Original Research Article

GENERATING SOIL PARENT MATERIAL ENVIRONMENTAL COVARIATES USING SENTINEL – 2A IMAGES FOR DELINEATING SOIL ATTRIBUTES

ABSTRACT

Soil mapping procedures typically involve the combination of possible soil-forming SCORPAN factors. Among the factors, parent materials/ mineralogy has been considered important for the soil classification besides the Organisms (O) and Relief (R). Inclusion of the parent material covariate for the Digital soil mapping involves implication through geological maps, spectral derivatives and predictive modelling. In this study, the most prominent parent materials identified were derived using the spectral indices formulated based on the Sentinel – 2A multispectral information. While considering the coarse spatial resolution constraints of the existing Landsat -8 bands that may limit certain applications, Sentinel-2 images were used for the indices derivation. The generated mineral maps can support the digital soil mapping of the soil attributes at different spatial scales.

Keywords: Parent materials/mineralogy, SCORPAN factors, Sentinel -2A, spectral indices

1. INTRODUCTION

Over the decade, estimating soil properties and their associated factors has been crucial for managerial practices and to propagate ‘soil security’ (McBratney et al., 2014). To ascertain the demands on the requirement of soil resource database, several methodologies have been instigated for the precise soil information. The developed repositories can be accessed as an important decision-making component in many of the applications, such as crop selection procedures, among others. Soil mapping involves the participation of the soil-forming factors as defined by Jenny (1994) (i.e.) SCORPAN factors, which can be utilized as the covariates. Among the factors, parent material/mineralogy has the most depictable soil information in regard to the historical and influential context. Brady and Weil (2014) defined mineral soil as “A soil consisting predominantly of, and having its properties predominantly determined by, mineral matter.” Understanding the relationships between the soil minerals and the underlying soil properties have been widely studied in different aspects. The parent mineralogy is essentially classified as basaltic and granitic parent materials. Basaltic minerals generally are characterized by little or no quartz, ferromagnesium minerals, N or K feldspar, and vice-versa in the granitic minerals (Wilson, 2006). Gray and Murphy (2002) studied the influence of the parent materials on the soil properties and soil distribution based on the information derived from the SALIS database. The nutrient retention and the physical properties of the soil stabilizes with increase in the mafic parent materials which indirectly affects the Cation Exchange Capacity as it controls the potential quality of the produced clay content.

The soil parent material maps are utilized by the soil surveyors for the soil attribute mapping, delineating soil boundaries and mineralogy associated and related soil properties. Dash et al. (2021) indicated that the utilization of the parent materials for DSM constituted about 8% of all the environmental covariates. Typical means of spatial parent material information are extracted from the digitized geological or lithological maps, which share the same data properties as the conventional survey maps. Several studies utilized the geological information of India obtained from the Geological Survey of India (Bhukosh) and Bhuvan portal as the covariates for the Digital soil Mapping. The data representation and availability depend on the mapping unit, mapping scale, spatial coverage of the features and source material of the soil under study. Nussbaum et al. (2018) compared digital soil mapping procedures based on the parent materials covariates derived through conventional geological maps, hydrogeological maps and raw mineral maps of different units. A subtle difference can be noticed between the geological maps and the soil parent mineral maps in regard to the grouping of the lithologies, where the latter requires the delineation exclusively based on the pedological information to indicate the soil formation and single unit representation of the information rather than grouping of the units as rocks formed from the similar geological period. To mitigate the constraints associated with the survey maps, parent material maps can be mapped through the predictive approaches based on different satellite data products or can be derived as a spectral derivative (Wilson, 2019).

Bonfatti et al. (2020) proposed a digital parent mineral mapping methodology with parent mineral information sampled from the existing geological and lithological maps. A total of 32 terrain and hydrological covariates were derived from DEM and Landsat – 8 images for generating a parent material map based on the machine learning algorithms. Boettinger et al. (2008) derived the parent material covariates based on the spectral information obtained from the Landsat spectral images. Spectral band ratios have been optimized pertaining to the exposed parent materials of the study area. P et al. (2020) determined and studied the iron ore distribution of the study area by digital processing and analyzing of ASTER data by calibrating the spectral ratios of the bands selected through Principal component analysis. The ratios were then compared with the geochemical data obtained through field investigations. Other means of inferring parent minerals include information derived from the regolith and topographic maps. Cook et al. (1996) studied the discriminative ability of the gamma radiometric information obtained through the airborne sensors by comparing it with the field radiometric measurements of different parent minerals. The radiometric information can be used further for generating weathering intensity maps and ultimately for deriving digital soil maps. Thus, the objective of the study aims at generating the soil parent material maps as defined, based on the spectral information derived from the Sentinel – 2 images for the study area.

2. STUDY AREA

The indices development of the study area was carried over for four districts of Tamil Nadu. (i.e.) Ariyalur, Cuddalore, Mayiladuthurai and Perambalur. The area of four districts collectively covered was about 8569.21 square kilometres. The extent of the study area is covered adjacently by various districts of Tamil Nadu, with coastal regions adjoining the Cuddalore and Mayiladuthurai districts. Ariyalur and Perambalur are considered to be the inland districts of Tamil Nadu, with Black and Red loam soil as the predominant soil types with a semi-arid climate. In contrast, the Cuddalore and Mayiladuthurai districts have tropical climates with alluvial, sandy loam and sandy clay loam as the predominant soil types.

The major irrigation source of the study area includes Cauvery and Vellalar basins in the Ariyalur and Perambalur districts and Gelidam, Kollidam and Pennaiyar river basins in the Cuddalore and Mayiladuthurai districts. With respect to the average temperature and average precipitation of the study area districts, the Cuddalore, Perambalur, Mayiladuthurai and Ariyalur districts have 28.01 degree Celsius and 4.71 mm, 26.81 degree Celsius and 3.68 mm, 27.57 degree Celsius and 4.48 mm, 27.57 degree Celsius and 4.48 mm, respectively and Fig.1 illustrates the study area map of the districts using True colour composite of the Sentinel-2 images. Considering the rainfed irrigation prevalence of Ariyalur and Perambalur districts, Maize and Cotton were the most cultivated crops, whereases situated in the Cauvery River basin regions, major crops cultivated in the Cuddalore and Mayiladuthurai districts range from Paddy, Cumbu, Maize, Pulses among others.

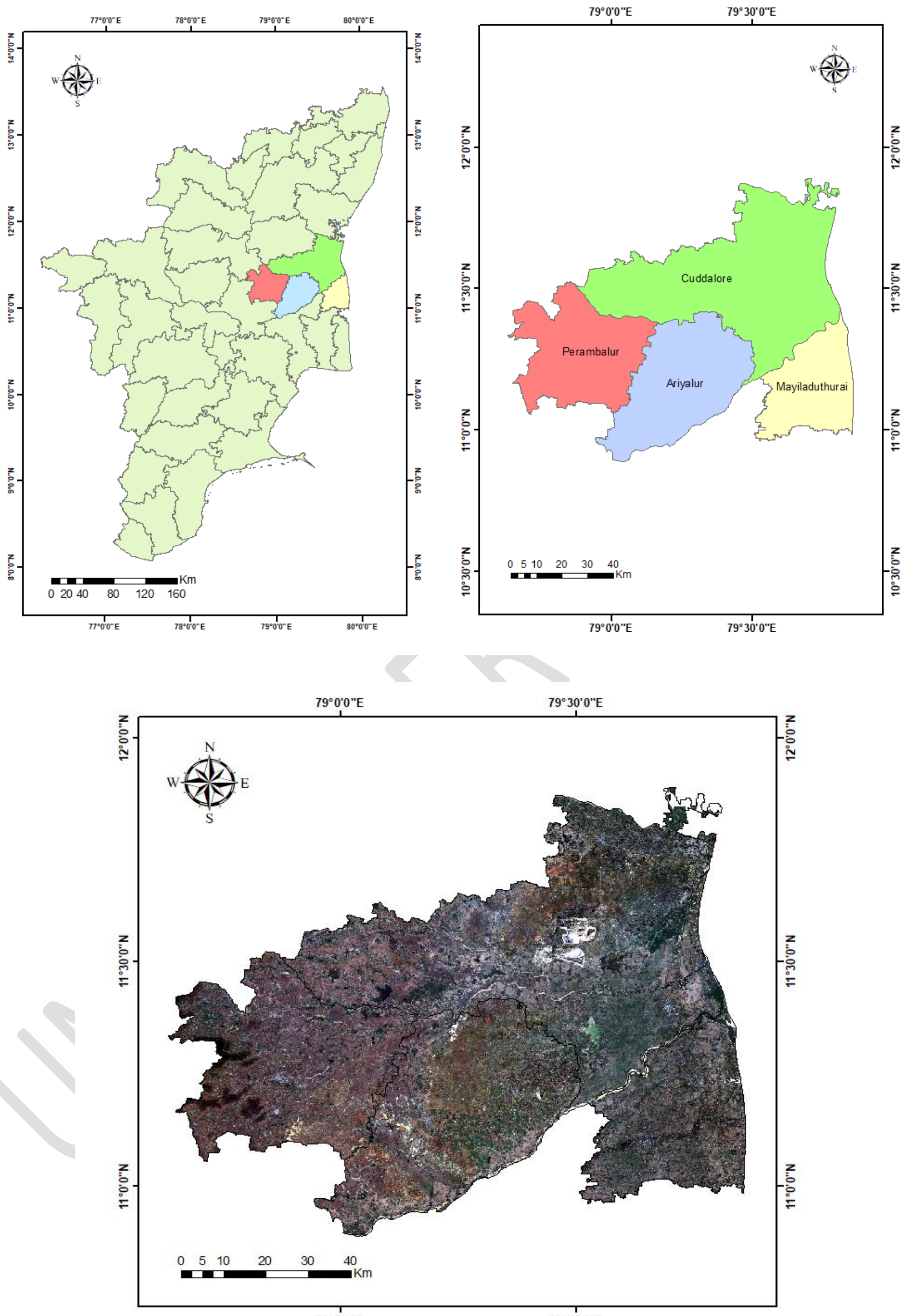
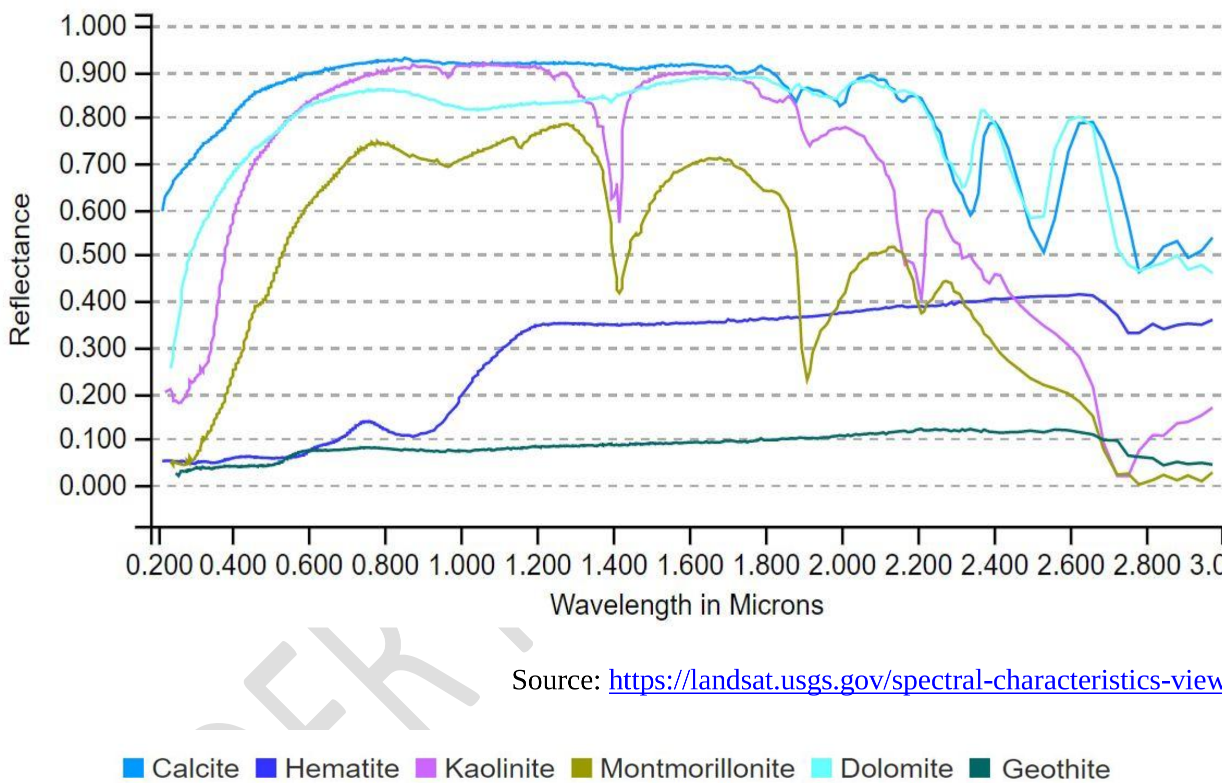


Fig.1. True Colour Composite and Study area Map of the districts.

3. MATERIALS AND METHODS

The spectral ratios of each of the parent mineral materials, as defined by Boettinger et al. (2008), have been aligned in regard to that of spectral information of the Sentinel – 2 data. The respective Sentinel-2 MSI ("COPERNICUS/S2_SR") data have been downloaded by applying the median reducer from Google Earth Engine. The data collection was limited to March to May (i.e.) to best discriminate the soil properties as a 3-month composite with a median reducer filter to reduce the effects of cloud cover and patches. Each parent material or the mineral has an associated spectral signature with differentiations that can be utilized to identify the individual parent materials. Fig. 2 illustrates the spectral signatures of the Calcite, Hematite, Kaolinite, Montmorillonite, Dolomite and Geothite, which are responsive particularly to the short infrared wavelength region.



Source: https://landsat.usgs.gov/spectral-characteristics-viewer

Fig. 2. Spectral characteristics of the different parent minerals

The methodology required for the generation of the parent material covariate is depicted in Figure 3. The Soil enhancement ratios as defined by the Bureau of Land Management and the existing maps corresponding to the parent mineralogy are mentioned in Table 1. Though the geology maps may be an important covariate and utilized in several studies, the spectral derivates better quantify parent materials than the existing maps, which may not be exclusive to all the study areas. For delineating the soil properties, the effect of geology and geomorphology are also included to increase the model's predictability that is to be calibrated and validated. The spectral properties of the particular parent minerals can be compared or explored through the spectral libraries defined for each parent material via the spectral characteristic viewer of USGS (Boettinger et al., 2008).

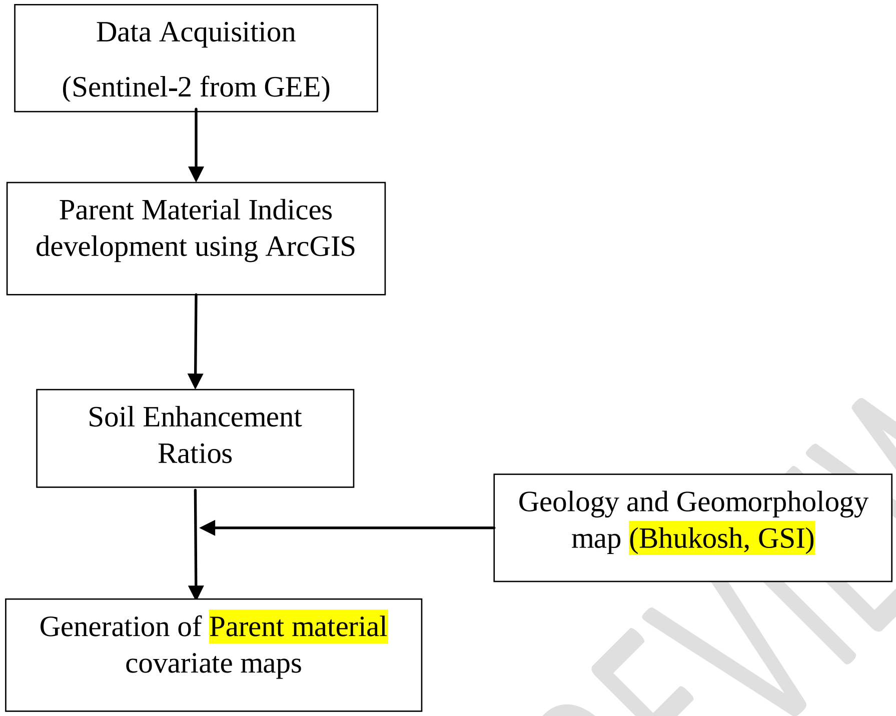


Fig. 3. Methodology Flow Chart

Table 1. Generated or Derived parent materials covariates for Digital Soil Mapping (Avello)

Covariate	Description	Resolution
Carbonate Difference Ratio	Differentiate carbonate-rich areas (Band 4 - Band 3) / (Band 4 + Band 3)	10m
Clay Difference Ratio	Differentiate areas of high clay hydroxyl influence (Band 11 - Band 12) / (Band 11 + Band 12)	20m
Ferrous Minerals Difference Ratio	Differentiate areas of higher ferrous mineral influence (Band 11 - Band 8a) / (Band 11 + Band 8a)	20m
Iron Difference Ratio	Differentiate areas of higher iron mineral influence (Band 4 - Band 12) / (Band 4 + Band 12)	20m
Rock Outcrop Difference Ratio	Differentiate sedimentary rock (lime/dolostone) from igneous rock (Band 11 - Band 3) / (Band 11 + Band 3)	20m
Geology	A kind of geologic map showing the rock types of a particular area	1: 2M
Geomorphology	Study of physical and Morphological features of the Earth’s landform	1:50,000

4. RESULTS AND DISCUSSION

Environmental covariates based on SCORPAN factors besides parent materials are to be selected depending upon the characteristics of the study area to model the soil properties under study. Ideally, the context of the parent materials defines the underlying sediments and bedrock that depicts the topography of the landscape. In most cases, the soil properties are majorly determined based on the confluence of the slope/Relief and parent material by influencing the thickness of the solum (Janarth et al., 2022). Though implementation of the existing soil legacy maps on Geology and Geomorphology does not reflect the detailed (coarse spatial resolution) and actual conditions of the soil environment, their implementation in the predictive modeling of the soil properties is considered essential to impart the weathering sequence of the rocks of the similar geological period (Bonfatti et al., 2020). The parameters or geospatial data layers required under parent material covariate for digital soil mapping (Avello) are depicted in Table 1.

The geological features found in the study area adapted from the database of bhukosh, GSI include, Ariyalur Group, Charnockite Gneissic Complex, Cuddalore Formation, Migmatite Gneissic Complex, Trichinopoly Group, Undifferentiated Fluvial / Aeolian / Coasta & Glacial Sediments, Upper Gondwana Group, Uttattur Group and Vriddhachalam Group and the features are depicted in the Fig.4. Sediments of Fluvial and Aeolian nature are found most predominantly covering 3450.07 square kilometres of the study area, followed by the Cuddalore Formation and Migmatite Gneissic Complex features.

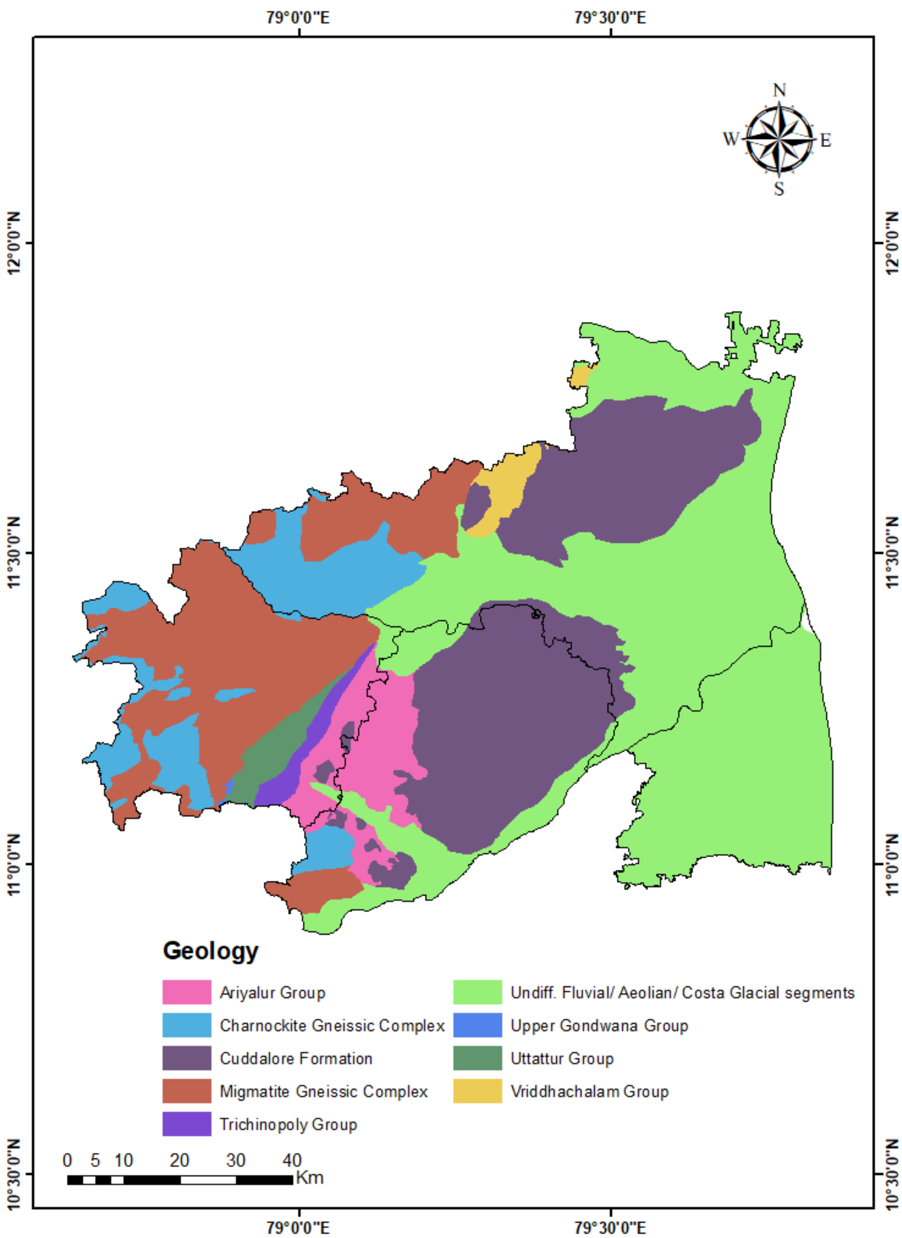


Fig.4. Geology map of the study area (adapted from Bhukosh, GSI)

Geomorphology map adapted from the database of Bhukosh, GSI is depicted in Fig.5. Geomorphology defines the physical, chemical and biological processes besides origin that affect the topographical and bathymetric characteristics of landforms. Major geomorphological features that represent the aspects of the study area include the erosional surfaces of the Pediment Pediplain Complex predominantly, covering about the 4736.74 square kilometres, followed by the Flood Plain and Deltaic Plains.

Schwertmann (1993) studied the concept of the pedogenesis of the soils based on the composition of the Iron oxides occurring in the soil environment. Soil colour is generally constituted based on the nature of the underlying parent materials. The relationship between the Iron oxide and the soil colour is studied to define the pedogenesis of the soil. Thus, propagating the idea of differentiation based on colour concerning the parent material, soil enhancement ratios, or normalized band ratios have been defined to perceive the spatial variability of several biogeophysical properties (Brungard, 2014). The interpretability and the discriminative facet with respect to that of the different rock types of the spectral imagery can be enhanced generally through image processing techniques, which attenuates the spectral differences of the image data (El Rakaiby et al., 1994). Several of the band combinations (normalized band ratios) have been accessed for their potential in discriminating the different rock types (i.e.) sedimentary or igneous rocks. ((El Rakaiby et al., 1994);(El Rakaiby, 1996)).

In general, each of the spectral derived indices (Carbonate Difference Ratio, Clay Minerals Difference Ratio, Ferrous Minerals Difference Ratio, Iron Difference Ratio, Rock Outcrop Difference Ratio) varies in the range of -1 to +1, indicating the low and high values for each of the respective parent materials. ((Suzann Kienast-Brown et al.); *(Bodily, 2005)*). Furthermore, the generated spectral derivatives exhibited unique patterns that distinguish the landform community. By analyzing the range of the band ratios, the prevalence of the respective parent material in the study area can be identified in near real-time, which can be imparted in deriving the predictive model of associated soil properties (Stum et al., 2010).

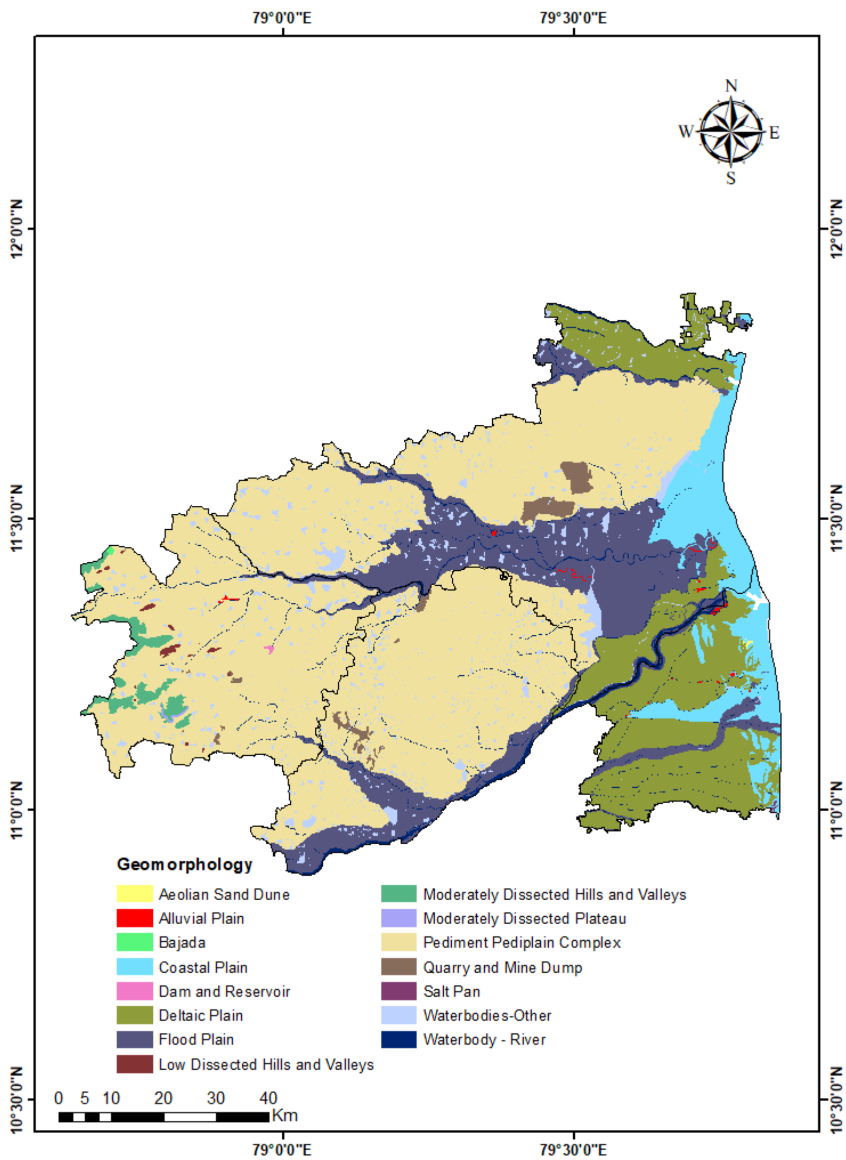


Fig.5. Geomorphology map of the study area (adapted from Bhukosh, GSI))

The Carbonate Difference Ratio of the study area falls between -0.56 to 0.51 (Fig.6). On comparing, the Carbonate Difference Ratio of the Ariyalur district had a low concentration of carbonate-rich sites with values ranging from -0.56 to 0.3. The low concentration of the Carbonate is usually accounted due to the presence of red loam soils as the predominant soil type followed by the mediocre presence of black soil. Similarly, sharing almost the same characteristics as the Ariyalur, the Perambalur district also had a low concentration of carbonate-rich sites with values ranging from -0.38 to 0.38, though the district has the highest percentage of red calcareous soil followed by Black soil (Mayilswami, 2013). Cuddalore and Mayiladuthurai districts had a mediocre concentration of the Carbonate rich sites with values ranging from -0.52 to 0.51 and -0.46 to 0.41, respectively. The mediocre range of Carbonate may be associated with the presence of sandy clay loam, river alluvium and sandy coastal alluvium as the predominant soil types in the Cuddalore and Mayiladuthurai districts ((Paramasivan & Pasupathi, 2016); (Mayilswami, 2013))

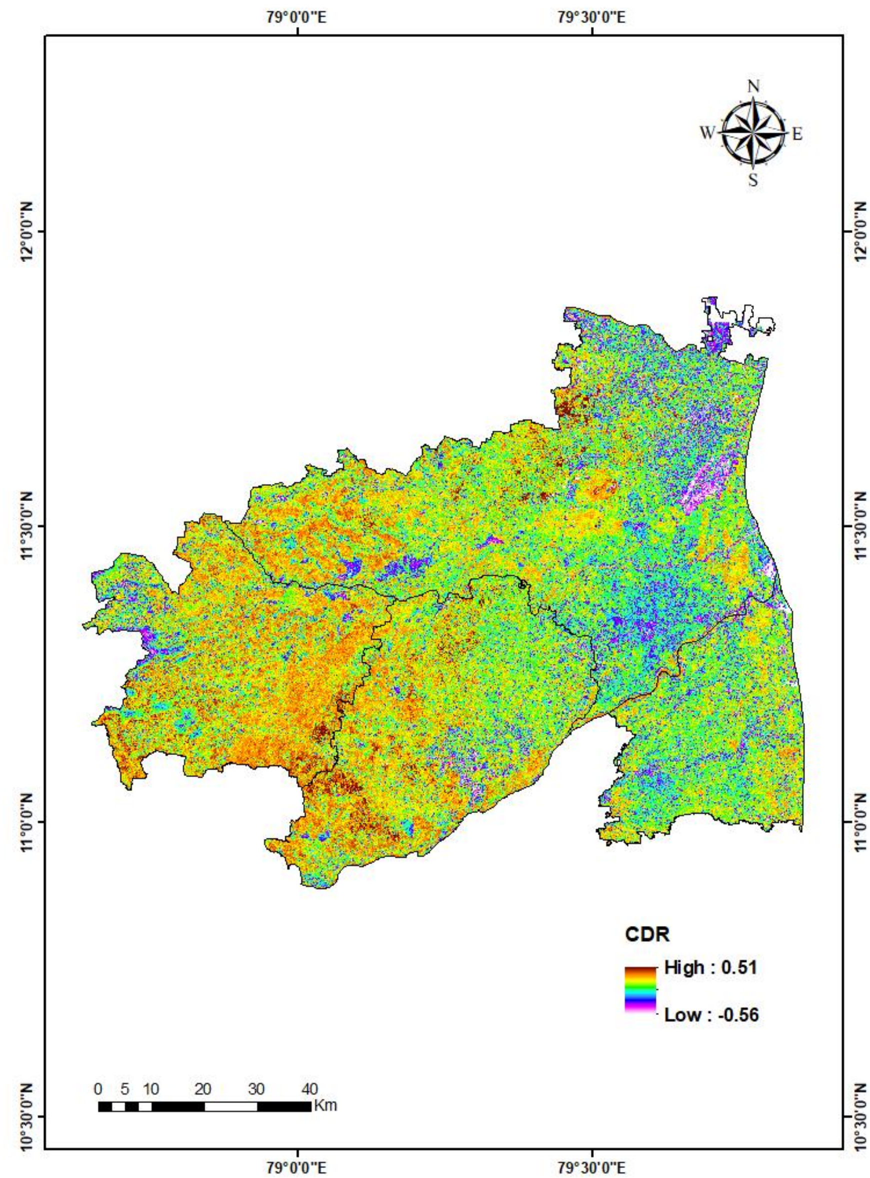


Fig.6. Carbonate Difference Ratio

The Clay Difference Ratio of the study area varies between -0.67 and 0.57 (Fig.7). The Clay Difference Ratio of Ariyalur, Perambalur, Cuddalore and Mayiladuthurai districts ranged from -0.67 to 0.43, -0.1 to 0.42, -0.34 to 0.57 and -0.19 to 0.48, respectively. The mediocre concentration of hydroxyl clay content of the regions is usually related to the predominant soil types, prevailing soil texture and CEC of the region.

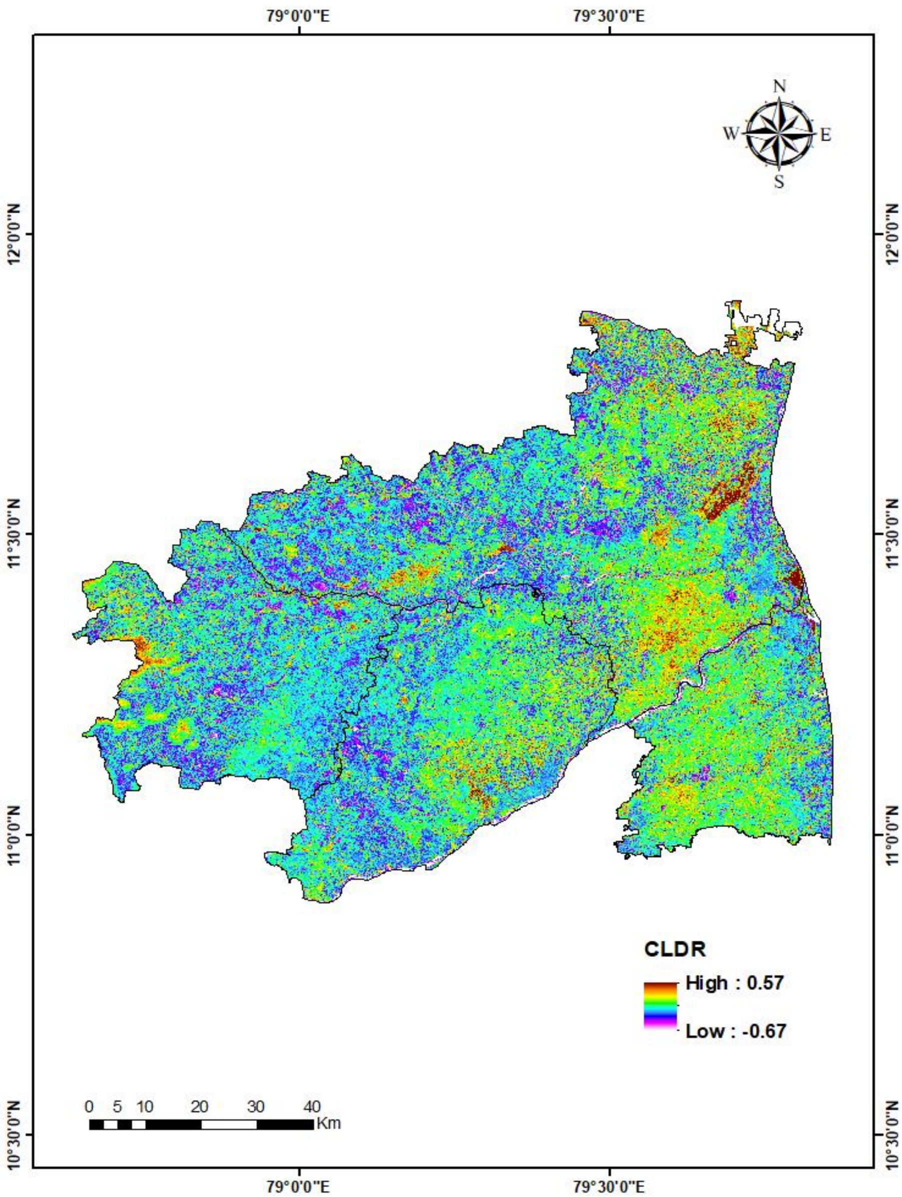


Fig.7. Clay Mineral Difference Ratio

The Ferrous Mineral Difference Ratio falls between -0.88 and 0.75 (Fig.8). The districts of Ariyalur, Perambalur, Cuddalore and Mayiladuthurai district had a Ferrous Mineral Difference Ratio of -0.82 to 0.75, -0.62 to 0.46, -0.88 to 0.67 and -0.75 to 0.68, respectively. Similarly, the Iron Difference Ratio falls between -0.78 and 0.95 (Fig.9). The Iron Difference Ratio of Ariyalur, Perambalur, Cuddalore and Mayiladuthurai districts ranged from -0.75 to 0.95, -0.70 to 0.86, -0.78 to 0.94 and -0.70 to 0.90, respectively. The higher concentration of Ferrous minerals and Iron Minerals in Ariyalur and Perambalur districts is usually associated with the presence of limestone ferruginous red loam soils and red loam, respectively (Mayilswami, 2013).

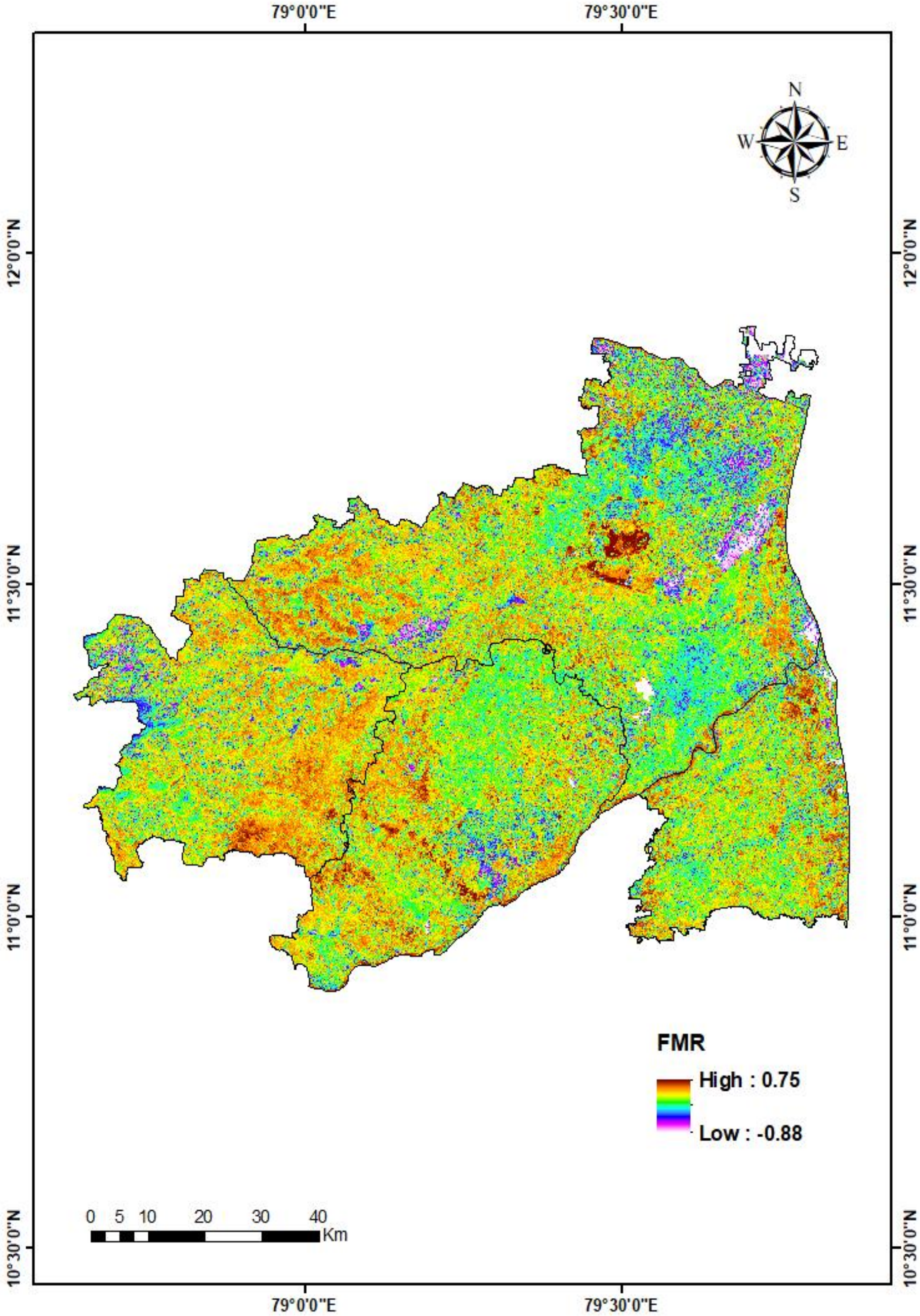


Fig.8. Ferrous Mineral Difference Ratio

The Rock Outcrop Difference Ratio varies between -0.94 and 0.82 (Fig.10). Most studies indicated the usefulness of rock outcrop detection through Landsat spectral imagery. The Rock Outcrop Difference Ratio is characterized by brighter pixels indicating the presence of sedimentary parent material, whereas the darker pixels indicate the presence of igneous parent materials (El Rakaiby et al., 1994). The districts of Ariyalur, Perambalur, Cuddalore and Mayiladuthurai district had a Rock Outcrop Difference Ratio of -0.94 to 0.73, -0.77 to 0.74, - 0.93 to 0.82 and -0.86 to 0.73, respectively.

The increased spatial variability associated with the Clay Difference Ratio, Carbonate Difference Ratio and

Ferrous Mineral Difference ratio indicates their higher probability of influencing the predictive modelling of the soil properties. Further, through the results generated, the derived indices maps along with the existing soil legacy maps of Geology and Geomorphology can be implemented as spatial data layers representing the parent material covariate to predict the soil properties under study.

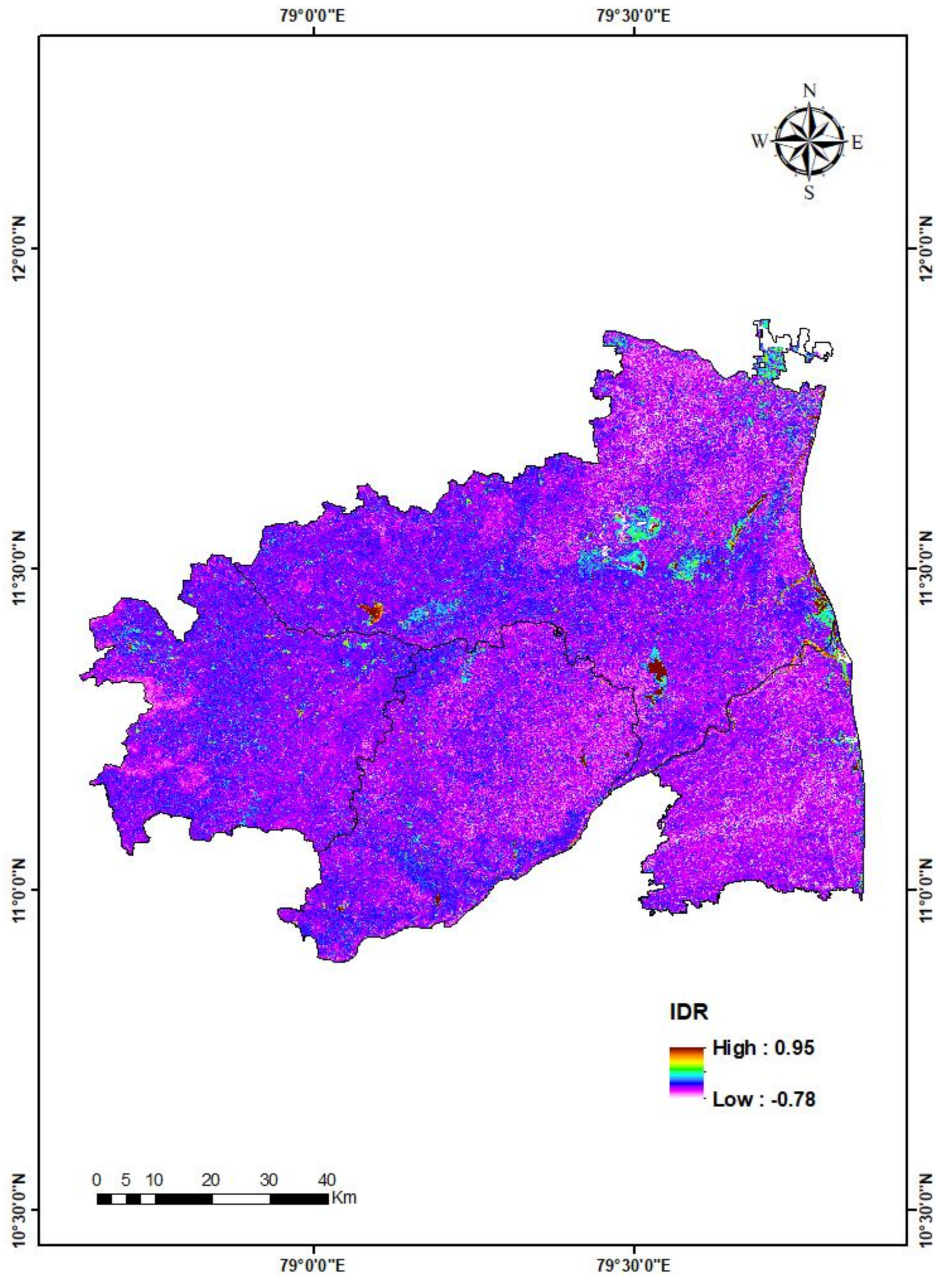


Fig.9. Iron Difference Ratio

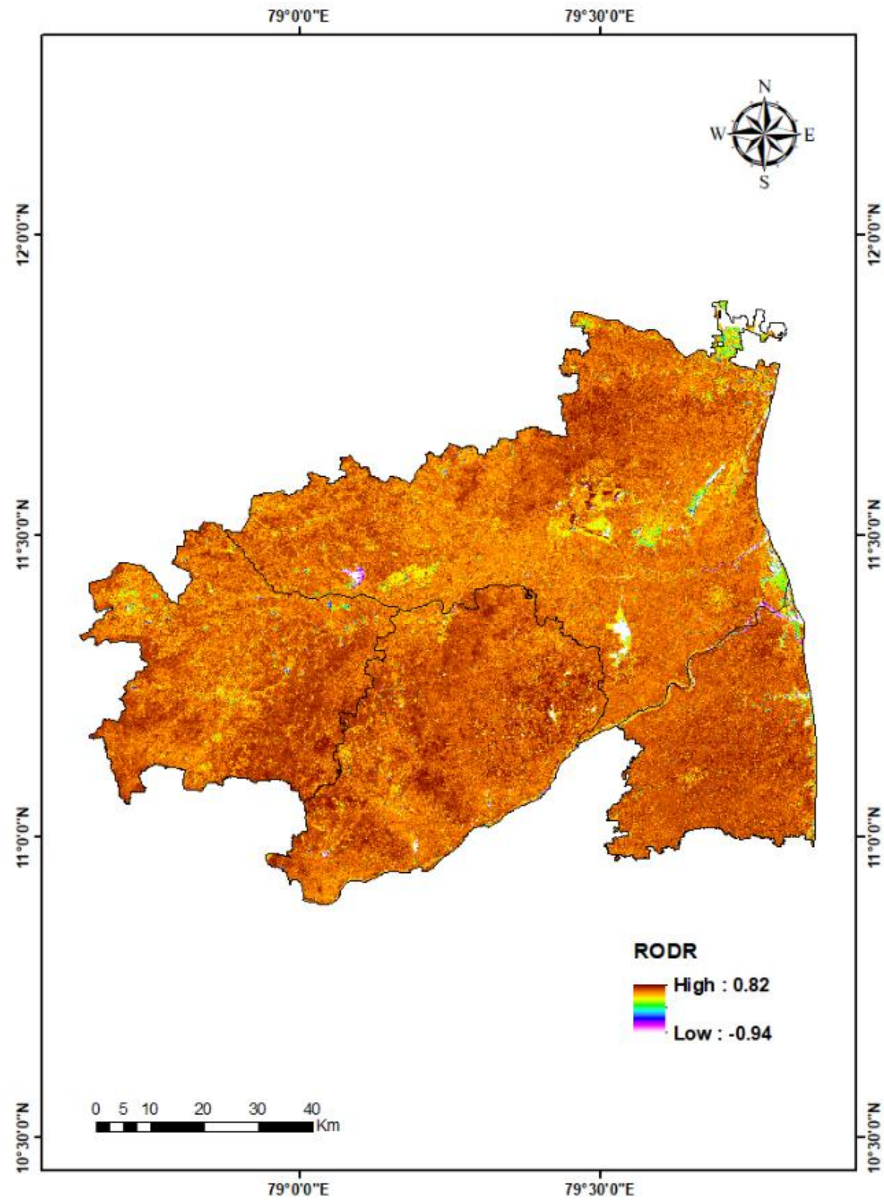


Fig.10. Rock Outcrop Difference Ratio

5. CONCLUSION

This study substantiated that remote sensing satellite datasets provide a wide range of application in the exploration of soil attributes of a larger area in a very short time and at a low cost. The use of remote sensing imagery for indicating the parent mineralogy compensates the demand on requirement of real-time assessment of parent material variability. In General, delineating soil properties and deriving a digital soil map includes modeling the soil attributes with respect to the generated specialized covariates. The modeling procedures are based on the machine learning algorithms such as Random Forest, Multinomial Logistic Regression, Cubist models etc., Selection of the appropriate learning algorithms, and the covariates are essential for increasing the efficiency of the model calibrated. In this study, Parent material covariate layers were generated using Sentinel- 2 images, which are to be included while calibrating a DSM model. In most of the studies on Digital Soil mapping, existing information on the bedrocks and sediments was imparted through Geology, Lithology and Geomorphology maps. Information on the spectral derivatives corresponding to parent mineralogy that were standardized based on their influence in the spectrum, can enhance the qualitative and quantitative characterization of the soil properties.

6. ACKNOWLEDGEMENT

The authors are grateful to the Department of Remote Sensing and GIS for providing the fund through the Indo-German GIZ – ICRI Project Innovative Climate Risk Insurance scheme to carry out the research work in a project mode and like to extend our sincere thanks to Professor and Head and staff members for their scrutiny, valuable comments and constructive criticism on the manuscript.

7. REFERENCES

Avello. https://www.nrcs.usda.gov/wps/PA_NRCSConsumption/download?cid=nrcseprd1079006&ext=pdf

Bodily, J. M. (2005). *Developing a digital soil survey update protocol at the Golden Spike National Historic Site*. Utah State University.

Boettinger, J., Ramsey, R., Bodily, J., Cole, N., Kienast-Brown, S., Nield, S., . . . Stum, A. (2008). Landsat spectral data for digital soil mapping. In *Digital soil mapping with limited data* (pp. 193-202). Springer.

Bonfatti, B. R., Demattê, J. A., Marques, K. P., Poppiel, R. R., Rizzo, R., Mendes, W. d. S., . . . Safanelli, J. L. (2020). Digital mapping of soil parent material in a heterogeneous tropical area. *Geomorphology*, *367*, 107305.

Brady, N., & Weil, R. (2014). The nature and properties of soil.(14th New Int. Ed.). In: Pearson Education Limited, Upper Saddle River.

Brungard, C. W. (2014). *Advancing digital soil mapping and assessment in arid landscapes*. Utah State University.

Cook, S., Corner, R., Groves, P., & Grealish, G. (1996). Use of airborne gamma radiometric data for soil mapping. *Soil Research*, *34*(1), 183-194.

Dash, P. K., Panigrahi, N., & Mishra, A. (2021). Identifying opportunities to improve digital soil mapping in India: A systematic review. *Geoderma Regional*, e00478.

El Rakaiby, M., Ashmawy, M., Yehia, M., & Ayoub, A. (1994). In situ reflectance measurements and TM data of some sedimentary rocks with emphasis on white sandstone, southwestern Sinai, Egypt. *International Journal of Remote Sensing*, *15*(18), 3785-3797.

El Rakaiby, M. L. (1996). Discrimination of igneous rocks using digital thematic mapper data in southern Sinai, Egypt. *Geocarto International*, *11*(4), 61-69.

Gray, J., & Murphy, B. (2002). Parent material and world soil distribution. 17th World Congress of Soil Science, Bangkok, Thailand,

Janarth, S., Ramalingam, K., Pazhanivelan, S., & Kaliaperumal, R. (2022). Deriving of Topographical Attributes using SRTM DEM for Tiruppur District, Tamil Nadu, India. *Ecology, Environment and Conservation*, *28*, 55-55. https://doi.org/10.53550/EEC.2022.v28i01s.055

Jenny, H. (1994). *Factors of soil formation: a system of quantitative pedology*. Courier Corporation.

Mayilswami, C. (2013). Guidelines for augmentation of groundwater resources under climate change in Tamil Nadu. ICAR collaborative network project, NICRA. *Water technology center, Tamil Nadu Agricultural University, Coimbatore, India*.

McBratney, A., Field, D. J., & Koch, A. (2014). The dimensions of soil security. *Geoderma*, *213*, 203-213.

Nussbaum, M., Spiess, K., Baltensweiler, A., Grob, U., Keller, A., Greiner, L., . . . Papritz, A. (2018). Evaluation of digital soil mapping approaches with large sets of environmental covariates. *Soil*, *4*(1), 1-22.

P, G., S, P., T, M., Fadhil Al-Quraishi, A. M., Singh, A. K., & Singh, P. K. (2020). Mapping of ferric (and ferrous (iron oxides distribution using band ratio techniques with ASTER data and geochemistry of Kanjamalai and Godumalai, Tamil Nadu, south India. *Remote Sensing Applications: Society and Environment*, *18*, 100306.

Paramasivan, C., & Pasupathi, R. (2016). An Overview of Cauvery Delta Zone in TamilNadu. *International Journal of Trend in Research and Development*, *3*, 2394-9333.

Schwertmann, U. (1993). Relations between iron oxides, soil color, and soil formation. *Soil color*, *31*, 51-69.

Stum, A. K., Boettinger, J., White, M., & Ramsey, R. (2010). Random forests applied as a soil spatial predictive model in arid Utah. In *Digital soil mapping* (pp. 179-190). Springer.

Suzann Kienast-Brown , Zamir Libohova, & Boettinger, J. https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/ref/?cid=nrcs142p2_054255

Wilson, M. (2006). Factors of soil formation: Parent material. As exemplified by a comparison of granitic and basaltic soils. 113-130. https://doi.org/10.1017/CBO9780511535802.010

Wilson, M. (2019). The importance of parent material in soil classification: A review in a historical context. *Catena*, *182*, 104131.