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Spatial estimation and climate projected change of cover-management factor in semi-arid region of India

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ABSTRACT

Soil erosion and its future projection play an important role in the changing climatic scenario. An attempt has been made to establish a relationship between NDVI and cover-management factor (C-factor) which varies with area and crop. IRS LISS III data with 23.5 m resolution is used to derive precisely NDVI and correlated with C-factor, the derived regression equation shows a good relationship between NDVI and C-factor value. An approach was made to use this area specific equation for getting C- factor for the whole Mahabubnagar district, Telangana from 2013 imagery data and the study was conducted in 2017. For future scenarios study, a relationship between rainfall, temperature, and NDVI of the whole district was derived. The NDVI value of the study area varies between 0.63 and 0.046. Based on the regression model C-factor for the future scenarios using available CMIP5 (Coupled Model Intercomparison Project-5) has been mapped for the whole district. Using the NDVI map, the C-factor map of the area was prepared in ArcGIS 10.0 software. The spatial distribution shows that the C-factor values varied between 0.52–0.86. On an average C- factor for 2020s, 2050s and in 2080s were 0.53, 0.76, and 0.77 respectively. The predicted C- factor values were then brought under the GIS environment and C- factor prediction maps were generated.

Keywords: C-factor, Climate change, GIS, RUSLE, Semi-arid tropics, Soil erosion, Watershed

Soil loss has become the major threat to agriculture sustainability. Arid and semi-arid regions are most vulnerable to soil loss *vis-à-vis* erosion and its prediction is critical in soil conservation planning (Josily *et al.* 2014, Wang *et al.* 2018, Yang *et al.* 2019 and Tessema *et al.* 2020). Soil loss estimation through remote sensing and geographical information system (GIS) (Pushpanjali *et al*. 2013) and the change across different climate and land use system is vital for planning agricultural development activities. Soil loss estimation requires various input parameters which are difficult to measure or capture spatially and temporally (Brazier *et al*. 2000). Cover management factor (C- factor) is one of the most critical co-efficient in commonly used RUSLE (Revised Universal Soil Loss Equation) model for soil erosion estimation. When the C-factor is correctly estimated, it helps in the proper estimation to soil loss (Panagos *et al.* 2015 and Almagro *et al.* 2019). Calculation of C- factor is region specific but difficult to assess, the researchers use value from literature or other available sources (Juergens and Fander 1993, Morgan *et al.* 1995, Folly *et al.* 1996) . The Normalized Difference Vegetation Index (NDVI) obtained through remote sensing data can be effectively used for determining C- factor (Van der Knijff *et al.* 2002, Cartagena 2004, Lin *et al.* 2002, 2006). A reliable estimate is essential for accurate identification and estimation of soil loss, which in turn, is needed for sound conservation planning. As climate change is and continues to be, the principal source of vulnerability to soil erosion, it is imperative to understand the impact of climate variability on C- factor to have more sustaining policies for climate resilient agriculture.

Keeping these in view this study attempts to establish a relationship between NDVI and C-factor for old Mahabubnagar district which was one of the drought prone districts in Telangana State and also India. Future projection of C-factor using climate scenarios RCP 4.5 data of CMIP5 (Coupled Model intercomparison project-5) for the district as a whole has also been attempted for precisely assessing the future soil loss.

MATERIALS AND METHODS

Study area: The Study was conducted in old Mahabubnagar district located at 16.73°N latitude and 77.98°E longitudes during 2017 with the freely available IRS P6 LISS III of 2013. It was bounded on East by Nalgonda, Guntur and Prakasam districts, on west by Raichur and Gulbarga districts of Karnataka state, on north by Rangareddy district and on south by Kurnool district.

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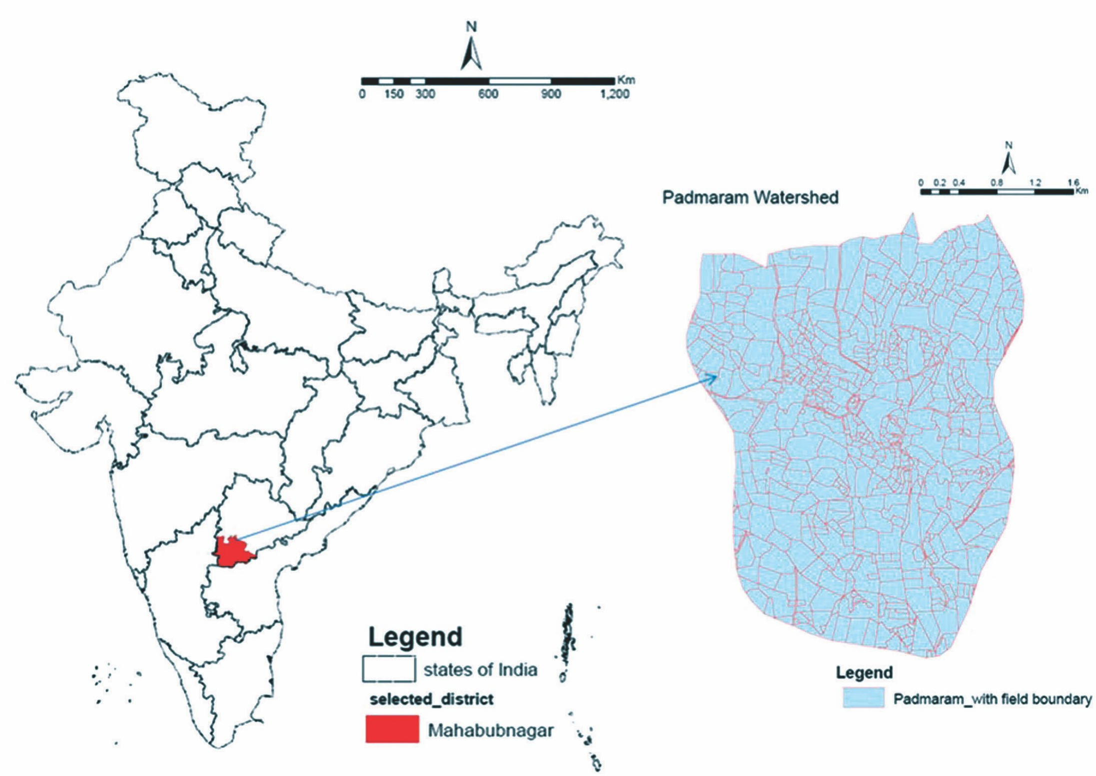

Fig 1 Study area: old Mahabubnagar with reference watershed, Padmaram

This district belongs to semi-arid area of deccan Plateau. The region receives an annual average rainfall of 749 mm of which 588 mm during the crop growing period. Soils of this area are Inceptisols, Vertisols and its intergrades along with some patches of Alfisols. Major crops grown were cotton, maize, redgram, jowar, and paddy.

For ground truthing a typical watershed (Padmaram, Mahbubnagar district) was selected (Fig.1). The primary data on the different crops and farm activities were collected through a pre-tested interview schedule. Data on location, major crops grown, cropping pattern, land use and sources of irrigation were collected from farmers of Padmaram watershed. The major crops grown were cotton, sorghum, paddy and groundnut. Cropping intensity of the watershed was found to be 148%.

Data collected: Forty one IRS P6 LISS III (Linear Image Self Scanning sensor) imageries (2nd February 2013) were downloaded and mosaiced together using Arc GIS 10.0 software for estimation of Land Use Land Cover (LULC) and Normalized Difference Vegetation Index (NDVI) for the whole district.

Primary data and remote sensing imagery were collected for the year 2013. Since the primary data were collected on first week of January, related 9th January 2013 remote sensing (IRS P6 LISS III) imageries were downloaded (NRSC's Bhuvan website (http://bhuvan.nrsc.gov.in/bhuvan_links.php) which was freely available for use) for the watershed, chosen for groudtruthing. For C-factor re-projection RCP 4.5 CMIP5 data were used. Freely available remote sensing and model data has been utilised for the purpose. Climate model simulations provide a cornerstone for climate change assessments. In this study, we use the most recent climate projected data made publically available through the CMIP5- Coupled Model inter-comparison project. It is the Global circulation models (GCMs) simulations for the fifth assessment report (AR5) of the projection of IPCC of the world climate research program (WCRP) (www.wcrp-climate.org).

C-factor estimation: The values of C depend on crop cover and management practices (Vijith *et al.* 2017). Swarnkar *et al.* (2018) has suggested the acceptance of the methodology based on NDVI instead of a single value method such as LULC. A two step approach has been applied here to derive c-factor from the NDVI imagery of the study area. A reference watershed has been chosen to establish a relationship between NDVI and C-factor. Based on LULC map of the watershed, field observation has been collected. LULC based C- factor (Reddy *et al*. 2005) was tabulated (Table 1). The highest C-factor value (Barren land) and the lowest c-factor value (Cotton cropped field) were selected to collect groundtruth data. Twenty points (Karaburun 2010) were selected for each highest and lowest C-factor value.

Table 1 Land use Land Cover of Padmaram watershed

LULC	Area (ha)	Percentage	C-factor
Barren	311	27	0.8
Fallow	372	32	0.7
Scrub land	329	28	0.6
Cropped land	158	14	
Cotton			0.5
Jowar			0.64

Those values are then correlated with the same period's imagery derived NDVI data. Further the regression equation from subjected area was used to derive C -factor map for whole district. For generating the C- factor (Fig 2), the NDVI was computed using the mosaiced IRS LISS III image of February, 2013.

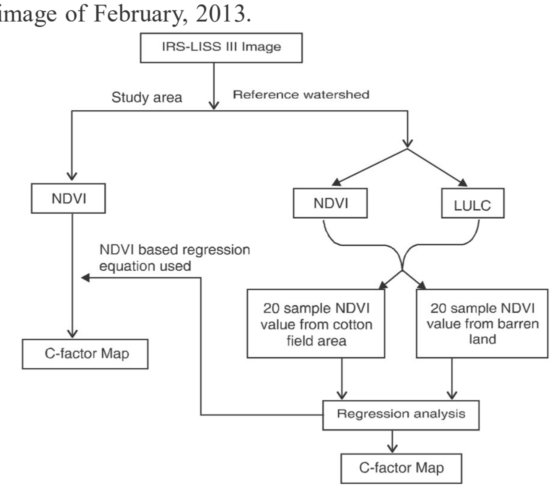

Fig 2 Workflow of C factor estimation.

C- factor re-projection: The NDVI images were acquired by the MODIS sensor (Moderate Resolution Imaging Spectro-radiometer) on board the Terra satellite. To avoid data gaps because of frequent cloud cover during the rainy season, the product MOD13Q1 "Vegetation Indices" was used, which is a 16-day composite at 250 m spatial resolution that is available globally and data were downloaded from: http://reverb.echo.nasa.gov/reverb/#utf8=%E2%9C%93&spatial_map=satellite&spatial_type=rectangle at a monthly time step for the year 2013 (as ground truth data has been collected in this year). Multivariate analysis for NDVI with rainfall and temperature variables was carried out in SPSS statistical software, because the growing season NDVI is better correlated to climate change than the annual NDVI. A multiple linear regression relationship between NDVI, rainfall and temperature for growing season (from April to October) were derived (Equation (1)). It is based on the assumption that the surface vegetation NDVI correlates directly with the temperature and precipitation, which is supported by previous studies focusing on the dry lands [Herrmann 2005 and Miao 2015].

$$\text{NDVI} = 5.03867+0.00038*(\text{Rainfall}) - 0.1475\ (\text{Temperature}) \text{ with } R^2=0.45 \quad (1)$$

The equation was further used to re-project NDVI *vis- a -vis* C-factor by using Twenty point extracted from RCP 4.5 data of CMIP5. Interpolation of the data for different scenarios was done using the kriging method. A five class geometric intervals were created by minimising the sum of squares in each class which made the changes within class more consistent.

RESULTS AND DISCUSSION

The NDVI map of Padmaram watershed was prepared using Arc GIS 10.0 software and IRS P6 LISS III satellite imagery with 23.5-meter resolution. The same imagery is being used to classify the land use land cover (LULC) of the watershed using supervised classification. To cover larger areas, one needs to rely on the land cover layer and known values of C-factor for certain vegetation and land cover types. The agriculturally dominated area, the C factor varies seasonally depending upon the cropping cycle (Alexandridis *et al.* 2015). October, February and March months' remotely sensed imageries were found to be appropriate for soil erosion studies (Wang *et al.* 2001). The study assumes a linear correlation between NDVI and C factor (Karaburun 2010) and uses bare soil and cotton cropped soil NDVI values as reference values in the absence of forest in the study area.

The regression equation was found as:

$$C\text{ –factor} = -0.694\ (\text{NDVI}) +0.900 \text{ -----(2) } (R^2=0.992)$$

The final C-factor map was generated using the regression equation in the spatial analyst tool of ArcGIS 10 software.

The NDVI value of the watershed varies between 0.54 - 0.050. Using the NDVI map, the C – factor map of the area was prepared in ArcGIS 10.0 software. The spatial distribution shows that the C- factor values varied between 0.52–0.86. The lower C-factor values indicate that the area possesses good vegetation cover and higher values indicate barren/open land. Using NDVI (equation 2), C-factor was derived for the whole district in ArcGIS 10.0 software. The spatial distribution of C-factor in the study area found to vary between 0.7 and 0.9. Lower value of C -factor indicates the area possesses good vegetative cover and higher value indicates barren/open land. The NDVI value of the study area (0.25 - 0.57) and the C- factor values (0.7- 0.9) indicates 80% of the total area was under high C-factor values thus less vegetation cover.

Change in C-factor under varied scenarios of future climate change: Climate and land use - vegetation dynamics was complex over the whole area, and the dominant factors are surface air temperature and precipitation (Propastin *et al.* 2008, Park and Sohn 2010). The mean annual rainfall in the whole district during the 2020s (2010-2039), 2050s (2040-2069) and 2080s (2070-2099) were estimated 767, 812 and 852 mm respectively. The C-factor in this region was predicted to increase due to high-intensity rainfall. Rainfall events of more than 1000 mm rainfall in all scenarios, 2020s two events were reported while in 2050s four events and 2080s seven such events were observed. Prediction of future vegetation dynamics (NDVI) and C- factor were done using Equation 1 and 2 on a decadal scale from 2010–2099. On an average C- factor for 2020s, 2050s and in 2080s were 0.53, 0.76, and 0.77 respectively. The interpolation for all the three scenarios shows (Fig 3) change in C- factor for Mahabubnagar district. Much more vegetation cover was observed in 2020s than in 2050s and 2080s. In 2020s 90% of the pixel counts falls between c-factor 0.42 to 0.62 which shows good vegetation cover while in 2050s it falls between 0.65-0.77 and in 2080s most of the pixel values were observed under C-factor 0.62-0.79. As C-factor towards the value 1 shows barren and waste lands, thus the values obtained for different scenarios confirms that soil loss from the region will likely to increase substantially if left unchecked. This study has enabled us to derive the major factor affecting soil degradation in semi-arid areas. C-factor lues can be precisely estimated using empirical equations that contain field measurements of land cover classes.

In this particular study, remote sensing and GIS techniques are used as it offers an optimal method to estimate Cover management factor (C) values of land cover classes of large areas in a short time. By cross-validation, at selected points, it was found that the equation can be fairly used for further research in this district for soil loss estimation as there is hardly any attempt to provide area-specific equation to calculate C- factor.

This work can be used to derive C-factor through NDVI without having the forest area as in many cases correct. Prediction for future climatic scenarios, C-factor values depict that slowly the agriculture lands are declining and reach an alarming situation in the 2050s and 2080s, the value increases from 0.43 to 0.86 which also confirms shifting of arable to non-arable land in this district.

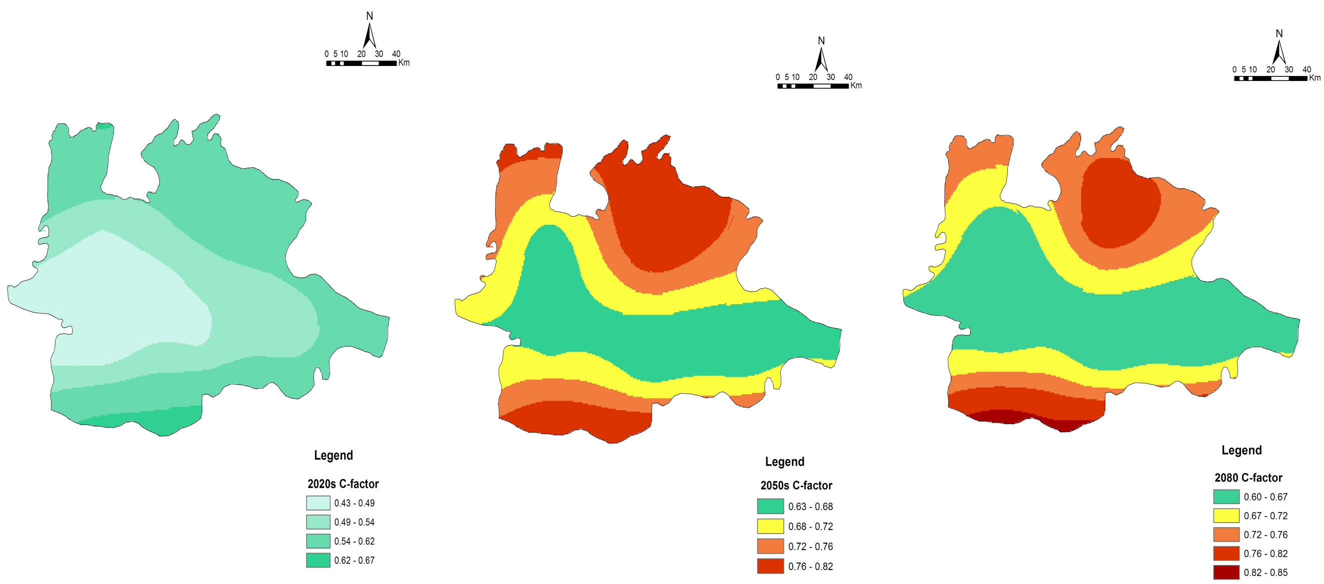

Fig 3 The 2020s, 2050s and 2080s climate projected scenarios' C-factor maps of old Mahabubnagar District, Telangana respectively.

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