Project Report for AG2413 Digital Image Processing and Applications

7.5 credits

Monitoring Soil Degradation with Remote Sensing in Karnataka

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Introduction

World War II is by far the biggest dent that we've had in the history of mankind. Approximately 11 to 12 billion people lost their lives and its after effects were faced by people even after decades. But in the foreseeable future, with the current unsustainable lifestyle practices, we're heading in the direction of a problem that would make World War II seem like nothing but a speck. The root cause for this boils down to soil. Soil is the fundamental entity necessary for the existence of species in all echelons of terrestrial life. There can be no life without soil and no soil without life; they have evolved together.(Kellogg 1938).

Soil degradation is the decline in the quality of soil that results from various human activities and environmental factors. It can be caused by a variety of factors, including overuse, deforestation, poor land management practices, and exposure to pollutants. Soil degradation can lead to a number of negative consequences, such as reduced crop yields, increased erosion, and loss of biodiversity. Soil is undergoing significant damage across the world due to an alarming trend of land resource exploitation (FAO 2021). 52% of the world's agricultural land is already degraded (ELD 2015), and if current trends continue, 90% of the Earth's land surface could be degraded by 2050 (UNCCD 2020). This is a cause for concern, as soil is a critical resource that is essential for producing the food we eat. Approximately 95% of the food we consume is grown on land (FAO Global Symposium on Soil Erosion 2019), and 87% of the planet's biomass is land-based (Bar-On Y. M. et al, 2018).

According to the HungerMap LIVE, as of January 4,2023, there are 621 million people across 89 countries who do not have access to sufficient food (HungerMap LIVE: Global insights and key trends). It is projected that nearly 670 million people will continue to face hunger in 2030, which represents 8% of the global population. This is the same percentage as in 2015, when the 2030 Agenda was launched. (The State of Food Security and Nutrition in the World (SOFI). (2022)). Figure. 1 shows the Food Insecurity Index in various parts of the world (The State of Food Security and Nutrition in the World (SOFI). (2022)).

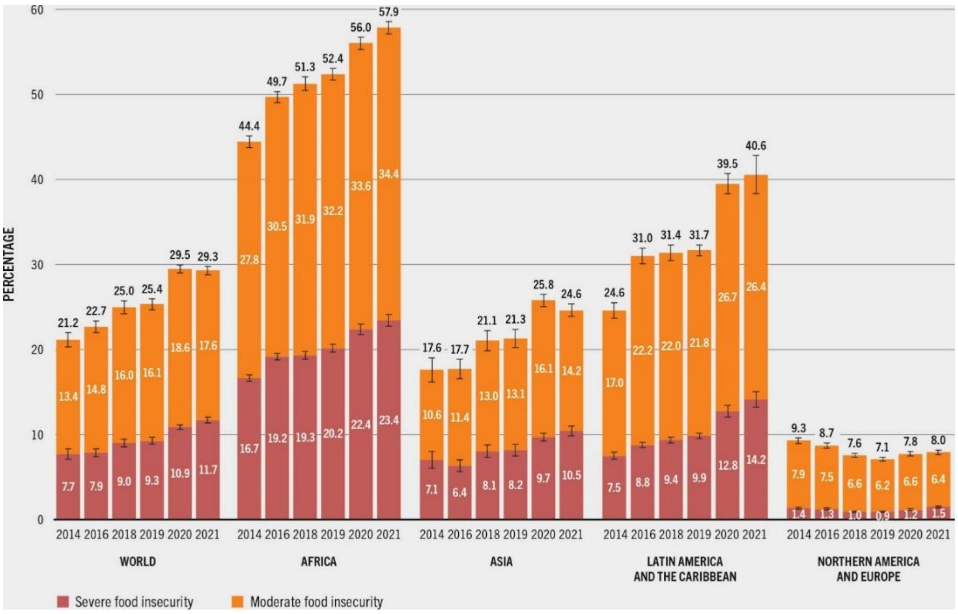


Figure 1: Food Insecurity Index

Agriculture has contributed to approximately one third of greenhouse gas emissions since 1850 due to improper and unsustainable land use practices. Soil organic matter (SOM) refers to the organic material present in soil, including plant and animal residues, living microorganisms, and humus. SOM plays a crucial role in soil health and fertility, as it contributes to soil structure, water-holding capacity, and nutrient availability.

One of the most important functions of SOM is its ability to store carbon. When plants photosynthesize, they take in carbon dioxide (CO2) from the atmosphere and convert it into organic matter. Some of this organic matter is incorporated into plant tissues, but a significant portion is returned to the soil through the process of decomposition, where it is broken down by microorganisms. This process of carbon sequestration can help to mitigate climate change by removing CO2 from the atmosphere and sequestering it in the soil. However, soil carbon stocks have been lost through various processes, including erosion, soil compaction, and the application of synthetic fertilisers. 133 gigatons of carbon have been emitted into the atmosphere since the beginning of agriculture due to loss of soil organic matter (SOM) and soil erosion (Lal R. 2018 , Sanderman et al. 2017 , Teague et al. 2016). 379 gigatons of carbon have been released through forest clearing and burning (Zomer et al. 2017). In general, cultivated soil has lost 50-70% of its carbon stocks (Zomer et al. 2017), and agricultural fields often contain less than 2% SOM (Beste, A. 2018), compared to 8-15% or more in grasslands or forests. If the soils of the world are not restored, carbon loss from soil heating could release 230 billion tonnes of carbon dioxide into the atmosphere, which is more than all of humanity's emissions in the last 30 years combined (University of Exeter, 2020).

Other problems include breakdown of peaceful social relations, loss of biodiversity, malnourishment and water scarcity. The areas of concern mentioned, along with other factors, are incorporated into the United Nations Sustainable Development Goals (SDGs). The SDGs provide a comprehensive plan for promoting peace and prosperity for people and the planet (Sustainable Development Goals, United Nations). Increasing SOM and revitalising soil will directly address four SDGs and indirectly impact eight other SDGs. It is important to prioritise these efforts in order to achieve the goals outlined in the SDGs and create a more sustainable future. Figure. 2 shows SDGs that are directly and indirectly addressed.

(a)

(b)

Figure 2: Increasing SOM and revitalising soil addresses (a) four SDGs directly, and (b) eight SDGs indirectly.

The objective of this research project to detect soil degradation over Karnataka between the years 2015 to 2019 by performing two change detection methods: change detection using index differencing, change detection using change vector index and change detection using ancillary data. Change detection method using index differencing with NDVI and BI can help detect soil degradation in a broader perspective as the indices that include vegetation cover and without vegetation cover can be visualised and compared. Change detection using change vector analysis consists of including the NIR, SWIR and Red bands to detect the areas of change. Change detection using ancillary data also includes other factors such as rainfall intensity and duration, land cover and information about the terrain and slope. This method would be much more comprehensive rather than using just indices that give information based on just a few factors. For instance, the two indices NDVI is sensitive only to changes in vegetation cover but not soil quality. An area with a low NDVI value might indicate a lack of vegetation, but it could also indicate a lack of water or nutrients, rather than soil degradation. Moreover, indices are affected by factors other than soil degradation, such as changes in weather or the timing of the image acquisition. Ancillary data can help to provide a more accurate assessment of changes in vegetation health. This is the reason of performing change detection using ancillary data so that other factors that impact the soil are also taken into consideration. Change vector analysis, on the other hand, does not rely purely on individual pixel values. The vectors of change, representing magnitude and direction of change, are calculated rather than just the comparison of pixel values.

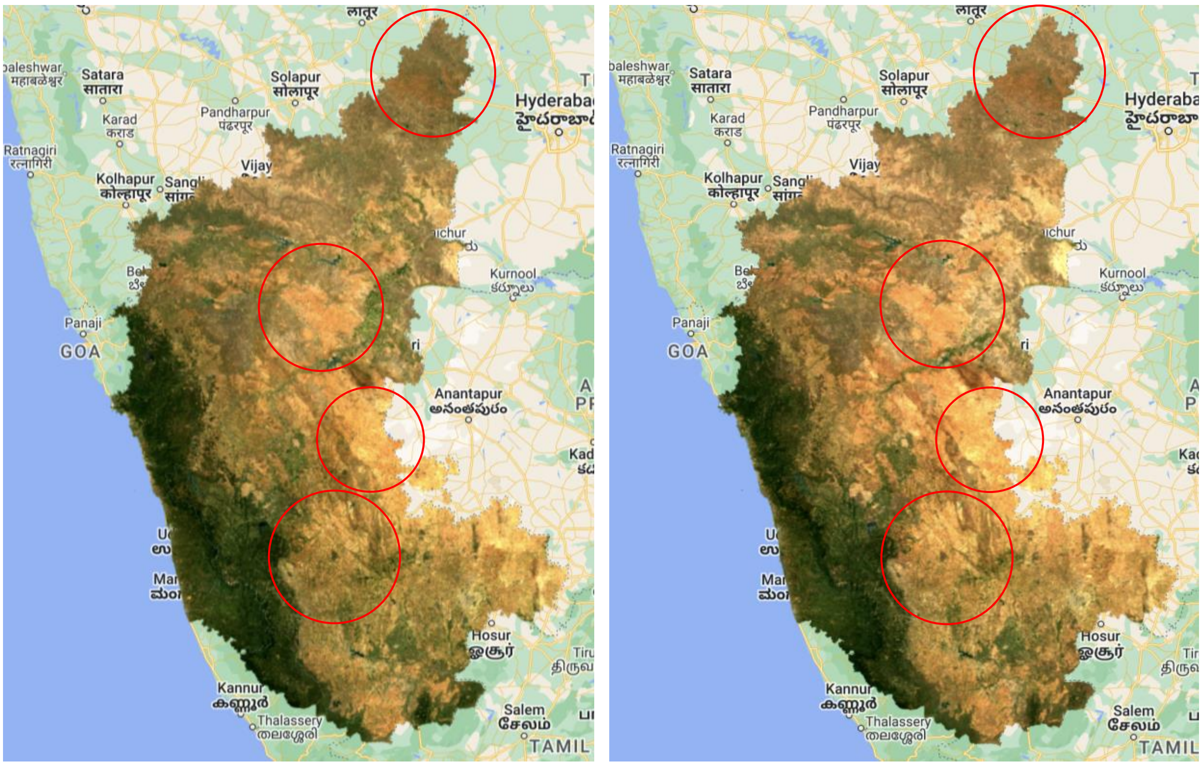
Materials and Methods

In India, approximately 120.72 million hectares of land are affected by various forms of soil degradation, with 82.57 million hectares being impacted by water-induced erosion at a rate of over 10 Mg $ha^{-1}yr^{-1}$. (Maji et al. 2010).

Amongst the various states in India, Karnataka is in the south with an area of 1,91,791 sq. km. Karnataka has four different regions as follows: western coast, the Western Ghats which are basically areas with high elevation, the Deccan plateau and the north eastern plains. An analysis of land degradation in the state of Karnataka found that 36.29% (6.96 million hectares) of the total area was experiencing desertification of soil degradation in the 2018-19 timeframe (Desertification and Land Degradation Atlas of India, ISRO, 2021). This represents a slight increase of 0.05% (8,847 hectares) from the 2011-13 timeframe and a 0.05% (10,057 hectares) increase from the 2003-05 timeframe, when the area experiencing soil degradation was 36.24% (6.95 million hectares) and 36.19% (6.94 million hectares), respectively (Desertification and Land Degradation Atlas of India, ISRO, 2021).

The USGS Landsat 8 Level 2, Collection 2, Tier 1 data in Google Earth Engine (GEE) was the satellite dataset used in this study because it provides high-resolution imagery that can be used to identify changes in land use, vegetation, and other features. The Landsat 8 sensor has 11 spectral bands, that includes two visible, four near-infrared, and five shortwave infrared bands. These bands can be used to analyse the different characteristics of an area and detect signs of soil degradation.

The time period of the entire study is considered over an entire year rather than one season due to a few reasons. Soil degradation can occur over time and can be affected by seasonal changes, such as precipitation and temperature. Additionally, certain types of soil degradation may be more apparent during certain seasons, for example, erosion caused by heavy rainfall can be much more evident during the rainy season, whereas dry spells can affect the vegetation growth which can be more visible during the dry season. Furthermore, considering different types of land use, different seasons may affect them differently. For example, crop fields may be more affected by soil degradation during the growing season. The repeat cycle is the time the satellite takes to reach the same spot on the Earth and take a new picture of the same area. This is every 16 days for Landsat 8. This means that the same area is visited just 22 times for an entire year. After passing the cloud mask, this could mean that some information could also be lost. For the above reasons, it does not seem to be a viable choice to consider the data for just one season. Figure. 3 shows the Landsat 8 images of Karnataka from 2015 and 2019. Over this time, there are multiple areas where the soil loss can clearly be seen. A few of the same areas have been marked in both images by a red circle to indicate the soil degradation.



(a) (b)

Figure 3: Landsat 8 image over Karnataka in 2015 and 2019

(a) 2015 (b) 2019

Change Detection Method Using Index Differencing

Change detection using index differencing is a method of identifying changes in an area of interest by comparing the value of the index in two or more images taken at different times. This method involves subtracting the values of an index calculated from one image from the values of the same index calculated from another image. The resulting "difference image" will highlight areas where there are changes in the index values, and hence changes in the area of interest. For this study, the indices NDVI and BI are used.

Using NDVI as the index

The Normalized Difference Vegetation Index (NDVI) is a widely used remote sensing index that measures the amount of green vegetation in an area. Change detection using index differencing with NDVI is a method of identifying changes in vegetation cover over time by comparing NDVI values from two images taken at different times. The difference image is created by subtracting the NDVI values of the first image from the NDVI values of the second image. Pixels that have increased NDVI values will have positive values on the difference image, while pixels that have decreased NDVI values will have negative values. This method allows to identify the areas where the vegetation has increased or decreased over time, which can be an indicator of soil degradation. It's important to note that NDVI only indicates the change in vegetation cover.

Krieger first proposed the following formula (Krieger et al. 1969)for calculating NDVI using Landsat 8 data :

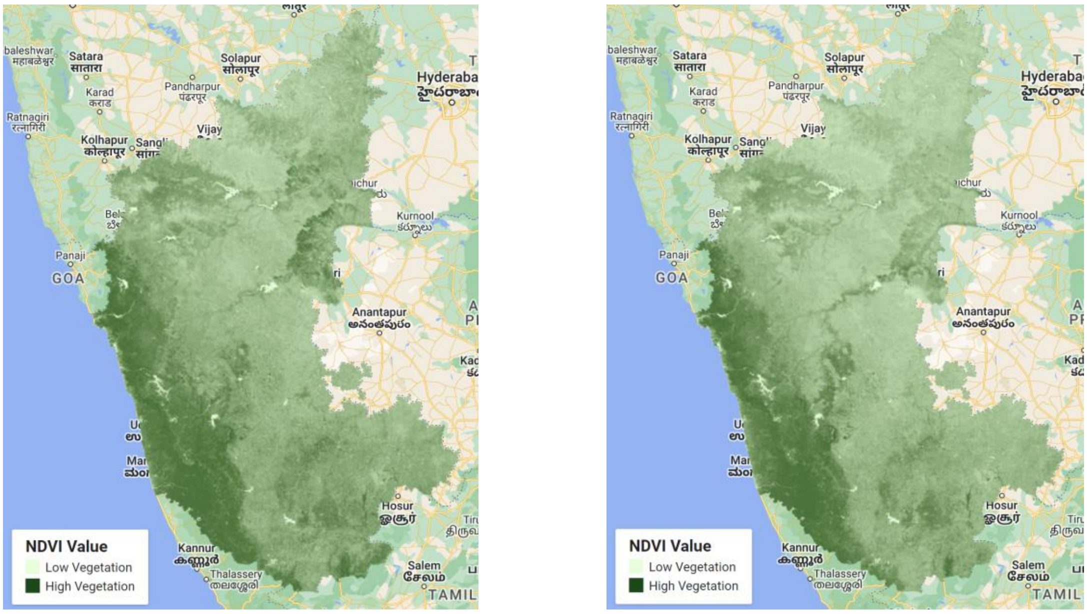
$$NDVI = \frac{NIR - Red}{NIR + Red}$$

Where:

NIR: value of the reflectance of the near-infrared band(B5)

RED: value of the reflectance of the red band(B4)

Band 5 is the NIR band and Band 4 is the RED band for Landsat 8. The normalised difference for the two bands were taken using the *.normalizedDifference* method. NDVI values range between -1 and 1, where values close to 1 indicate high vegetation cover and values close to -1 indicate bare soil or water. Figure. 4 shows the resulting NDVI images where Figure. 4(a) shows the NDVI visualisation from 2015 or the "Pre NDVI" and Figure. 4(b) shows the NDVI visualisation from 2019 or the "Post NDVI".



(a) (b)

Figure 4: NDVI over Karnataka (a) Pre NDVI in 2015, and (b) Post NDVI in 2019

Using BI as the index

The Bare Soil Index (BI) is an index used to monitor bare soil in the region. Change detection using index differencing with BI is a method of identifying changes in bare land cover over time by comparing BI values from two images taken at different times. The difference image is created by subtracting the BI values of the first image from the BI values of the second image. Pixels that have increased BI values indicate that the area has increased in bareness or decreased in the vegetation cover.

BI was calculated with the following formula:

$$BSI = \frac{(RED + SWIR) - (NIR + Blue)}{(RED + SWIR) + (NIR + Blue)}$$

Where:

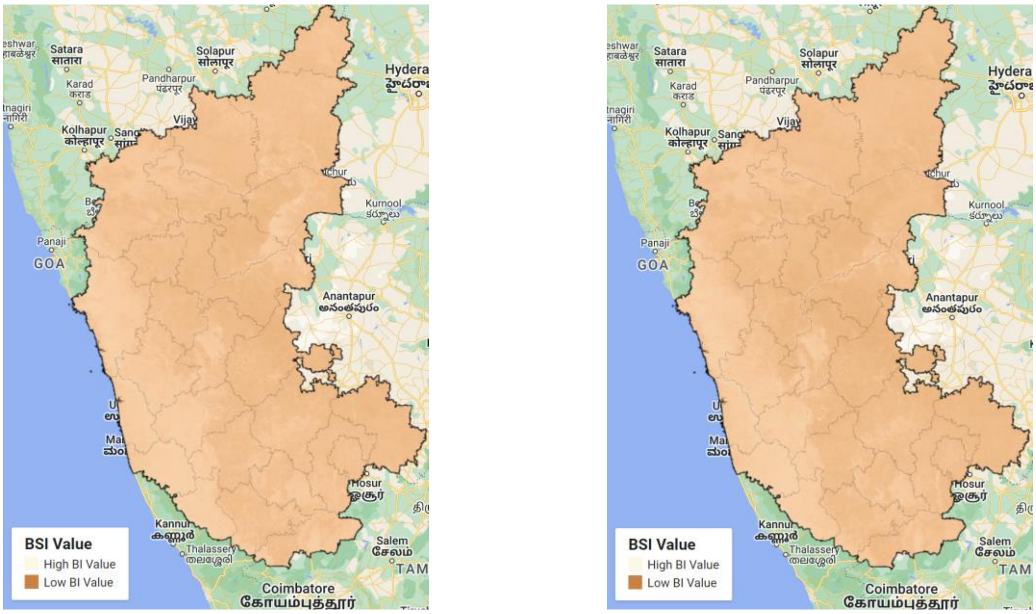
NIR: value of the reflectance of the near-infrared band(B5)

SWIR: value of the reflectance of the short-wave infrared band (B6)

RED: value of the reflectance of the red band (B4)

BLUE: value of the reflectance of the blue band (B2)

BI values range between 0 to 1, where 0 indicates the presence of high vegetation and 1 indicates the presence of barren areas with less vegetation. Figure. 5 shows the resulting BI images where Figure. 5(a) shows the BI visualisation from 2015 or the “Pre BI” and Figure. 5(b) shows the BI visualisation from 2019 or the “Post BI”.



(a) (b)

Figure 5: BI over Karnataka (a) Pre BI in 2015, and (b) Post BI in 2019

Change Detection Method Using Change Vector Analysis

Change Vector Analysis another method for identifying the type of change that has occurred in an area. This method utilizes all the available bands to quantitatively assess the magnitude and direction of changes in a given area. By representing the changes in a polar coordinate system, it can provide a comprehensive 2D characterization of the temporal dynamics in the study area. The parameters alpha and rho are used to quantify the change in an area over time. Alpha (α), is the angle of the change vector, representing the direction of change. In the context of soil degradation, a positive alpha value would indicate an increase in bare soil cover and a negative alpha value would indicate an increase in vegetation cover. Rho(ρ), is the magnitude of the change vector, representing the intensity of the change.

The SWIR, NIR and Red bands were chosen as they have different spectral characteristics and thus, can be used to distinguish between different types of vegetation and bare soil. Usually before performing change vector analysis, normalization must be done. Due to computational limitations in GEE, change vector analysis was done without normalization.

Change Detection Method Using Ancillary Data

Ancillary data, in the context of digital image processing, refers to information from sources other than remote sensing that is used to help with analysis and classification, or to provide additional information about the data being analysed. With respect to soil degradation, ancillary data can mean ground surveys carried out over the area of interest, weather data, demographic data, soil data, elevation information and even land use data. Ground data can provide insights about the type of vegetation and crops and the soil conditions of the area. Weather data, such as precipitation and temperature, can be used to understand the environmental conditions that may have led to the degradation of the soil. Demographic data, such as population density and land use patterns, can be used to understand the human impact on land cover changes.

Karnataka has several climatic zones, soil properties, slope, land cover and crop phase hence making it important to choose the right factors. Revised Universal Soil Loss Equation is the most widely used model for estimation of soil erosion, the factors, namely rainfall erosivity, soil erodibility, slope length and steepness, cover management and conservation practice. In this change detection method, the soil degradation is monitored by considering various factors for the varying landmass of Karnataka.

The Revised Universal Soil Loss Equation (RUSLE) (USDA 2022) is a widely accepted equation for predicting and assessing soil erosion. It is based on the principle that soil erosion is a result of the interaction between climate, topography, and land use. The RUSLE consists of six factors that contribute to soil erosion: rainfall erosivity (R), soil erodibility (K), slope length and steepness (LS), support practices (C), and erosion control practices (P).

The equation for RUSLE is as follows:

$$A = R * K * LS * C * P$$

Where:

A is the average annual soil loss in tons per hectare per year

R is the rainfall erosivity factor, measured in units of erosivity index in MJ * mm $\backslash$ ha * yr

K is the soil erodibility factor, measured in units of soil erosion index in ton * ha * h/ha * MJ * mm

LS is the slope length and steepness factor (dimensionless)

C is the cover management (dimensionless)

P is the conservation practice factor (dimensionless)

For performing this method, the entire duration from January 1st, 2015 to December 31st, 2019 was considered as RUSLE is used to estimate long-term soil loss due to erosion (IPBES Policy Support RUSLE). Factors like soil texture, structure, organic matter content, etc can vary over time due to a range of factors, including weather patterns, land use, and management practices. By considering the values of these factors over a full year, a more comprehensive view can be observed of the soil erodibility and how it may change over time. These values also vary for different regions accordingly which in turn indicates that various areas would have different values of the annual soil loss.

Rainfall Runoff Erosivity Factor (R)

The rainfall erosivity factor (R) is an important component of the Revised Universal Soil Loss Equation (RUSLE), which is a factor used for predicting and assessing soil erosion caused by rainfall and runoff. R measures the intensity and duration of rainfall events, which are important factors in determining the amount of soil erosion that occurs. The Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) dataset was used to obtain data on rainfall intensity and duration for the purpose of calculating R. The CHIRPS dataset is a widely used and well-respected global dataset that provides high-resolution rainfall data for a range of applications, including soil erosion modelling. R is measured in units of MJ * mm \ ha * yr., which stands for megajoules per millimetre per hectare per year. This unit of measurement reflects the amount of energy that is delivered by rainfall to the soil surface.

The following equation was used to compute the R factor proposed by Arnoldus (Arnoldus 1980).

$$R = \left(4.17 * \left(\frac{P_i^2}{P}\right) - 152\right)$$

Where:

P_i is the average monthly precipitation in millimetre

P is the average annual precipitation in millimetre

The average monthly precipitation was first calculated by iterating through each day from 2015 to 2019 followed by calculating the average annual precipitation in millimetre for every point in Karnataka. The R factor then generated by using the formula. A low R-factor value, represents a low erosive power of rainfall and low soil erosion potential. This could be due to a low amount of precipitation, or a low erosivity of the rain, which are dependent on the precipitation intensity, duration, and frequency. Figure 6 shows the visualisation of R Factor or the *R Factor Map*. It can be observed that, overall, the northern parts of the state experienced a decline in rainfall and thus results in low values of R. On the other hand, some parts in southern Karnataka have seen an overall rise in precipitation over the period from 2015 to 2019.

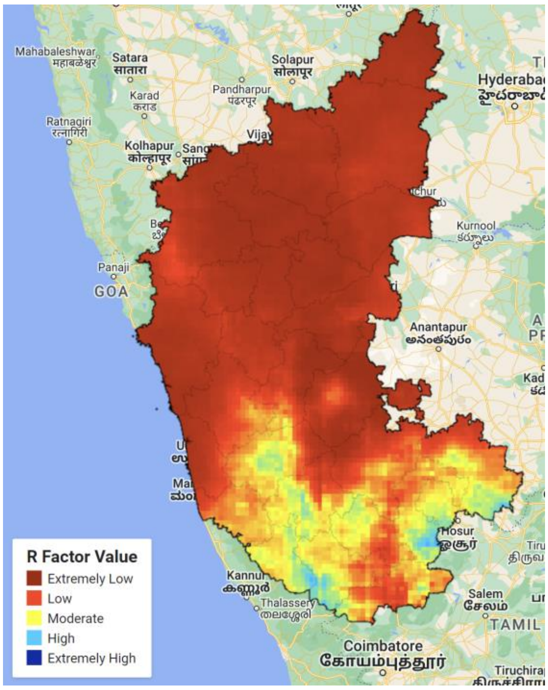


Figure 6: Rainfall erosivity factor map of Karnataka (2015 – 2019)

Soil erodibility factor (K)

The K-factor (Soil Erodibility Factor) is a measure of the resistance of soil to erosion caused by runoff and raindrop impact. Essentially, it represents the erodibility of the soil. K is measured in units $t\ ha\ h\ ha^{-1}\ MJ^{-1}\ mm^{-1}$, which stands for tons per hectare per hour per hectare per megajoule per millimetre. This unit of measurement reflects the amount of soil erosion that is likely to occur under the influence of a given amount of rainfall energy.

The OpenLandMap dataset contains information about the soil texture and erodibility in different regions. This dataset was selected and the *'b0'* band was chosen as it gives information of the 12 different soil types up to 0 cm. This soil texture class is then used to assign the K values for the various regions. This is calculated by using a series of if-else statements where the expression compares the values of the 'soil' band to specific ranges and assigns a K-factor value based on the range. The ranges and values used in the expression are based on the K-factor ranges proposed by Thammadi et al (Thammadi et al. 2022).

The K-factor value is dependent on several factors such as the soil texture, soil structure, soil organic matter content, and soil pH. Higher K values indicate lower resistance to soil. Sandier soils are typically more erodible than clay soils, and soils with higher organic matter content are typically less erodible than those with lower organic matter content. Figure. 7 shows the resulting *K Factor Map* that includes the type of the soil and the K value according to the soil type. Based on the K values, we can notice that most of the area from 2015 to 2019 has land with soil that provides enough resistance against erosion. A very small area towards the central east of Karnataka has soil of the sandy loam type. This could indicate that the area, compared to the rest of the state is far more susceptible to erosion.

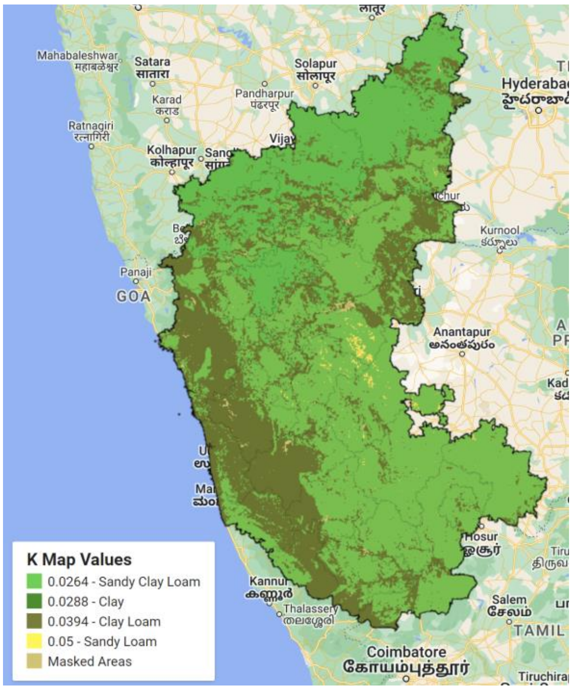


Figure 7: K Factor Map

Slope length and steepness factor (LS)

The slope length and steepness factor (LS) measures the effect of slope length and steepness on soil erosion. It represents the relationship between the slope gradient and the slope length, and it is used to estimate the total soil loss per unit area per unit time. The WWF HydroSHEDS Flow Accumulation dataset was used to obtain data on flow accumulation for the purpose of calculating LS. Flow accumulation is a measure of the amount of water that flows into a particular location, and is typically calculated using a digital elevation model (DEM). A DEM is a digital representation of the topography of a landscape, and is used to generate maps and three-dimensional models of the terrain. In this study, the WWF HydroSHEDS Hydrologically Conditioned DEM dataset was used to obtain a DEM for the purpose of calculating flow accumulation and LS. LS factor is essentially the ratio of soil loss per unit area from a field slope to that from a 22.13 m length.

The following equation, proposed by Moore and Burch(Moore and Burch 1986), was used to compute the LS factor:

$$LS = (\frac{\lambda}{\psi})^m \, (\frac{\sin\beta}{0.0896})^n \, Z$$

Where:

λ is the flow path length

ψ is 22.13 (SI units)

β is slope angle in radian

Z is 1

λ is the product of flow accumulation, which is a measure of the amount of water that flows into a given point in a watershed, and cell size. Here, according to the dataset used, the cell size value is 30. The slope angle was determined from the DEM using the function ‘ee.Terrain.slope’. Z or the rilling factor is based on the theory of unit stream power, which suggests that the amount of erosion that occurs is related to the energy of the flowing water and the characteristics of the soil and vegetation on the slope. This is used to account for the effects of small rills or channels that may form on the slope surface during erosion, which can increase the amount of erosion that occurs. According to Moore and Burch (Moore and Burch 1986) the value of Z can be taken as 1 or 1.4.

Figure. 8 shows the *LS factor map* of Karnataka from 2015 to 2019. Karnataka can roughly be divided into the coastal regions, the Western Ghats which are immediately adjacent to the coastal regions, the north eastern plains and the Deccan plateau. The Western Ghats are at a much higher elevation compared to other regions in the state. This indicates that this region is the steepest as well which in turn means that water flow is more likely to move downwards rather than remain stagnant. In the north eastern part of the state, however, the plains clearly show lesser slope as most of the areas are covered in red. In coastal areas, flow accumulation values may be affected by tides and storm surge, which can cause fluctuations in the amount of water flowing into the area. In the Western Ghats, flow accumulation values may be affected by changes in precipitation patterns and land use changes such as deforestation. In plains and plateaus, flow accumulation values may be affected by changes in land use such as agriculture and urban development, which can alter the natural flow of water in the area.

Two contradicting train of thoughts occur in trying to address the soil degradation and its relation with the slope and flow accumulation. High flow accumulation can lead to soil erosion and degradation, as the high volume of water flowing over the land can wash away topsoil and other soil particles. Additionally, as the water flows over the land, it can carry with it fertilizers, pesticides, and other pollutants which can contaminate the soil and make it less fertile. Soil erosion can lead to a loss of soil productivity, increased runoff and sedimentation and can even lead to landslides. On the other hand, low flow accumulation can also lead to soil degradation. The lack of water can cause drought, which can make it difficult for plants to grow and can lead to desertification. Also, in areas with low flow accumulation, the soil may become compacted, which can make it difficult for water and air to penetrate, making it difficult for plants to grow and for the soil to support life. No firm conclusions can be deducted with the help of just the LS factor but it can be one factor that plays quite an important role in order to deduce the final value, *A*, in the RUSLE equation.

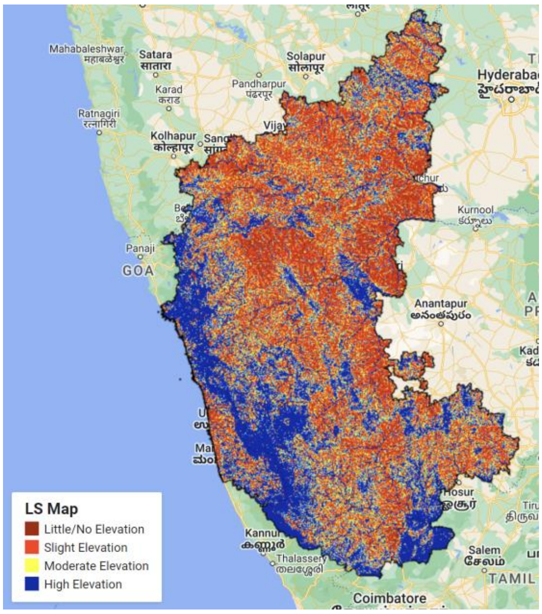


Figure 8: LS factor map

Cover management factor (C)

The cover management factor (C) is a measure of the protective effect of vegetation and cover on the soil. It is a dimensionless number that represents the percentage of soil surface covered by vegetation and other protective cover such as mulch. It takes into account several sub-factors such as the canopy cover, surface cover, surface roughness, prior land use, and antecedent soil moisture to determine the soil loss ratio. Research has shown that the C factor, along with the slope length and steepness factors, is particularly sensitive to soil loss (Benkobi et al. 1994; Biesemans et al, 2000).

To calculate the value of C, the NDVI values over the region for the time period has to be obtained. The MOD13A2.061 Terra Vegetation Indices 16-Day Global 1km dataset was used to calculate the NDVI by selecting the NDVI band. This results in a simple NDVI visualisation, as seen in Figure. 9. The greener areas show an increase in vegetation and the red and brown areas show a decrease in vegetation.

To generate the C factor with the help of NDVI, the formula proposed by Van der Knijff et al. (Knijff et al. 1999, 2000) was used and is as follows:

$$C = e^{-\alpha\left(\frac{(NDVI)}{\beta - NDVI}\right)}$$

Where $\propto$ and β are parameters to determine the shape of the NDVI-C Curve. According to Van der Knijff et al. (Knijff et al. 1999, 2000), an α-value of 2 and a β-value of 1 gives good results.

Figure. 10 is the *C factor Map* of Karnataka. A high C factor value can indicate that the potential for soil erosion is high and that the soil surface is not well protected by vegetation or other protective cover. In coastal regions, the C factor value may increase due to the presence of salt-tolerant vegetation, which typically has a lower density and less protective cover than other vegetation. In the Western Ghats, the C factor value may decrease due to the presence of dense vegetation cover and the use of conservation practices such as terracing and contour planting. In north eastern plains and the plateaus, the C factor value may decrease due to the presence of dense vegetation cover and the use of conservation practices. We can see that the Western Ghats and the coastal region are whiter compared to any other, indicating lower C factor values.

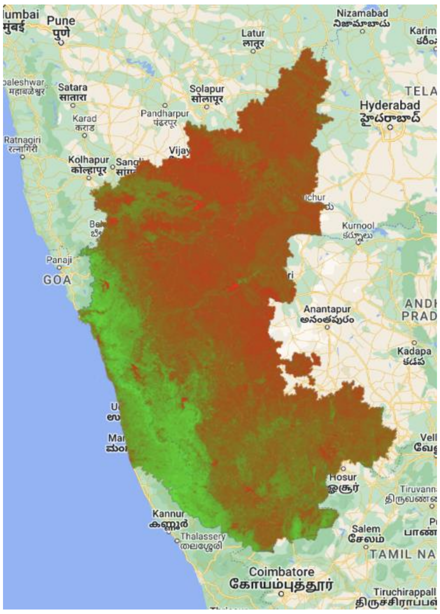


Figure 9: NDVI image from MOD13A2.061 Terra Vegetation Indices over Karnataka

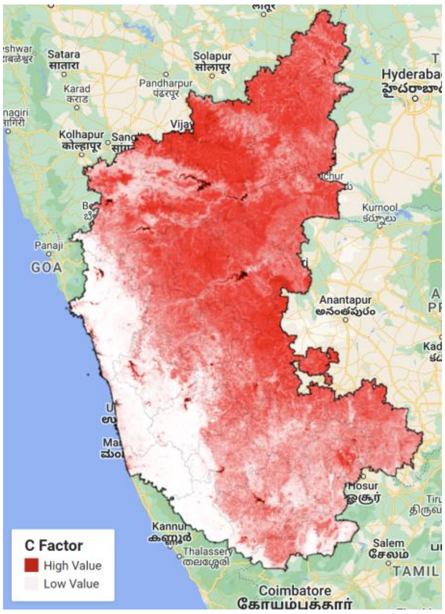


Figure 10: C factor map

Conservation or Support Practice Factor (P)

The erosion control practices factor (P) reflects the impact of different land management practices on soil erosion, such as conservation tillage, terracing, contour farming, and vegetative cover. These practices can be implemented on sloping or contoured land, and may involve changes to tillage practices or the use of vegetation to slow down and intercept runoff according to Wischmeier and Smith (Wischmeier and Smith 1957).

The P factor is often used in conjunction with land use and land cover maps to evaluate the effectiveness of conservation practices in reducing soil erosion. Land use and land cover maps provide information about the different types of land cover and land use in a given area, such as cropland, grassland, forest, and urban areas. By linking land use and land cover information with the P-factor, it is possible to estimate the soil erosion potential for different land use and land cover types. For example, cropland is typically more susceptible to erosion than forest or grassland, due to the fact that the soil is often exposed to runoff and is subject to intensive management practices such as tillage. By taking into account the land use and land cover information in conjunction with the P-factor, it is possible to identify the areas that are most at risk of erosion and to develop conservation plans that are tailored to specific conditions. Figure. 12 shows the land use land cover with the help of MODIS Land Cover Type Yearly Global 500m dataset. As the study area was not visited to observe the presence of any conservation practice, the value of P is assumed to be 1. (Ghosal and Bhattacharya 2019).

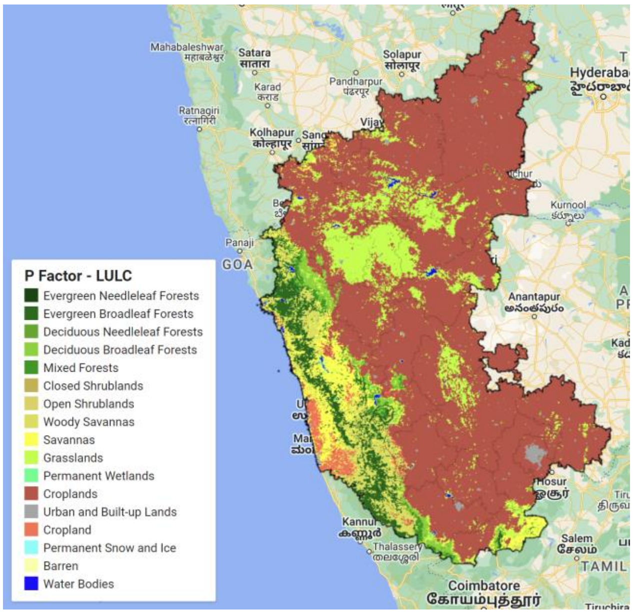
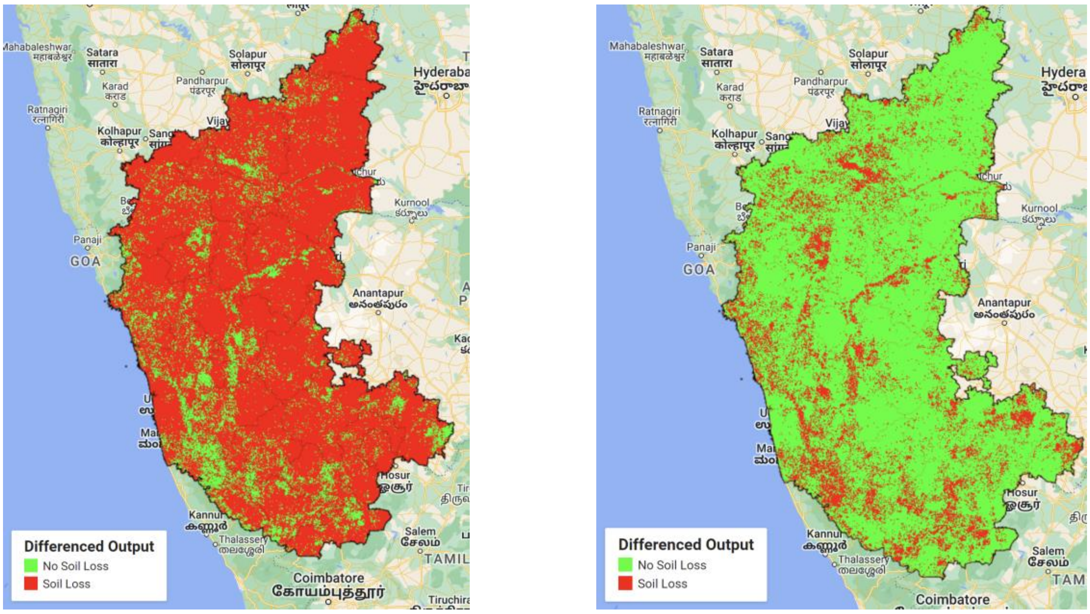


Figure 12: Land use land cover Map

Conclusions

Change Detection with Index Differencing

Figure. 13(a) and Figure. 13(b) show the differenced NDVI and BI result between 2015 and 2019 by performing change detection using index differencing, respectively.



(a) (b)

Figure 13: Differenced Output of Change Detection using Index (a) NDVI (b) BI

For the accuracy assessment, the ground truth is created by performing a visual analysis between the images, as shown in Figure 3. “Class 0” or the “no soil loss” class indicates areas that showed an increase in the greenness in 2019 compared to 2015. Not many polygons could be created for this class as it was fairly difficult as the changes in this scenario were not apparent. On the other hand, areas that are shown in the red circle in Figure. 3 and a few other areas where the loss of soil was visible were marked as “class 1” or “soil loss” class. These areas were much easier to detect however, detecting the severity of the losses would have been much more difficult. Figure. 14 shows the ground truth created. The results of NDVI and BI were binarized for this accuracy assessment. The values for the binarization were selected with the following process. Points from the different regions (Western Ghats, the coastal region, the plateau and the north eastern plains) were selected and the mean value of the differenced NDVI and differenced BI were calculated. These values would be the threshold for the respective indices. In this case, it is 0.17 for NDVI and -0.15 for BI. The results for NDVI and BI with this method are shown in Figure. 15 where Figure. 15(a) is for NDVI and Figure. 15(b) is for BI. 1000 pixels are sampled from each class to be used for NDVI and BI evaluation. For this, the *tileScale*, which is used to control the resolution, is set to 4 and *dropNulls*, which will remove any null values from the output, is set to true. The results are shown in Figure. 16, visualised over the binarized result. Figure. 16(a) is the NDVI result and Figure. 16(b) is the BI result.

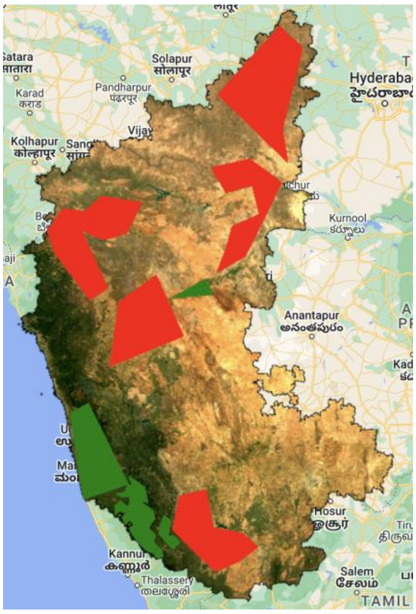
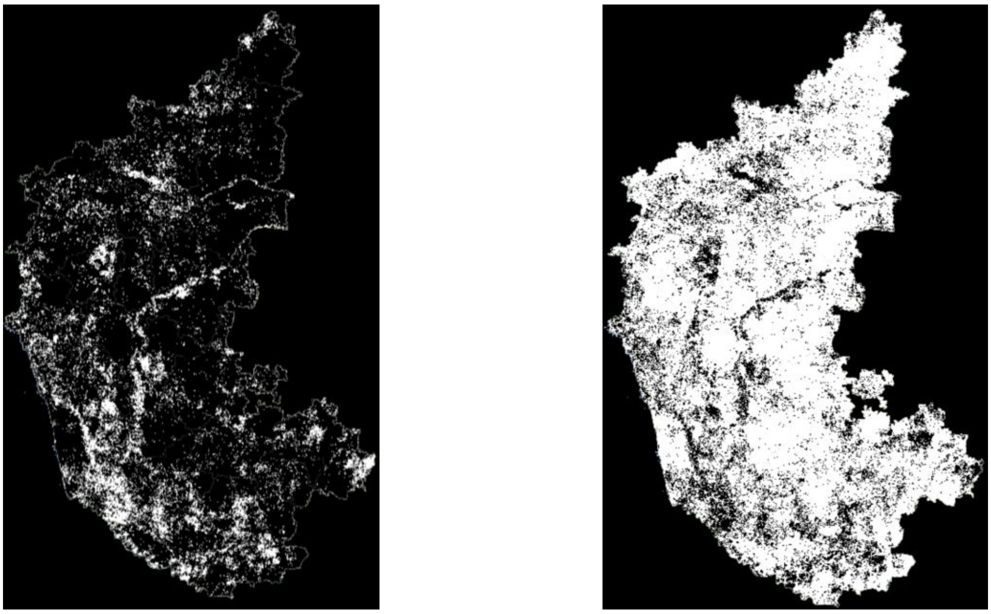
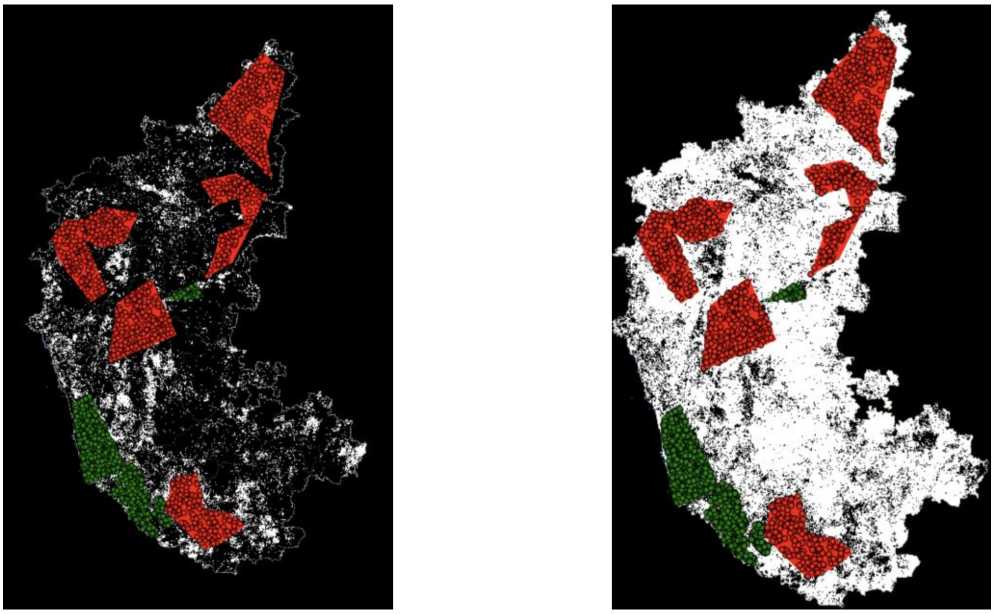


Figure 14. Ground truth for Change Detection using Index Differencing



(a) (b)

Figure 15: Binarized Results (a) NDVI (b) BI



(a) (b)

Figure 16: Class Samples over the Binarized Result (a) NDVI (b) BI

The overall accuracy when using NDVI as the index is ***0.3825*** or ***38.25%***. The consumer's accuracy is `[0.4161313347608851,0.3038397328881469]` and the producer's accuracy is `[0.583],[0.182]`. Table 1. shows the confusion matrix, when using NDVI. It can clearly be seen that more samples have been misclassified than being classified in the right category, which is the reason behind such a poor value for accuracy. This is also why the kappa has a value of -0.235, indicating that the agreement between the two sets of data is low. The values for precision, recall and f1 score are 0.182, 0.3038 and 0.2276 respectively.

Table 1. Confusion Matrix of change detection using index differencing - NDVI

	0	**1**
0	583	417
1	818	182

The overall accuracy when using BI as the index is ***0.603*** or ***60.3%***. The consumer's accuracy is `[0.6619496855345912,0.5755131964809385]` and the producer's accuracy is `[[0.421],[0.785]]`. Table 2. shows the confusion matrix, when using BI. The increase in accuracy shows that BI classifies more accurately compared to using NDVI as an index. This could possibly be due to the .The kappa value is 0.2059. The values for precision, recall and f1 score are 0.785, 0.5755 and 0.6641 respectively.

Table 2. Confusion Matrix of change detection using index differencing - BI

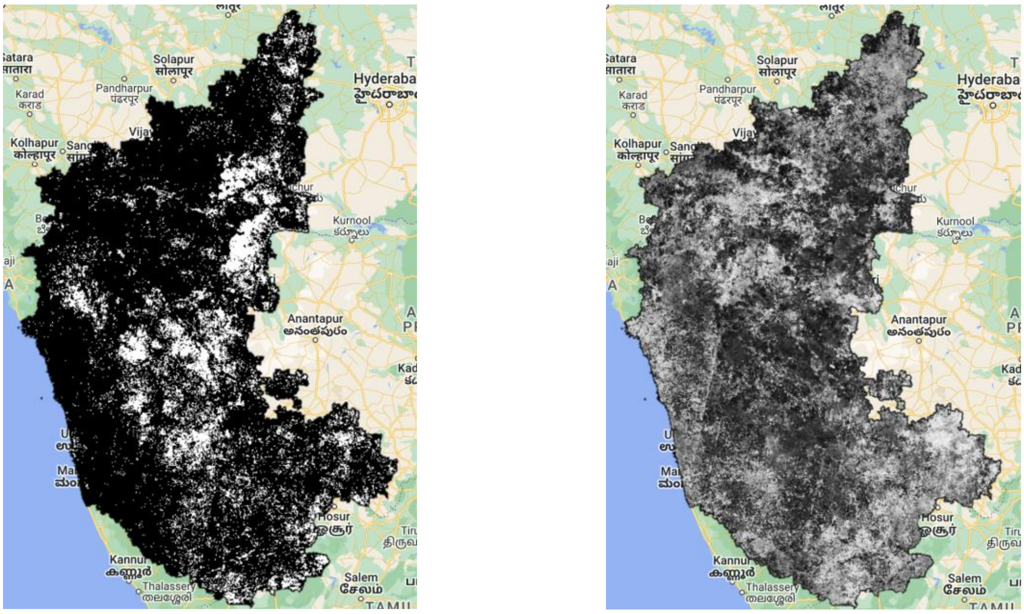
	0	**1**
0	421	579
1	215	785

We can observe that index differencing with BI performs better compared to NDVI. This could be due to the fact that BI is sensitive to bare soil whereas NDVI is sensitive to vegetation. As one of the indicators of soil degradation is areas with bare soil and lack of vegetation, BI is a better choice. BI is also not affected by the presence of dry vegetation, which can be misidentified as bare soil in NDVI.

For this change detection method in this study, the method to set the threshold value followed here is not reliable. An expert can perhaps help with what threshold values are to be set in order to binarize the results properly. More polygons being created could also help with increasing the accuracy.

Change Detection with Change Vector Analysis

The change in parameters rho and alpha was visualised as shown in Figure 17 where Figure 17(a) shows the change in rho and Figure 17(b) shows the change in alpha.



(a) (b)

Figure 17: Result of change in (a) Rho (b) Alpha

The ground truth remains the same as shown in Figure 14. The amount of soil change is shown by considering the magnitude or the value of rho. For the binarization of rho, as the value ranges from 0.86 to 52040, the median value was considered. The overall accuracy with this method is ***0.5005*** or ***50.05%***. The consumer's accuracy is [[0.6666666666666666,0.5002503755633451]] and the producer's accuracy is [[0.002],[0.999]]. Table 3. shows the confusion matrix. We can see that the class 1 samples are classified better than the class 0 samples. The kappa value is 0.0009999. The values for precision, recall and f1 score are 0.999, 0.5002 and 0.6666 respectively.

Table 3. Confusion Matrix of change detection using change vector analysis

	0	**1**
0	2	998
1	1	999

Change Detection with Ancillary Data

The RUSLE method classifies the value A into 5 different classes: *slight soil loss*(<10 t/hac/year), *moderate soil loss*(10 - 20 t/hac/year), *high soil loss*(20 - 30 t/hac/year), *very high soil loss*(30 - 40 t/hac/year) and *severe soil loss*(>40 t/hac/year). Figure 18 shows the classes from the RUSLE method. We can observe that most of the areas in Karnataka has undergone severe soil loss. Figure 18 shows a pie chart that summarizes the soil loss of the different categories that occurred in Karnataka from 2015 to 2019. The mean soil loss is estimated to be around 468.959 t/hac/year from 2015 to 2019.

For this method, if a similar procedure as the accuracy assessment for change detection method using index differencing is followed, classes have to be made for each of these categories. However, the changes between the classes are not easy to differentiate. For example, trying to highlight places with *high soil loss* and *very high soil loss* , by just visual inspection, is not easy as the differences are extremely subtle.

Due to this reason, an alternative approach was taken for the accuracy assessment. The classes *slight soil loss*, *moderate soil loss* and *high soil loss* were combined as one class for ***No Soil Loss*** and the classes *very high soil loss* and *severe soil loss* were combined as another class for **Soil Loss**. This also makes the results between the two change detection methods comparable. The output with this classification is visualised as seen in Figure. 19. Now that the classes have been binarized, a similar procedure as the first method can be followed. The ground data remains the same, as shown in Figure. 12.

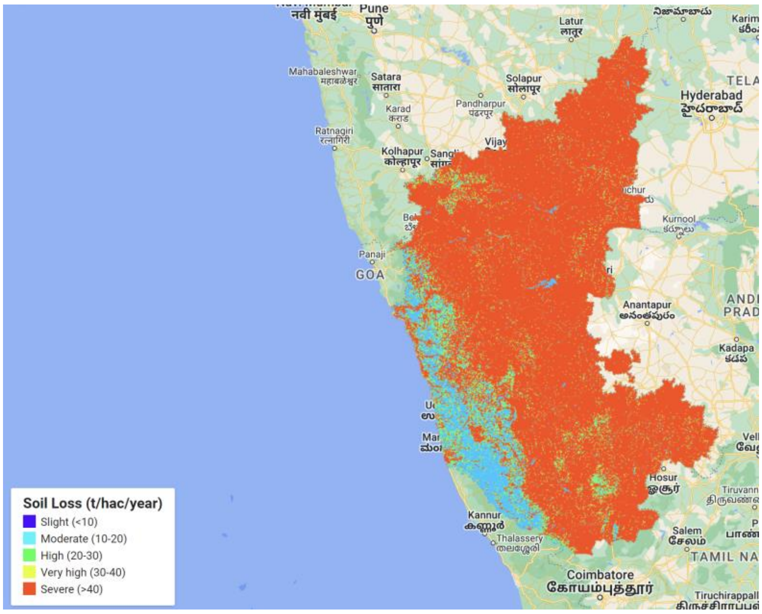


Figure 18: Soil Loss Classification Map

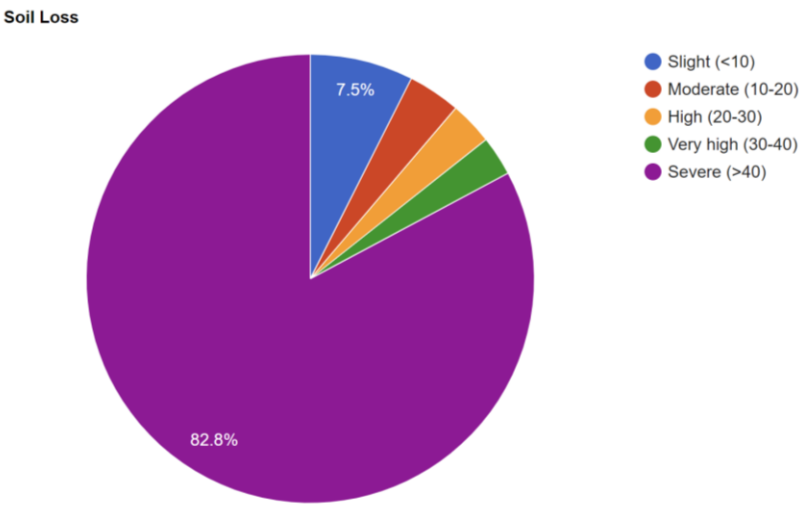


Figure 19: Percentage of soil loss for each category

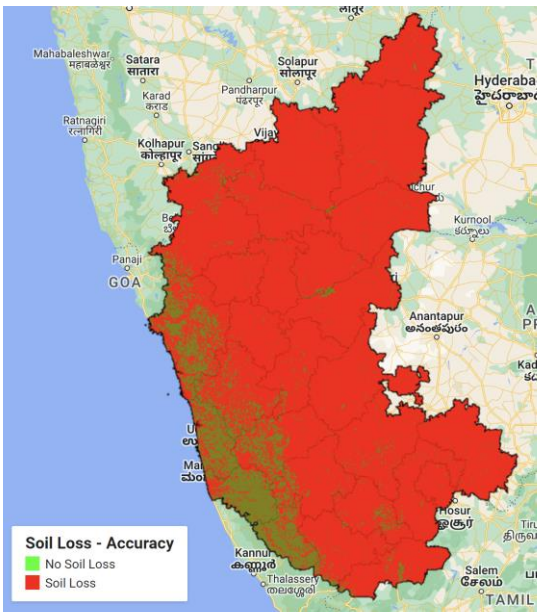


Figure 20: Binary Classes for Soil Loss using RUSLE

The results of the binarization can be observed in Figure. 20 where the areas in white show soil loss and the rest of the areas within the state imply that no soil loss has taken place.

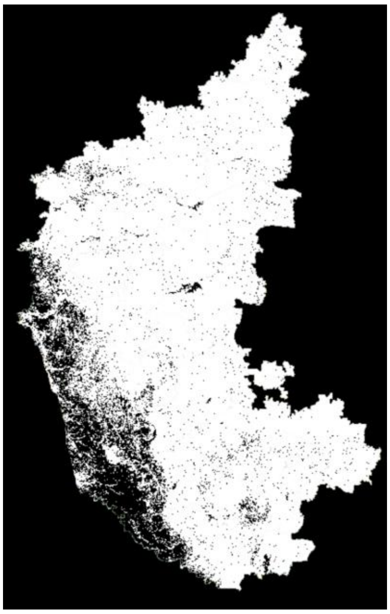


Figure 21: Binarized Results (a) No Soil Loss (b) Soil Loss

There are 2000 samples in total where 1000 represent soil loss and 1000 for no soil loss. The overall accuracy is ***0.763*** or ***76.3%***. The consumer's accuracy is [0.9472789115646258,0.6862606232294618] and the producer's accuracy is [[0.557],[0.969]]. Class 0 shows no soil loss and class 1 shows soil loss. Table 4 shows the confusion matrix for change detection using RUSLE for this class. The kappa, precision, recall and F1 score have values of 0.526, 0.969, 0.6862 and 0.8034 respectively.

Table 4. Confusion Matrix of change detection using ancillary data (RUSLE)

	0	**1**
0	557	443
1	31	969

With the results from the accuracy assessment, it can be concluded from this project that the **change detection method using ancillary data performs far better than change detection method using index differencing AND change detection using change vector analysis**. It can be argued that as normalisation was not performed for the change vector analysis, making it not comparable. However, we can infer that although soil degradation is related to the vegetation cover and bareness of the ground, it also depends on other factors such as the few that we have worked with in the ancillary data method.

Discussion and Future Work

Designing a system that can predict the real time soil loss would be far more useful than merely plotting the soil loss from previous time periods. Taking action in real time, however, supersedes everything. Without sustainable agricultural and lifestyle practices, soil degradation would continue to persist and worsen to the point of irreversibility.

Policy-level interventions are urgently needed to address the issue of soil degradation. The government should identify and protect fragile areas, and invest in watershed programs to improve the ecosystem. In order to effectively address this issue, it is necessary to prioritise and invest in conservation efforts.

The degradation of soil can lead to the most lethal domino effect which has the potential to wipe out masses of human existence. Soil degradation can have serious and far-reaching consequences for food production and human populations. As soil degrades, the nutrients and minerals that plants need to grow may become depleted, leading to decreased crop yields and lower nutritional value of the food produced. If soil degradation continues, it may eventually become completely infertile, leading to a loss of cropland and a reduction in food production.

This can put pressure on the population in the region, potentially leading to migration in search of food and resources. If the destination countries are not open to immigrants, this can create conflicts and potentially lead to war. If they don’t migrate, soil degradation can lead to famine, with billions of people dying due to a lack of food. Therefore, it is important to understand the causes and impacts of soil degradation and take steps to prevent and mitigate it to ensure sustainable food production and avoid potential social and political conflicts and loss of life.

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Link To Code

Change detection using Index Differencing:

https://code.earthengine.google.com/5e4594401a9413b3ef1cf2e82d5f7e1c

Change detection using Change Vector Analysis:

https://code.earthengine.google.com/73e6bb0e8c80807650e877b75629e6ec

Change detection using Ancillary Data:

https://code.earthengine.google.com/a546c5de7d028d2de7e7884051e95da4