

Where, SW_{in} represents Incoming Shortwave Radiation, and SW_{net} represents Net Shortwave Radiation (Blok et al., 2011). Albedo product of MODIS at 500m resolution for months Jan2018 to Jun2018 and Dec2018 has been computed and downloaded by utilizing Google Earth Engine (GEE) open platform. Again, other months were not taken due to presence of cloud cover. Resampling of all the obtained products was done to 1km.

Table 1 Description of the dominant and second dominant land cover class for each grid

S. No.	NAME	DESCRIPTION
1	Forest & Agriculture	Grids with **60% and above** area of grid covered by **forest** pixels and **20% and above** grid area covered by **agriculture** pixels
2	Forest & Built up	Grids with **60% and above** area of grid covered by **forest** pixels and **20% and above** grid area covered by **built up** pixels
3	Agriculture & Forest	Grids with **60% and above** area of grid covered by **agriculture** pixels and **20% and above** grid area covered by **forest** pixels
4	Agriculture & Built up	Grids with **60% and above** area of grid covered by **agriculture** pixels and **20% and above** grid area covered by **built up** pixels
5	Built up & Forest	Grids with **60% and above** area of grid covered by **built up** pixels and **20% and above** grid area covered by **forest** pixels
6	Built up & Agriculture	Grids with **60% and above** area of grid covered by **built up** pixels and **20% and above** grid area covered by **agriculture** pixels

Table 2 Steps to calculate LST using Planck's Equation

Step	Description	Formula
1.	Conversion of DNs to radiance / Top of Atmospheric Reflectance (TOA)	L_λ = M_L* Q_{CAL}+ A_L Where M_L and A_L are band specific multiplicative and additive rescaling factor respectively, Q_{CAL} is the thermal band
2.	Brightness Temperature (BT)	BT = (1321.0789/ ln((774.8853/L_λ)+1) - 273.15 Where L_λ is calculated in step 1 and ln is natural log
3.	NDVI	NDVI = (NIR-R)/ (NIR+R)
4.	Proportion of Vegetation (Pv)	Pv = $((NDVI - min)/(max - min))^2$
5.	Emissivity (ε)	ε = 0.004*Pv+0.986
6.	LST	LST = BT/(1+(0.00115*BT/1.4388)*ln(ε)) Where ln is natural log

Vegetation Indices: Normalized Difference Vegetation Index (NDVI) is a remote sensing based vegetation index which has shown its wide application in the vegetation monitoring (Xue & Su, 2017). It is being calculated as "a normalized ratio between red and near infrared" based on the multispectral information. Its direct application is to distinguish between different plant canopy height and vigor; and various studies have already been conducted and many are in the process of comparing them with the Leaf Area Index (LAI), where LAI is understood as "the area of one-sided leaves per soil area" (Xue & Su, 2017).

$$\text{NDVI} = \frac{\rho nir - \rho red}{\rho nir + \rho red} \quad \text{Eq (2)}$$

Where ρ is the reflectance at the particular band.

The Modified Chlorophyll Absorption Ratio Index (MCARI) is more sensitive to the concentration of chlorophyll in the vegetation. Some studies have found that "LAI, chlorophyll and chlorophyll-LAI" interactions resulted into 60%, 27% and 13% respectively of the MCARI variation.

$$MCARI = \frac{1.5*[2.5(\rho_{800}-\rho_{670})-1.3(\rho_{800}-\rho_{550})]}{\sqrt{(2*\rho_{800}+1)^2-(6*\rho_{800}-5*\sqrt{\rho_{670}})-0.5}} \qquad \text{Eq (3)}$$

Where ρ is the reflectance at particular wavelength. After computing all the parameters i.e., LST, NDVI, MCARI and Albedo, grid analysis have been carried out by overlaying grids of 1km*1km over the whole region (Figure 2).

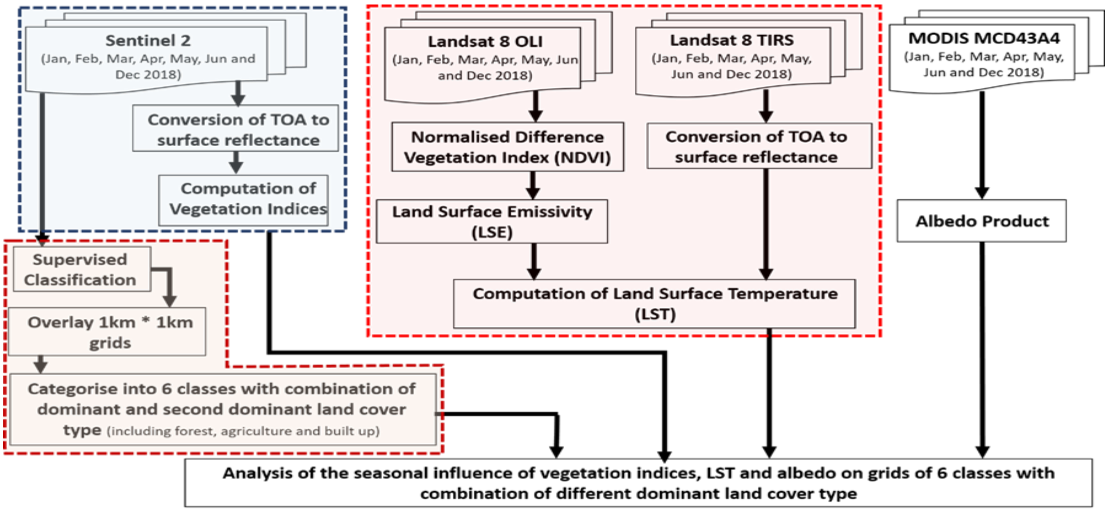

Figure 2 Overall adopted Methodology

Various statistical measures were calculated for MCARI and NDVI, LST and Albedo on each grid. Then the Area Weighted Mean (AWM) was calculated for every grid to get the mean value of all the parameters for each grid. Finally spatial variation of identified vegetation indices and LST with dominant LULC (Table 1) has been analyzed.

4. RESULTS & DISCUSSION

4.1. LULC Mapping

The results indicate that LST shows prominent variation with different classes of LULC as expected (Karakuş, 2019). It is clear from the LULC distribution that forest is dominant class covering 55% of the study area. Figure 3 shows the LULC distribution of a particular month. Classification accuracy assessment of all LULC shows acceptable accuracies (>85%) (Table 3).

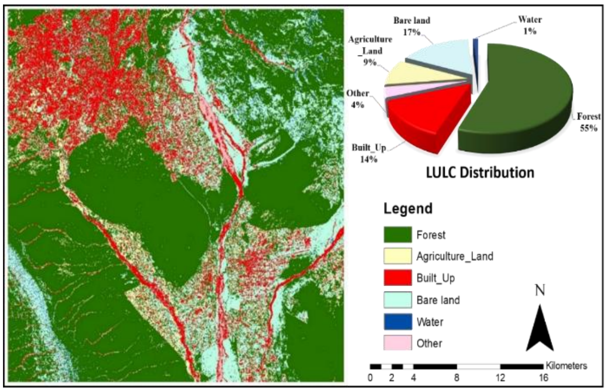

Figure 3 Land Use Land Cover of the Study area

Table 3 Accuracy Assessment of Sentinel-2 Image Classification

Accuracy Assessment Results		
Month	**Overall Accuracy**	**Kappa Coefficient**
January, 2018	94.70%	0.93
February, 2018	88.01%	0.85
March, 2018	86.80%	0.84
April, 2018	88.11%	0.85
May, 2018	86.89%	0.83
June, 2018	87.55%	0.84
December, 2018	86.45%	0.84

4.2. Spatial Variability of LST, albedo & Vegetation Indices

LST is surface or skin temperature which is significantly impacted by different LULC components. Figure 4 represents the gridded LST results where vegetation cover represented by yellowish shades, depicts low temperature and the area in reddish shades covering built up, riverine sand, barren land, etc., represents higher temperature. Albedo describes the solar radiation reflectance or absorption property of the object and therefore, objects with higher albedo shows higher reflectance and contributes more towards increasing temperature, whereas, lower albedo depicts the absorption of the solar radiation by the objects. Figure 5 shows gridded albedo results in which the spatial variability shows that region of forest and vegetation cover with yellowish green shades have low albedo, whereas other classes have bluish shades with comparatively high albedo. NDVI is generally used to differentiate vegetation from other land use land cover sections. NDVI ranges between -1 to 1 where -1 shows the presence of water, 0 shows the absence of vegetation and 1 shows the abundance of vegetation. Gridded variation of NDVI has been shown in Figure 6. As it has been noticed in earlier studies (Valor & Caselles, 1996) that NDVI values below 0.2 majorly includes built up, so values below 0.2 have been masked, hence in this study NDVI ranges from 0.22 to 0.97. region shown with reddish shades represents very less vegetation with low NDVI values, whereas greenish shade are observed over dense vegetation area with higher NDVI values. MCARI represents vegetation health and vigor by giving the chlorophyll content of leaves. Figure7 shows MCARI gridded variability where greenish shades depict the area with high chlorophyll content, while shades of red shows the vegetation with low chlorophyll content.

4.3. Quantitative Analysis

Grid based quantitative analysis has been performed to study the spatial variation of identified vegetation indices, Albedo and LST with dominant land cover type. Value of NDVI is observed to be varying with changing season due to changes of values in forest and agricultural land. Agricultural practice keep on varying with change in season as different crops are best grown in particular season with specific weather conditions. Grids comprising of the vegetation (forest and agriculture) as the dominant and second dominant land cover type have been observed with higher NDVI value (Figure 8), whereas grids with built-up as the dominant or second dominant land cover type gives lower NDVI value depending on the percentage area covered by the vegetation type. Figure 8 depicts that NDVI in the month of May and June has shown a decline in ‘built-up n forest’ category compared to ‘built-up n agriculture’ class. This is primarily due to sugarcane crops in the region which has good amount of growth during this season (Shukla et al., 2017). Lower NDVI values represents the built up, bare soil, etc., and hence sometimes get mixed with the grassland or low vegetation pixels and it becomes difficult to differentiate purely vegetation pixels from other land cover type (Gross, 2005). Therefore to observe the vegetation condition, health and vigor, another vegetation index, MCARI has been studied.

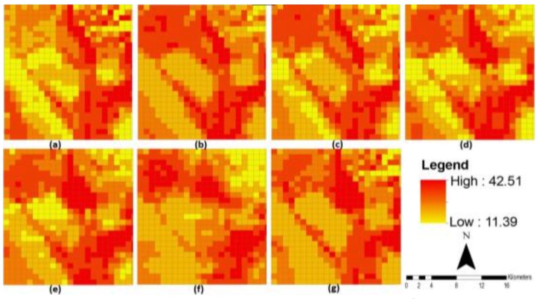

Figure 4 Month wise spatial distribution of LST in 2018, where (a), (b), (c), (d), (e), (f) and (g) depicts gridded LST of Jan, Feb, Mar, Apr, May, Jun and Dec months

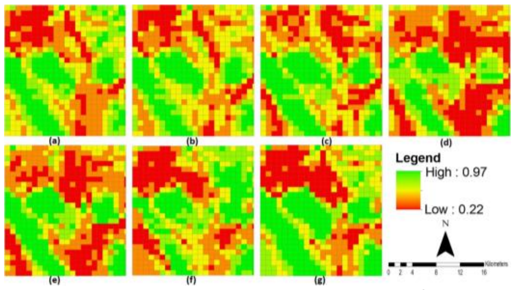

Figure 6 Month wise spatial distribution of NDVI in 2018, where (a), (b), (c), (d), (e), (f) and (g) depicts gridded NDVI of Jan, Feb, Mar, Apr, May, Jun and Dec months

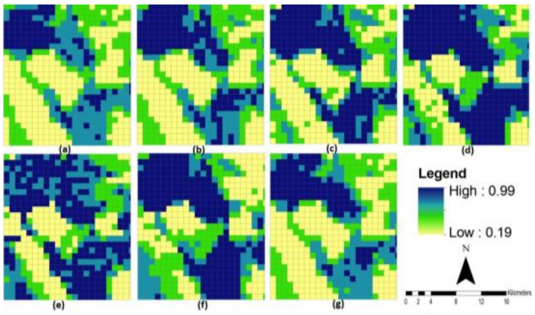

Figure 5 Month wise spatial distribution of Albedo in 2018, where (a), (b), (c), (d), (e), (f) and (g) depicts gridded ALBEDO of Jan, Feb, Mar, Apr, May, Jun and Dec months

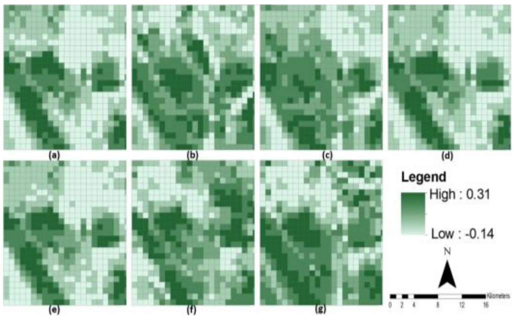

Figure 7 Month wise spatial distribution of MCARI in 2018, where (a), (b), (c), (d), (e), (f) and (g) depicts gridded MCARI of Jan, Feb, Mar, Apr, May, Jun and Dec months

High level of chlorophyll content in the plant leaf makes it healthy. Dense forest canopy with healthy leaves results in higher MCARI value, although here it was noticed (figure 9) that Apr, May and Jun has shown prominent decline in the MCARI values of land cover combination with forest as dominant or second dominant land cover type compared to agriculture because study area face intense forest fires (either natural or due to human activities) during these months, and the event has shown an increasing trend over the years (Pant & Purohit, 2019). Also in the month of Feb and Mar, forest shows somewhat low MCARI value probably because of the leaf shedding in Sal, which is the dominant vegetation species in the study region. On the other hand, agriculture fields show considerable amount of MCARI value or chlorophyll content even in the months of dry season (Apr, May and Jun) because of good quality of sugarcane crops in the agriculture fields (Shukla et al., 2017). MCARI value in the agriculture fields keep on fluctuating seasonally because of type and quality of crop pattern present in the field.

Forest canopy has lower albedo as compared to the crops or agricultural fields, therefore albedo increases with decrease in the forest percentage (Choi, Lee, & Moon, 2018; Oguntunde & Van De Giesen, 2004). Lower albedo means less amount of reflected radiation and more amount of absorbed radiation. Absorption of radiation results in increasing the temperature of the surface (LST) which ultimately helps in warming the climate. But because of the high chlorophyll content of the leaf, plants absorb high amount of solar radiation and use it in the process of photosynthesis which results in the evapotranspiration and hence, reducing the temperature

(Jones & Rotenberg, 2001). Therefore, grids with dominant percentage of forest cover represents lower albedo values compared to the agriculture fields (Figure 10). Though seasonally (Feb-Mar and May-Jun) albedo increases in the forest dominated grids too due to leaf shed and forest fire. Impervious surface /concrete and asphalt surfaces of the built up area has low albedo compared to the dense forest (Choi et al., 2018), hence absorbs the major portion of the solar radiation and reflects very less, resulting in increased surface temperature. Therefore as the built up increases, albedo declines which further results in intensification of LST. Albedo of 'built up n forest' and 'built up n agriculture' shows almost similar value in summer season (Figure10), because of the forest fire reducing the absorption of solar radiation by the trees. Albedo in agriculture dominated grid is comparatively high than albedo of forest grids. Therefore, from Figure10 and Figure11, it is clear that albedo of built up is low and that is why LST is very high compared to the other classes. Although, presence of avenue trees regulate the temperature of built up/urban environment of the region, but the temperature depends on healthy or diseased state of avenue trees (Tamang et al., 2018).
LST of a region directly or indirectly depends on various factors like, soil moisture, vegetation health and vigor, type of land use land cover, anthropogenic activities, etc. (Datta, Prasad, & Mandla, 2017). Generally LST is lower in the vegetation dominated region/grid, but in Jan and Feb (figure4) the forest dominated area with built up as second dominant class shows somewhat similar temperature to the grids having agriculture as the dominant land cover type. This is probably because of the leaf shed by the vegetation type in the forest. Whereas the forest fire also results in the loss of the healthy vegetation and hence increase the temperature in the forest dominated grids.

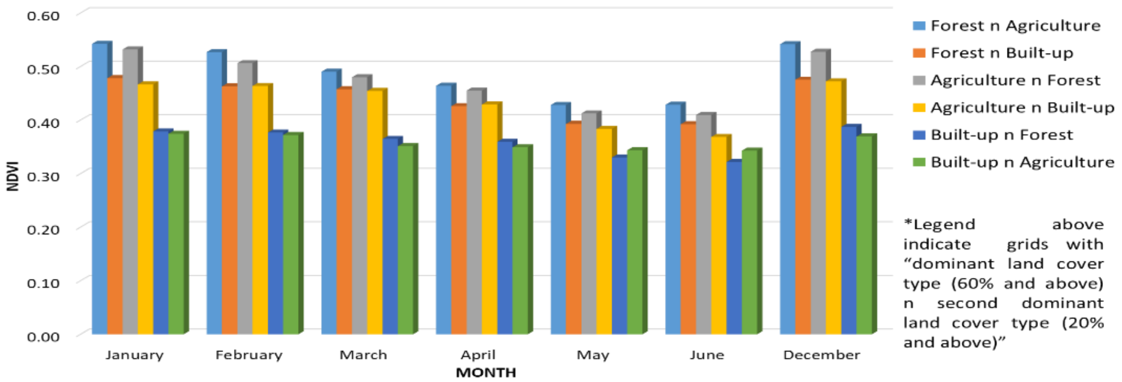

Figure 8 Seasonal variation in NDVI for grids with different combination of land cover types, which consists of dominant (covering 60% and above area of grid) and second dominant (covering 20% area and above) land cover type

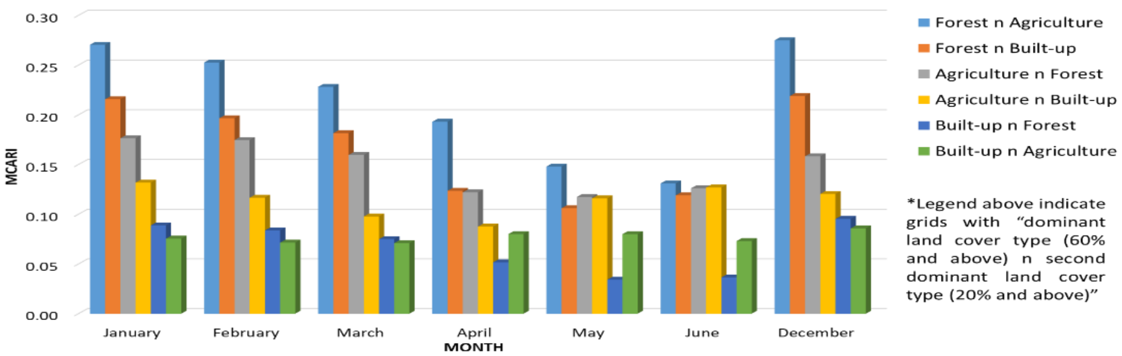

Figure 9 Seasonal variation in MCARI for grids with different combination of land cover types, which consists of dominant (covering 60% and above area of grid) and second dominant (covering 20% area and above) land cover type

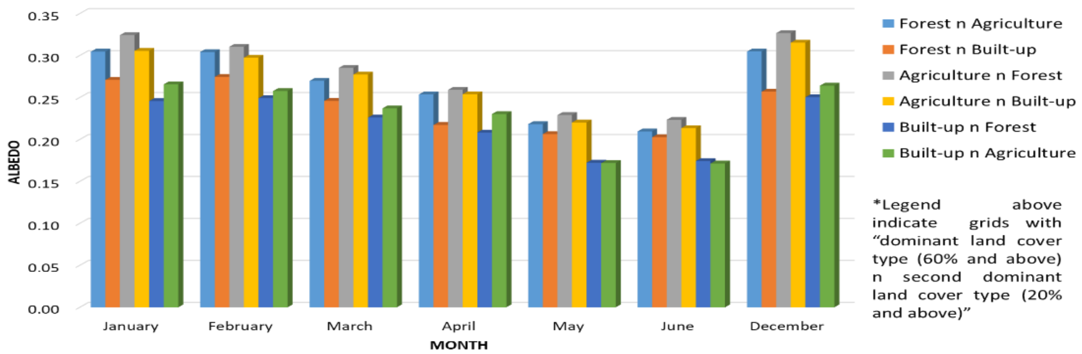

Figure 10 Seasonal variation in ALBEDO for grids with different combination of land cover types, which consists of dominant (covering 60% and above area of grid) and second dominant (covering 20% area and above) land cover type

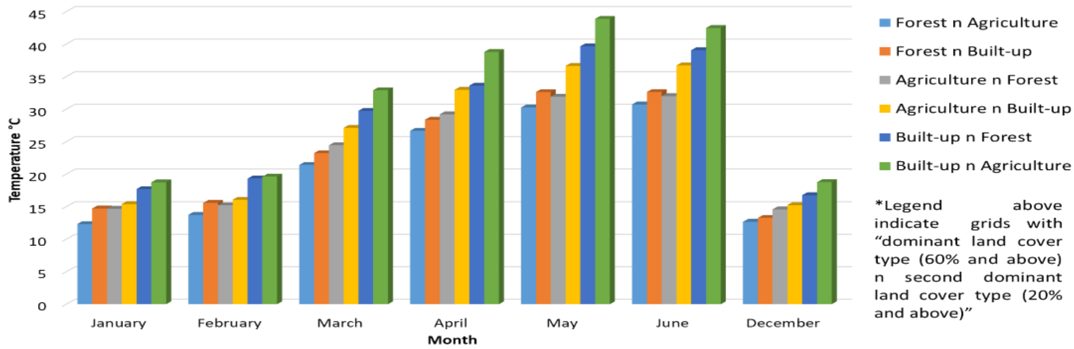

Figure 11 Seasonal variation in Land Surface Temperature (LST) for grids with different combination of land cover types, which consists of dominant (covering 60% and above area of grid) and second dominant (covering 20% area and above) land cover type

5. CONCLUSION

It can be concluded spatio-temporal variations in VIs, LST and Albedo is dominantly influenced by dominant land cover. Even within a single LULC class, temperature variations have been observed with changing seasons. Although forest has displayed lesser temperature and higher albedo, NDVI and MCARI values in most of the seasons. But it has displayed nearly opposite phenomenon of higher LST and lower albedo, NDVI and MCARI values than agricultural areas in summer season. It is primarily attributed to forest fires in this season and presence of sugarcane crops in agricultural fields which results into higher values of NDVI and MCARI in cropped areas. Builtup has displayed higher LST values and lower values of NDVI, MCARI and albedo due to presence of highly absorptive impervious surfaces. This study has helped to understand the behavior of vegetation indices and LST with dominant land use land cover, which will ultimately aid to understand the problem of increasing LST, leading to global warming. Use of fine resolution datasets can further improve the results with better accuracy, and finer details.

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