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COURSEWORK COVERSHEET

Student ID number	2	0	1	9	0	2	5	3	8
Module code	GEOG5710M								
Module title	Digital Image Processing								
Assignment title	Oregon report								
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Declared word count	2445								

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Quantifying Forest Clearance and Vegetation Change in Sutherlin, Oregon, Using Multi-Temporal Satellite NDVI Analysis (1984–2019)

Abstract

Deforestation poses a significant environmental challenge globally, with adverse effects on biodiversity and ecosystem services. Remote sensing technology plays a crucial role in natural resource monitoring, particularly in detecting and quantitatively assessing green vegetation to monitor vegetation cover. (Dutta,2014).In this study, the extent and spatial distribution of deforestation in the Sutherlin region of Oregon, USA, were assessed using NDVI (Normalized Difference Vegetation Index) derived from satellite imagery of 1984, 1999, and 2019. The NDVI-based binary classification method enabled the identification of persistent forests, transitional areas, and non-forested zones. The results indicate that approximately 49.2% of the region maintained stable forest cover, while 47.7% underwent dynamic forest change, including deforestation and regeneration. The period from 1984 to 1999 saw substantial forest recovery, while the 1999–2019 period experienced notable forest loss. The study highlights the increasing landscape pressure due to deforestation and emphasizes the need for improved forest management practices and more robust conservation policies to ensure sustainable forestry in the region.

1. Introduction

Deforestation is a significant environmental issue worldwide. In Oregon, the main drivers of deforestation include overharvesting, the conversion of natural forests into industrial tree plantations, forest loss due to road and infrastructure development, and a long-term decline in land productivity (Talberth & Fernandez, 2015). These factors accelerate the depletion of forest resources and the degradation of the ecological environment, posing a threat to ecosystem health. Since forest ecosystems play a crucial role in maintaining ecological stability (Chazdon, 2008), understanding the long-term changes in forest cover is essential for effective environmental management and policy formulation.

The Normalized Difference Vegetation Index (NDVI) has been proven to be an important tool for monitoring land cover and vegetation changes (Viovy, Arino & Belward, 1991), effectively tracking forest changes such as deforestation, regeneration, and degradation. NDVI measures vegetation health and coverage by calculating the difference in reflectance between the red and near-infrared bands, and it is widely used in remote sensing to monitor forest health and vegetation changes (Kinyanjui, 2010). Areas with higher NDVI values typically represent healthy, chlorophyll-rich vegetation, while low or negative NDVI values usually indicate non-vegetated areas such as bare soil or water bodies. As plant cover increases, NDVI values rise, while they decrease as plants age and die (Viovy, Arino & Belward, 1991).

This study aims to quantify the extent and spatial distribution of deforestation in the Sutherlin region of Oregon between 1984 and 2019. By analyzing satellite imagery from three periods (1984, 1999, and 2019), this research uses an NDVI-based binary classification method to explore changes in vegetation cover in the region. The results will provide data support for understanding land-use pressures in the area and enhance the understanding of forest changes, offering valuable insights for land managers and policymakers in assessing sustainable forestry practices and planning future conservation measures.

2. Materials and Methods

2.1 Study Area

The study area is located in the Sutherlin region of Oregon, USA, with the area of interest (AOI) defined by the coordinates 423000–463000 E (East) and 4804000–4824000 N (North). Forests cover nearly 50% of Oregon's landscape, supporting the livelihoods of more than 61,000 people through forestry-related industries (Oregon Forest Resources Institute, 2019). Historically, this region's land use has revolved around intensive timber harvesting, where forest resources have been systematically managed for economic output. In recent decades, logging has become the main driver of land use change, resulting in both forest clearance and regeneration. In addition, infrastructure development such as road construction has contributed to forest fragmentation.

2.2 Datasets

This study utilizes multi-temporal satellite imagery from three sources: Landsat Thematic Mapper (TM) for 1984, Landsat Enhanced Thematic Mapper Plus (ETM+) for 1999, and Sentinel-2A for 2019. These datasets provide a comprehensive view of the study area over a span of nearly four decades. Landsat TM and ETM+ data provide a spatial resolution of 30 meters per pixel, while Sentinel-2A offers higher spatial detail, with a resolution of 10 meters for the visible and near-infrared bands used in NDVI calculation.

Before analysis, all images were pre-processed to ensure consistency across the datasets. The preprocessing steps involved atmospheric correction to mitigate atmospheric interference and geometric correction to rectify spatial discrepancies.

2.3 NDVI Calculation

Normalized Difference Vegetation Index (NDVI) was calculated using the red and near-infrared (NIR) bands, which are most sensitive to vegetation vigor and density. The NDVI formula is:

NDVI=(NIR-Red)/(NIR+Red)

For Landsat 5 and 7, NIR corresponds to Band 4 and Red to Band 3. For Sentinel-2A, NIR is Band 8 and Red is Band 4. All NDVI values were linearly rescaled to a 0–255 range for simplified thresholding and classification. A binary classification scheme was applied using an NDVI threshold of 224, above which pixels were classified as "vegetated" (0), and below as "non-vegetated" (1). This threshold was selected based on NDVI histogram distribution and manual inspection of known forested areas. A schematic overview of the NDVI processing workflow is presented in Figure 1.

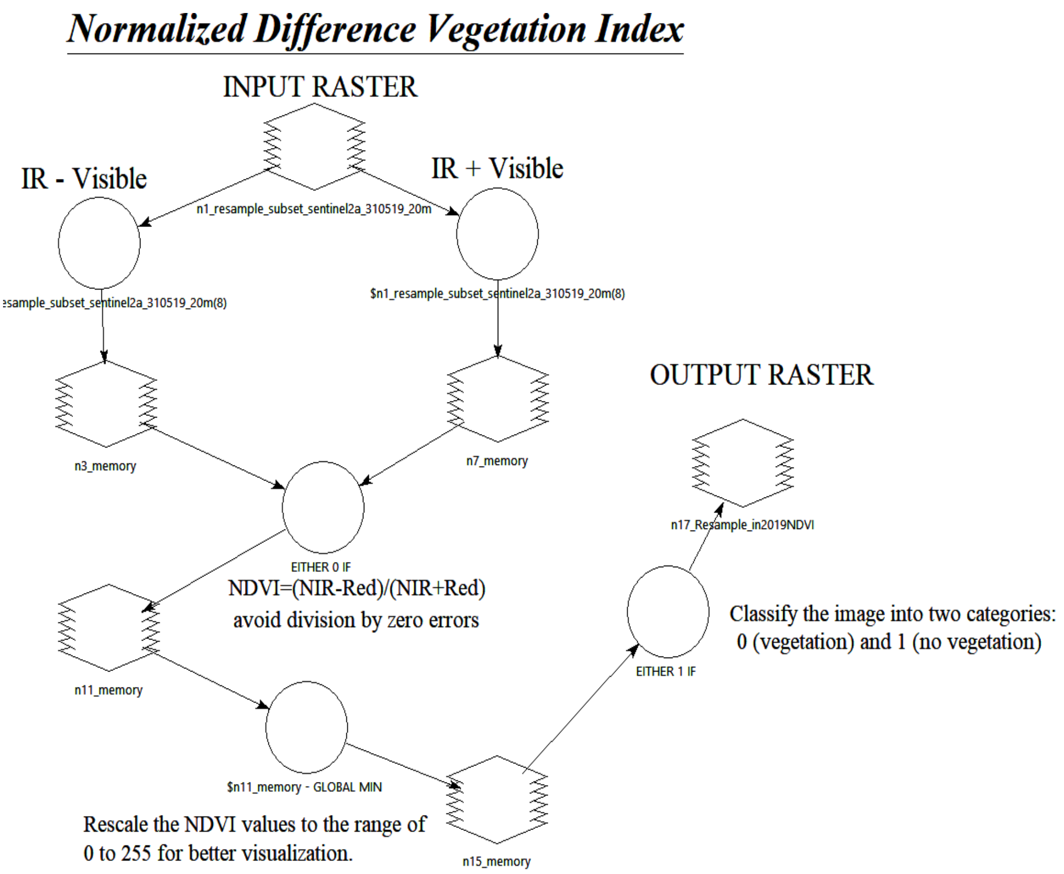


Figure 1. NDVI calculation workflow using red and NIR bands for Landsat and Sentinel-2A imagery.

2.4 Accuracy and Area Statistics

To assess cumulative vegetation dynamics, binary NDVI layers for 1984, 1999, and

2019 were summed using pixel-wise addition in the raster calculator. This produced a composite Summed Layer, with values ranging from 0 to 3, indicating the vegetation persistence or change status over the study period:

- Value 0: Forest present in all three years, representing areas of persistent vegetation cover (i.e., continuous forest);
- Value 1 or 2: Vegetation cover was present in some, but not all, years. These pixels represent areas that underwent land cover change, such as deforestation or regeneration;
- Value 3: Non-vegetated in all three years. These areas likely correspond to permanently non-forest land covers such as urban zones, water bodies, or barren lands and were excluded from further forest change statistics.

Based on the binary NDVI maps, total forest cover area was calculated for each time point (1984, 1999, and 2019). Forest change between the two periods—1984–1999 and 1999–2019—was quantified in terms of loss and recovery.

This classification enables spatial quantification of persistent forests and dynamic areas, facilitating further analysis of forest loss and gain. However, it should be noted that using a fixed NDVI threshold across multiple years may introduce classification uncertainty due to inter-annual variability, atmospheric conditions, and sensor characteristics.

3. Results and Discussion

3.1 Results

Using NDVI analysis from satellite images acquired in 1984, 1999, and 2019, forest cover changes in the study area were identified and classified. A cumulative NDVI binary layer (Summed Layer) was generated by summing pixel values from three time points. As shown in Figure 2, the spatial distribution of forest dynamics is summarized as follows:

- Persistent forest areas (value = 0): Approximately 49.2% of the land remained continuously forested throughout the study period, indicating stable forest cover;
- Transitional areas (value = 1 or 2): About 47.7% of the area experienced forest change in at least one time point, likely due to logging, degradation, or other anthropogenic disturbances;
- Non-forest areas (value = 3): Around 3.1% consistently fell below the NDVI

threshold, representing permanent non-vegetated land such as water bodies, urban zones, or barren areas, and were excluded from forest change analysis.

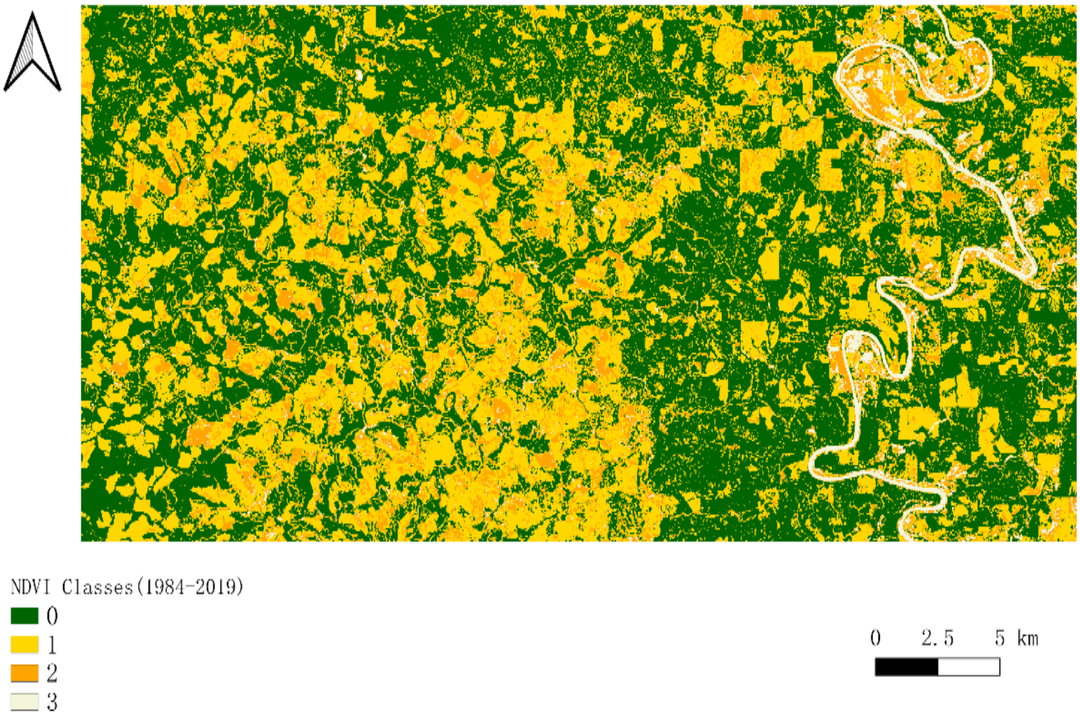
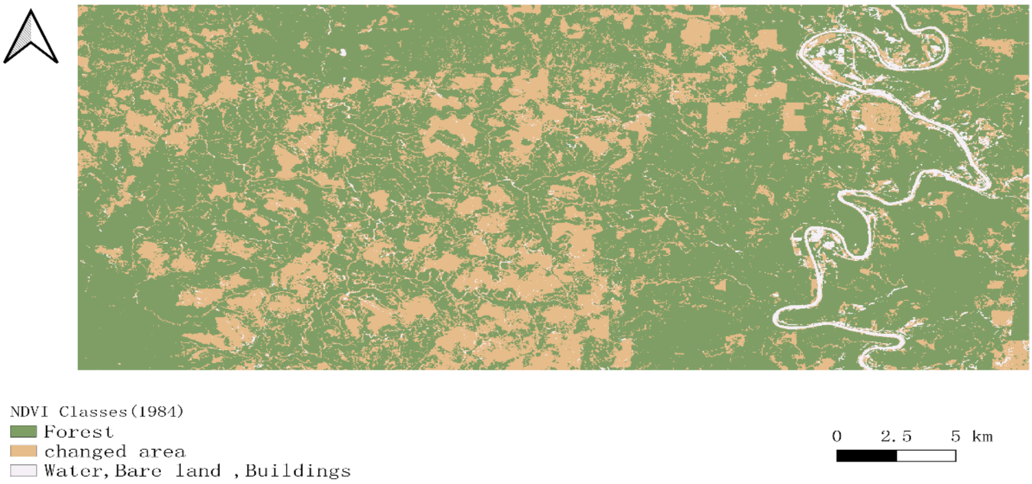


Figure2. illustrates the spatial pattern of cumulative NDVI values: green denotes persistently forested areas (value = 0), orange and yellow represent transitional zones (value = 1 or 2), and white indicates permanent non-forest land (value = 3).

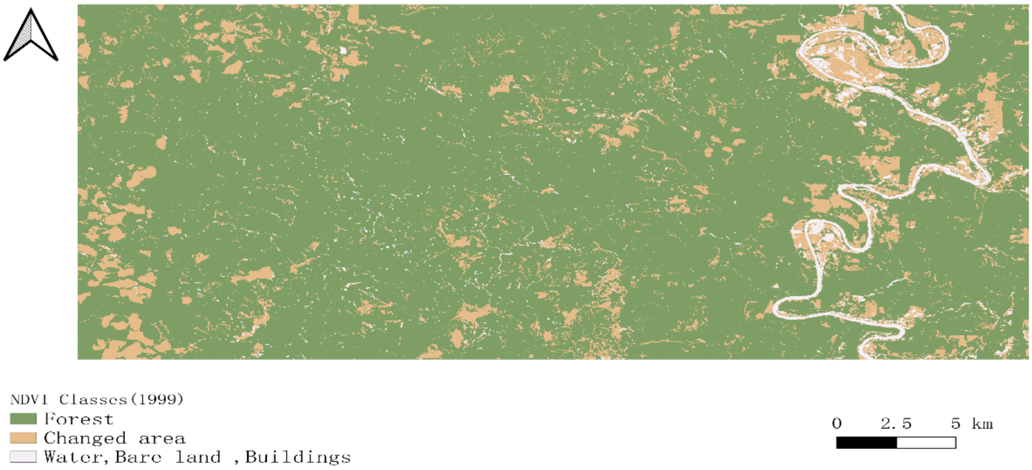
Further comparison of forest change between the two periods reveals notable differences (as shown in Figure 3):

- **1984–1999:** Forest change affected approximately 10,819.6 hectares, with extensive regrowth observed. The net change in forest cover was **-19.1%**, indicating that regeneration dominated this period;
- **1999–2019:** Forest change covered about 5,456.1 hectares, characterized mainly by forest loss. The net forest loss rate was **8.1%**, reflecting a substantial decline in vegetation cover.

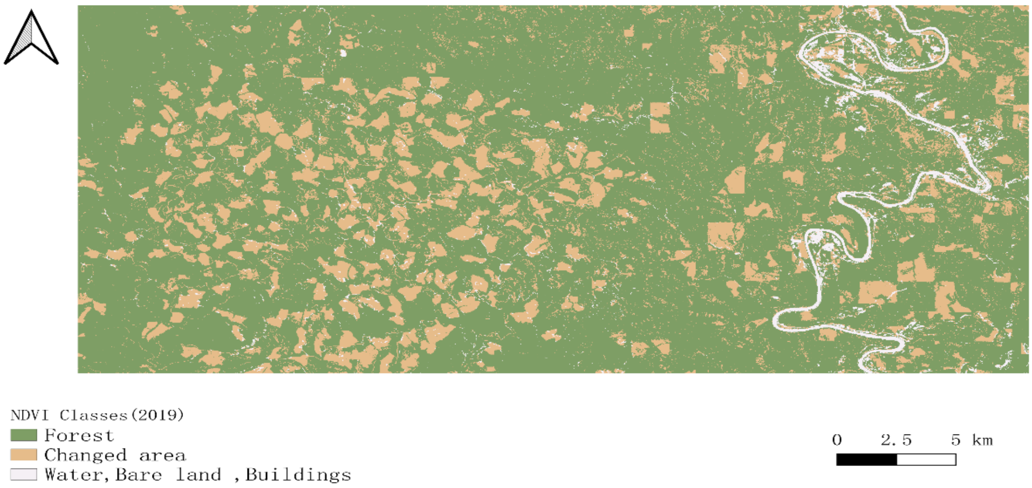
Overall, while nearly half of the study area maintained consistent forest cover across the 35-year period, the remaining land experienced dynamic transitions between forest loss and recovery. In particular, the 1999–2019 period showed a marked reduction in forest area, highlighting increasing landscape pressure and intensified human impact in recent decades.



(a)



(b)



(c)

Figure 3. NDVI-based forest classification maps of the study area in (a) 1984, (b) 1999, and (c) 2019. Green areas represent persistent forest cover, brown areas

indicate regions where vegetation change occurred (either due to logging or regrowth), and white areas represent non-forest land, such as urban, water bodies, or bare soil. The spatial patterns highlight a notable forest recovery between 1984 and 1999, followed by a significant forest loss from 1999 to 2019.

3.2 Discussion

The results of this study reveal the trend of forest dynamics in the Sutherlin area of Oregon over the past 40 years. First, the existence of persistent forest areas (approximately 49.2%) suggests that forest cover in the region has remained relatively stable, possibly due to certain protective measures or natural regeneration processes. However, nearly half of the area (approximately 47.7%) experienced changes, indicating that the forest cover in the region has been subject to varying degrees of disturbance during this period.

From 1984 to 1999, there was large-scale forest recovery in the study area (about 10,819.6 hectares). This recovery could have been influenced by several factors, including improved forest management practices, natural regeneration, and possible policy changes. The negative forest reduction rate (-19.1%) during this period indicates that, despite some periods of deforestation or degradation, recovery dominated the landscape.

However, from 1999 to 2019, there was a noticeable reduction in forest area (net loss of 8.1%). This suggests that, although some recovery occurred, deforestation and degradation intensified in the late 20th and early 21st centuries. According to existing studies, more than 4 million acres of natural forests in Oregon have been converted to industrial plantations (Oregon Forest Resources Institute, 2019), a trend that may have negative impacts on the stability of forest ecosystems and biodiversity. Additionally, factors such as industrialization, agricultural expansion, and climate change could have exacerbated the reduction in forest cover in this region.

3.3 Implications

The Oregon Forest Resources Institute (2019) pointed out that forest cover changes in Oregon are closely related to climate change, land use policies, and forest management practices. However, the pressures of deforestation and degradation remain. To ensure the sustainable use of forest resources in the region, it is recommended to adopt stricter forest protection policies and strengthen the regulation of deforestation. Additionally, promoting natural restoration projects and enhancing forest management, especially to prevent illegal logging and overexploitation, is crucial for achieving forest conservation goals.

3.4 Limitations

The NDVI method has proven to be a valuable tool for detecting changes in forest cover (Dutta, 2014). One of its main advantages is its ability to effectively reflect vegetation health and land cover changes. However, the NDVI method also presents certain limitations that should be taken into account. It is sensitive to atmospheric conditions, including cloud cover and shadows, which can introduce significant errors into the analysis. To address these challenges, integrating advanced techniques such as the Multi-date Data Differencing (MDD) algorithm has been suggested to improve deforestation detection accuracy under such conditions (Candra, 2020). Furthermore, NDVI often struggles to distinguish between different vegetation types or land covers. For instance, it may not effectively differentiate dense forests from low-density vegetation, potentially resulting in misclassifications of specific forest types or land uses. In areas experiencing extreme drought or those containing large water bodies, NDVI values may also become unreliable, as the index is less effective in separating non-vegetated surfaces from sparse or stressed vegetation. My threshold selection was based on the calculated average NDVI value. However, the method of manually selecting thresholds has its limitations, as it does not account for the varying characteristics of different regions and time periods. A fixed threshold may not accurately reflect the vegetation conditions in specific areas, leading to a decrease in classification accuracy, especially in regions with diverse vegetation types or complex environmental conditions.

4.Conclusion

This study provides valuable insights into the forest dynamics of the Sutherlin region in Oregon over the past 40 years, utilizing NDVI analysis of satellite imagery from 1984, 1999, and 2019. Key findings include:Nearly half of the study area (47.7%) experienced changes in forest cover, with significant forest regeneration observed between 1984 and 1999. However, the period from 1999 to 2019 saw a marked decline in forest cover, indicating a shift toward increased deforestation.

The NDVI and ERDAS modeling approach proved effective in quantifying forest cover changes and providing a spatially explicit view of vegetation dynamics. In this study, we used the Model Maker tool in ERDAS Imagine software to build a processing model for NDVI calculation and forest change analysis, which improved analysis efficiency and reduced human errors through automation, ensuring the effectiveness and accuracy of data processing. This method can serve as a valuable tool for long-term forest monitoring.

The results underline the need for continued monitoring and proactive forest management strategies. While the region has seen substantial recovery, the ongoing pressure from deforestation and land-use changes calls for stricter forest protection measures, sustainable land management practices, and enhanced regulatory frameworks to mitigate further degradation. Additionally, promoting natural regeneration and addressing illegal logging will be crucial for maintaining forest ecosystem stability.

5.Reference

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