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FIS TOOLBOX – A GEOPROCESSING FRAMEWORK FOR PREDICTING CLIMATE CHANGE WITH SPATIO-TEMPORAL DATABASE

Dr. C. Rajabhushanam

Professor CSE, Bharath Institute of Science & Technology, Bharath Institute of Higher Education & Learning

rajabhushanamc.cse@bharathuniv.ac.in

Abstract

Fuzzy Inference Engine is a framework that develops a rule base for performing spatial segmentation of objects in Satellite Imagery, Landsat-8. The engine is implemented using concepts and principles of Fuzzy Inference and Hierarchical Scale Space with a detailed set of computer vision algorithms in java, for the delineating of objects in a given scene. This geoprocessing toolbox is referred to as Fuzzy Inference System (FIS). Geo-processing and Geo-computation are two major research areas in computer vision and pattern recognition that are driving the concepts in High-Performance Satellite Imagery processing and machine learning. In the geospatial domain there are not detailed research methodologies developed for Landsat-8 Thematic classification using state-of-art Digital Image Analysis techniques. In this research endeavor, we propose and implement a Geo-computation toolbox for edge boundary detection, feature sampling and Laplacian of Gaussian Smoothing, Hierarchical Scale Space Generalization with higher level Specialization for multi-scale analysis, Image Compression with Pyramid Tiling, Scene objects delineation with Region contouring and labelling, and finally, computation within R Statistical Software. Multivariate image statistics are derived for understanding of the inherent geometrical and pattern recognition feature objects. Specifically, Spatial Autocorrelation, spatial feature variation using variograms and change detection visualization in vegetation with Normalized Difference Vegetation Index. Initial results are encouraging with an intent of developing subsequent version of the toolbox using data science fundamentals.

Key words: Geocomputation Toolbox, Geoprocessing framework, NDVI, LAI, Multivariate statistical modelling, Landsat-8 Satellite Imagery, Multi-Scale analysis, Region labelling and Blobs, Spatio-Temporal databases.

Introduction

In Geo-spatial distributed applications, climate change detection are considered as land use and land cover change information such as deforestation, incident damage assessment, environmental monitoring, urban expansion and land management. The climate change detection frameworks use multi-temporal datasets to study the large temporal frequencies with synoptic views. The fundamental theme behind remote sensing data for change detection is that changes in the region-of-interest, will alter the spectral values (reflectance value or local texture). Statistical explanation to the spatial distribution of the pixels in the image are computed for settlements which have higher texture value compared to the non-settlement regions. By measuring relative frequency of the spatial adjacency minimizes the impact of using multi-sensor images.

With advent of Earth Observation studies from various high resolution satellite image sensors, it has become imperative to focus on one platform for conducting detailed validation and verification of algorithms and models. Developing computer vision algorithms for applications in high performance and high resolution remote sensing, is possible by scaling the spatial resolution from 5m to 30m. With the Landsat-8 platform, multi-spatial and multi-temporal datasets are available periodically for the design, build and operate of complex algorithms for in-situ earth observation. Several researchers have employed the Landsat series of sensors for change detection and spatial phenomena understanding. The results are promising and extend to the Big-Data area of processing and computing in geospatial applications.

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By conducting detailed analysis with Landsat-8 sensor imagery for chosen region of interest (ROI), previously unknown hidden patterns become distinct from geo-visualization based open-source software configuration items. With reference to recent publications in Geographic Object Based Image Analysis (GEOBIA), change detection and segmentation of objects in scenes, is performed automatically using complex algorithms in machine learning, computer vision, and digital image analysis. The scale of variation in output result sets has become finer and finer with resolution varying from 30m-10m-5m-1m. Previously unknown spatial phenomena can now be delineated accurately with remote sensing imagery from high performance computer studies/models. Thus, from research employing 30m spatial datasets with high spatial and temporal variations, we can confidently predict scale-space-time-duration (climate change) events and their importance to Geo-computation in big data.

By using spatio-temporal database technologies such as MySQL, it has become imperative to extend geoprocessing of active scenes to the cloud domain with data-science. While using the toolbox for the determination of climate change, feature objects are merged and splitted to form super-regions and super-objects within distinctive clusters. For now, only unsupervised machine learning techniques have been implemented.

Spatial data mining of remote sensing images permits us to search through Big Data datasets for spatio-temporal distributed or delineated patterns. We can perform feature identification, feature selection and feature extraction knowledge for classifying relationships with advanced clustering and region growing operations. Multiscale object-based approach is more appropriate for the chain of operators that process the image data sets, resulting in varying object (regions) size and shape.

Fundamentally, a segmentation process partitions the input imagery dataset into homogeneous objects that are spectrally similar and spatially produced adjacent regions. The within class variance is minimal compared with inter-object variations due to hierarchical scale space transformation and local variance of image data. Image-object change detection, Class-object change detection, multitemporal object change detection and hybrid change detection techniques in GEOBIA are measured on layer features, shape features and nearest neighbor relations with object-class membership.

Literature Review

There have been fundamental research in methods and technologies that encapsulate the majority of research in Geocomputation. Gahegan (1999) notes that the right framework for enabling technologies is a fusion of four areas in geocomputational research. Computer Architecture and design; search, classification, prediction, and modeling, knowledge discovery, and visualization. They are not mutually exclusive and are interrelated, but differ in the core algorithms. The advances made in spatial data mining are documented in the book by Miller and Han (2009). Significant hurdles remain in scalability, interoperability, visualization of spatio-temporal patterns and validation (Andrienko et al., 2007).

Space-time variations in deriving covariance structures and auto-correlation gray area studies have stressed the importance of interpolation and prediction techniques (Heuvelink & Griffith, 2010). Machine learning techniques are applied to a wide range of problems such as classification, clustering, automated segmentation and evidence related studies. Artificial neural networks are potentially useful in modelling hidden complex dependency structures inherent in spatio-temporal datasets that may not be described using traditional statistical methods. Kanevski, Timonin, and Pozdnukhov (2009) and Hsieh (2009) have applied innovative types of ANN to environmental remediation problems.

High Performance computing (HPC) has a pivotal shift from deductive science to inductive in data science studies and has the ability to implement and model techniques and methods from computational science (Armstrong 2000). There are two paradigms in HPC, namely Grid distributed computing and cluster computing. Both methods introduce massive parallelization of computationally intensive tasks. (Wright and Wang 2011).

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Methodology & Results

We adopt the enabling technologies of (i) computer architecture and design, (ii) search, classification, prediction and modelling, (iii) knowledge discovery (spatial data mining) and (iv) visualization. These techniques represent the key tasks of geocomputation. Also, we need to focus on geovisual analytics to produce output that is meaningful and interpretable. Geostatistical approaches that are based on machine learning can be extended to the geocomputation core areas by deriving space-time covariance structures and semivariogram for forecasting of the observed variability.

Using existing Java Standard Edition (J2SE), ImageJ (benchmark Image Analysis Software) and proprietary java enabled algorithms, a toolbar of algorithms is implemented. The proposed system is a toolbox dedicated for image analysis, region detection, feature extraction, and knowledge discovery using Fuzzy Inference System (FIS). See Figure 1 and Figure 2.

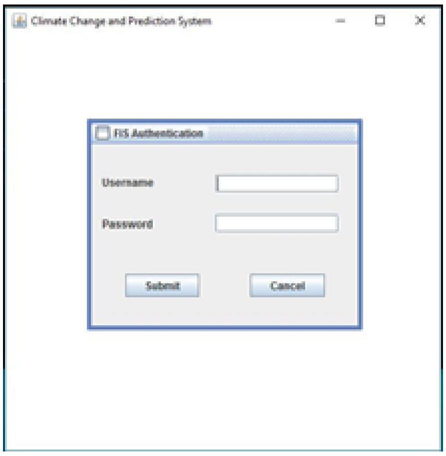

Figure 1: FIS-Toolbox Authorization

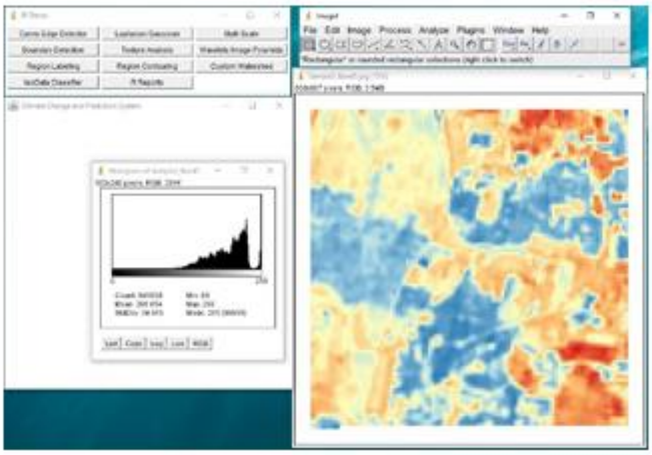

Figure 2: Typical workflow in FIS

Image Analysis Toolbox Operators

(i) Edge detector with boundary demarcation for usage of feature objects that have sharp transitions – Canny Edge Detector.

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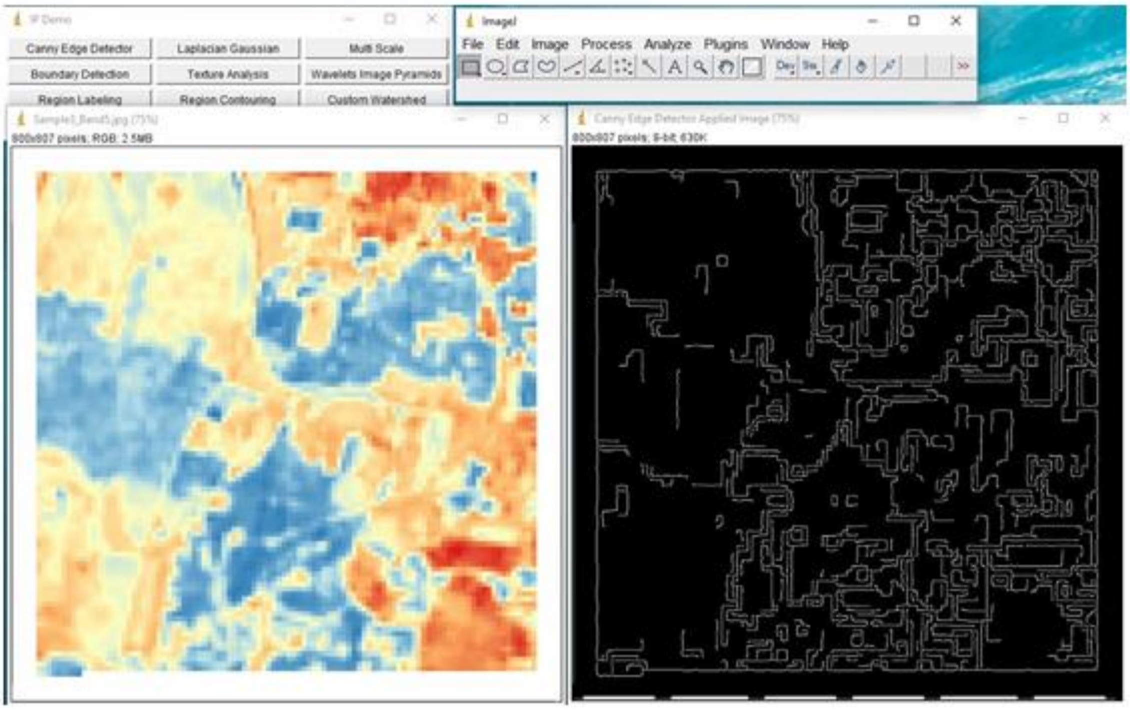

Figure 3: Customized Canny Edge Filter Applied

(ii) Image region smoothing with zero crossing detector for identification of objects with Laplacian of Gaussian operator.

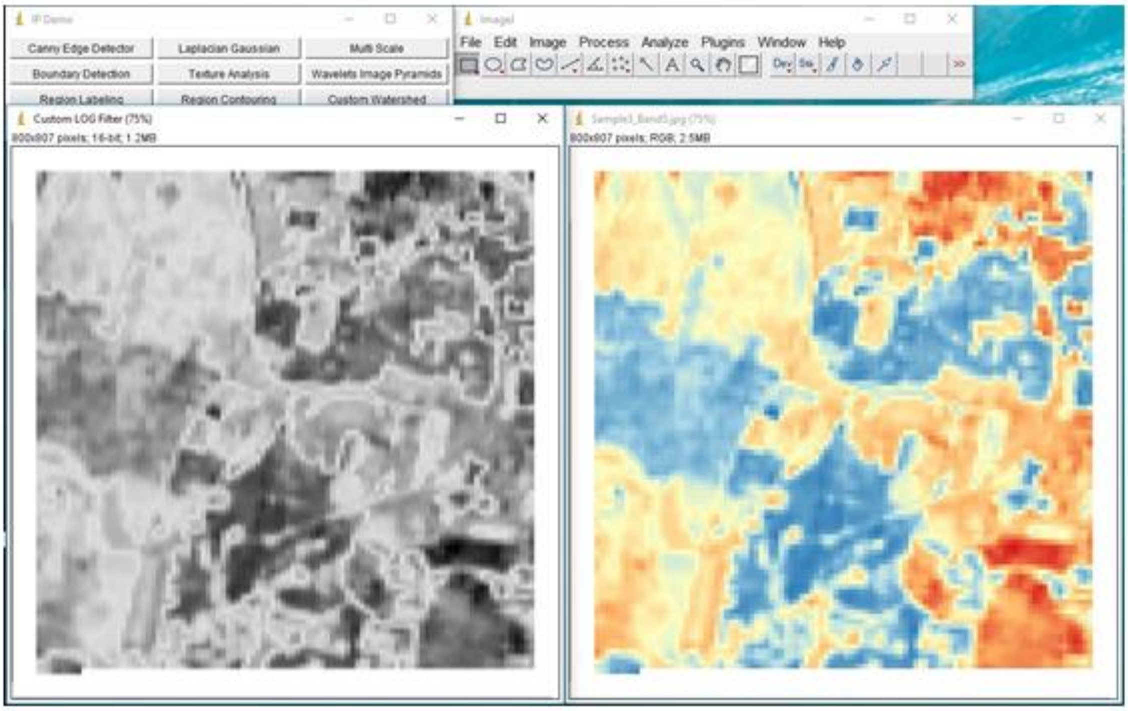

Figure 4: Customized Laplacian of Gaussian (LOG) Filter Applied

(iii) Inter-Region Variance computation with Gray-Level-Co-occurrence-Matrix (GLCM) as a measure of producing output with meaningful texture classes.

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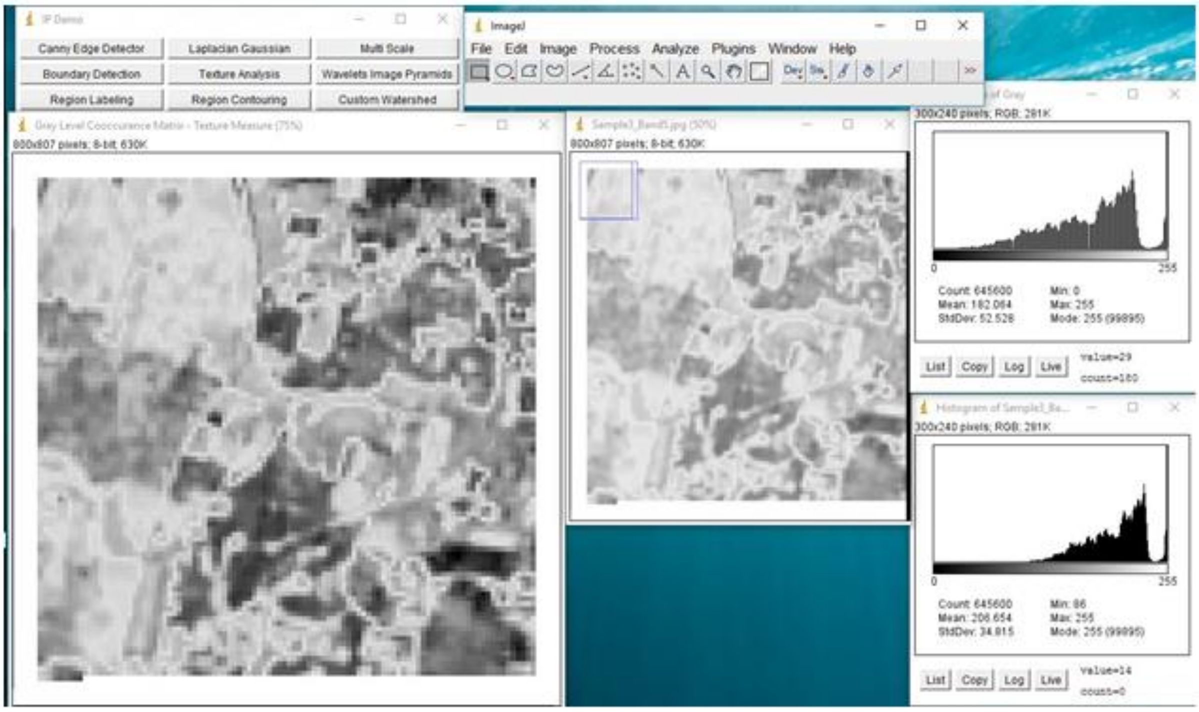

Figure 5: Customized Texture (variance) Analysis Applied

(iv) Multiscale operator – Hierarchical Scale Space with varying parameter for sigma (Gaussian scale)

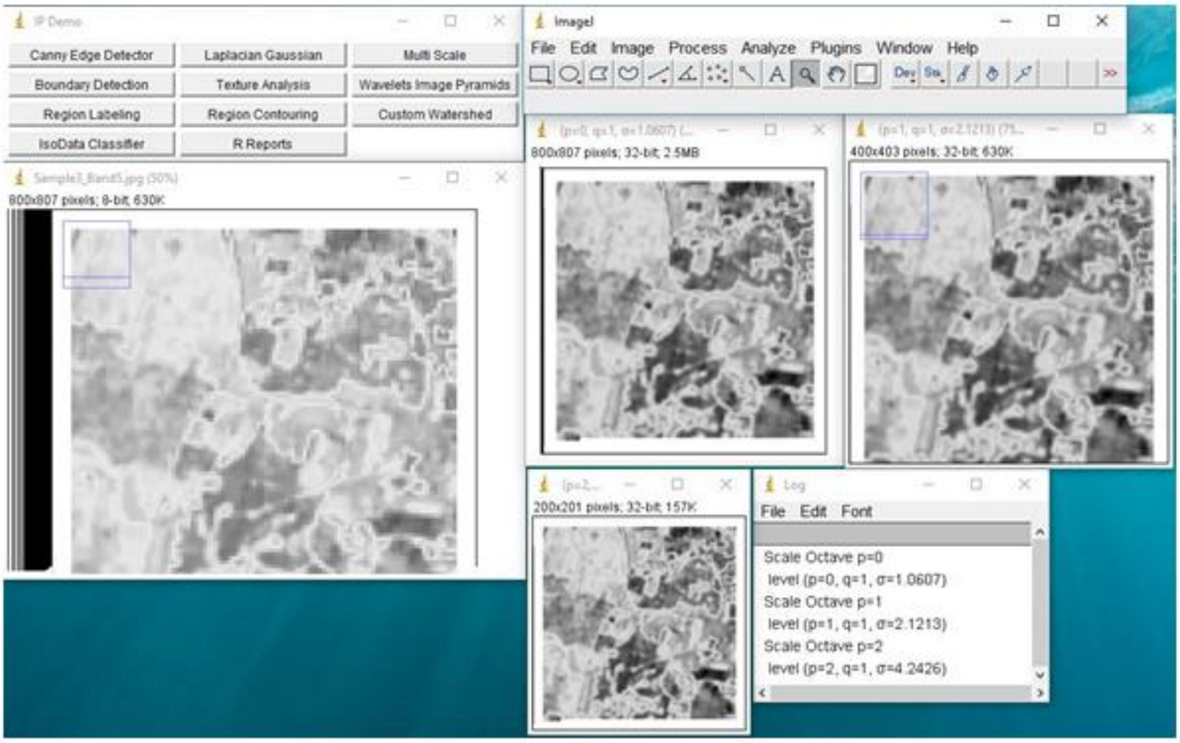

Figure 6: Customized Hierarchical Scale Space – SIFT Applied

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(v) Image Pyramids – Forming image tiles with user specified scale operator

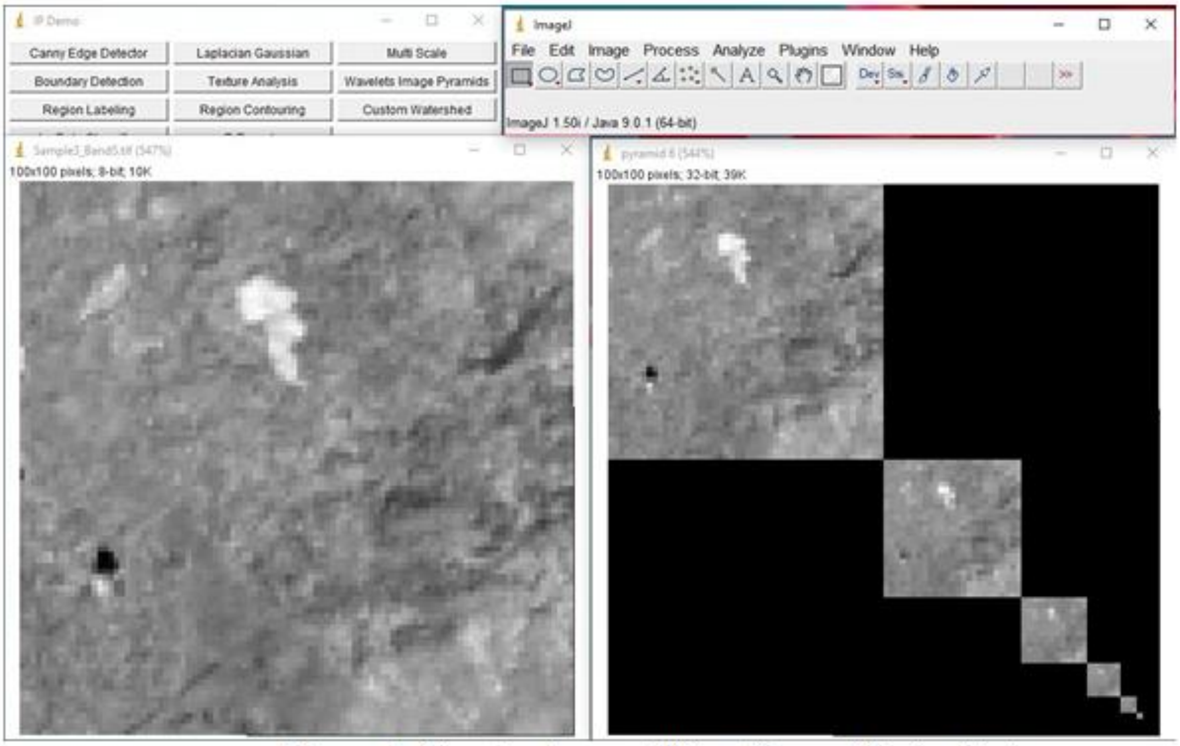

Figure 7: Varying Image Tiling (Pyramid) Applied

(vi) Region Labelling – Creating clusters within regions demarcated by multivariate statistical measures

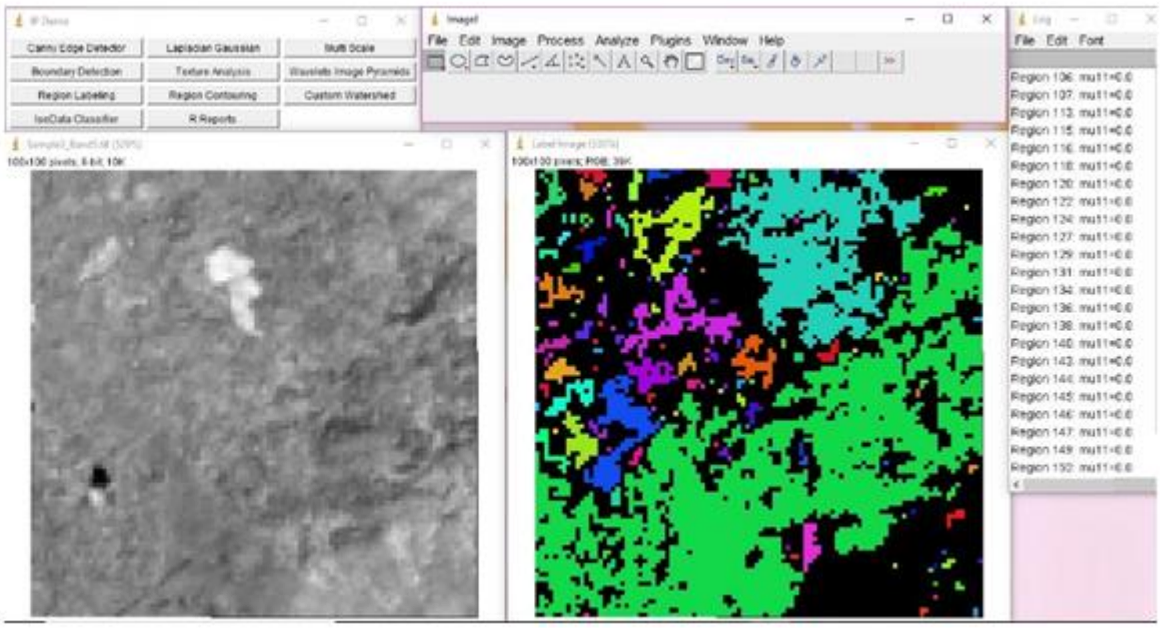

Figure 8: Customized Region Labelling algorithm applied

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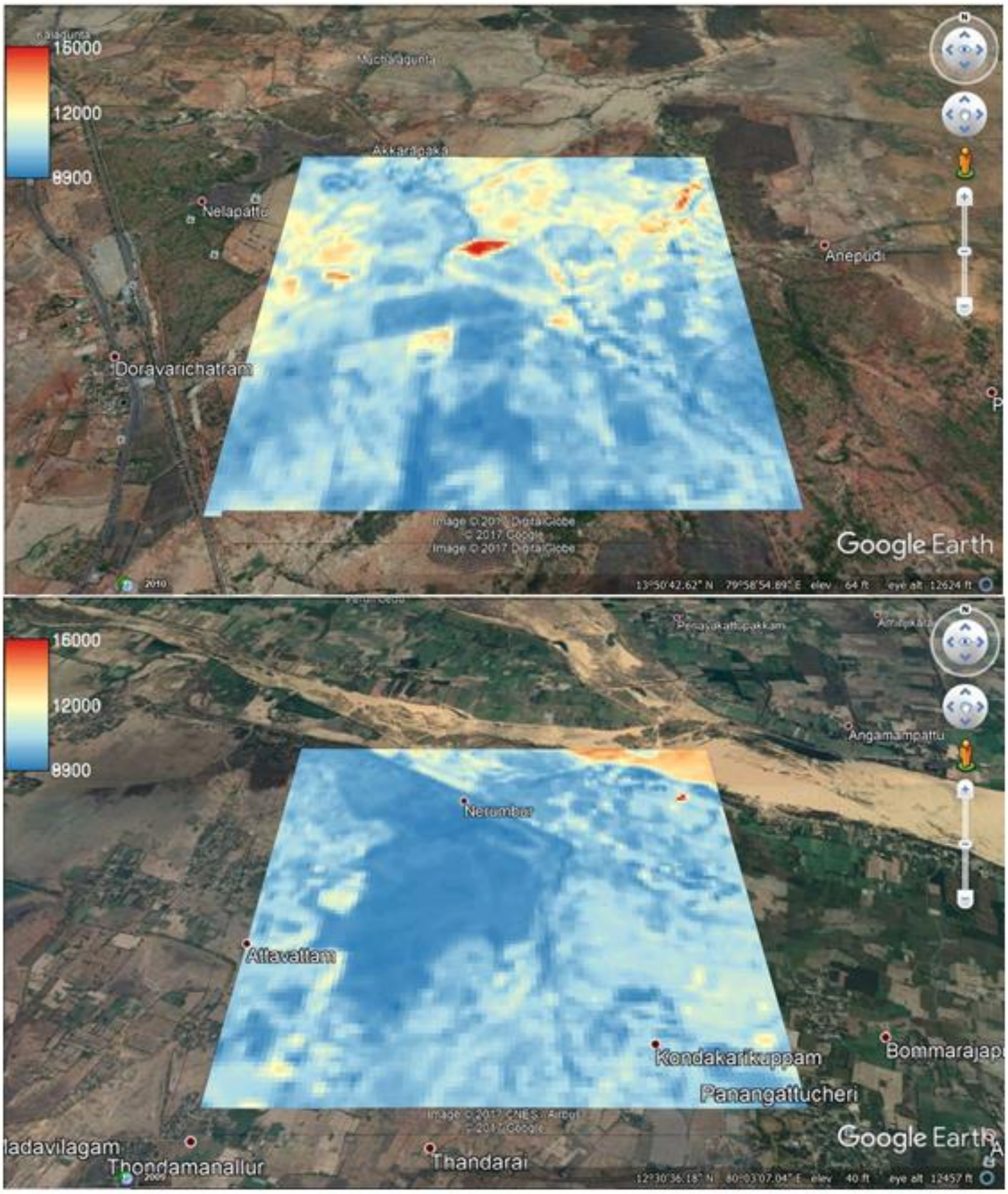

Figure 9: Region 1 and Region 2 – Area of Interest (superimposed on Google Earth)

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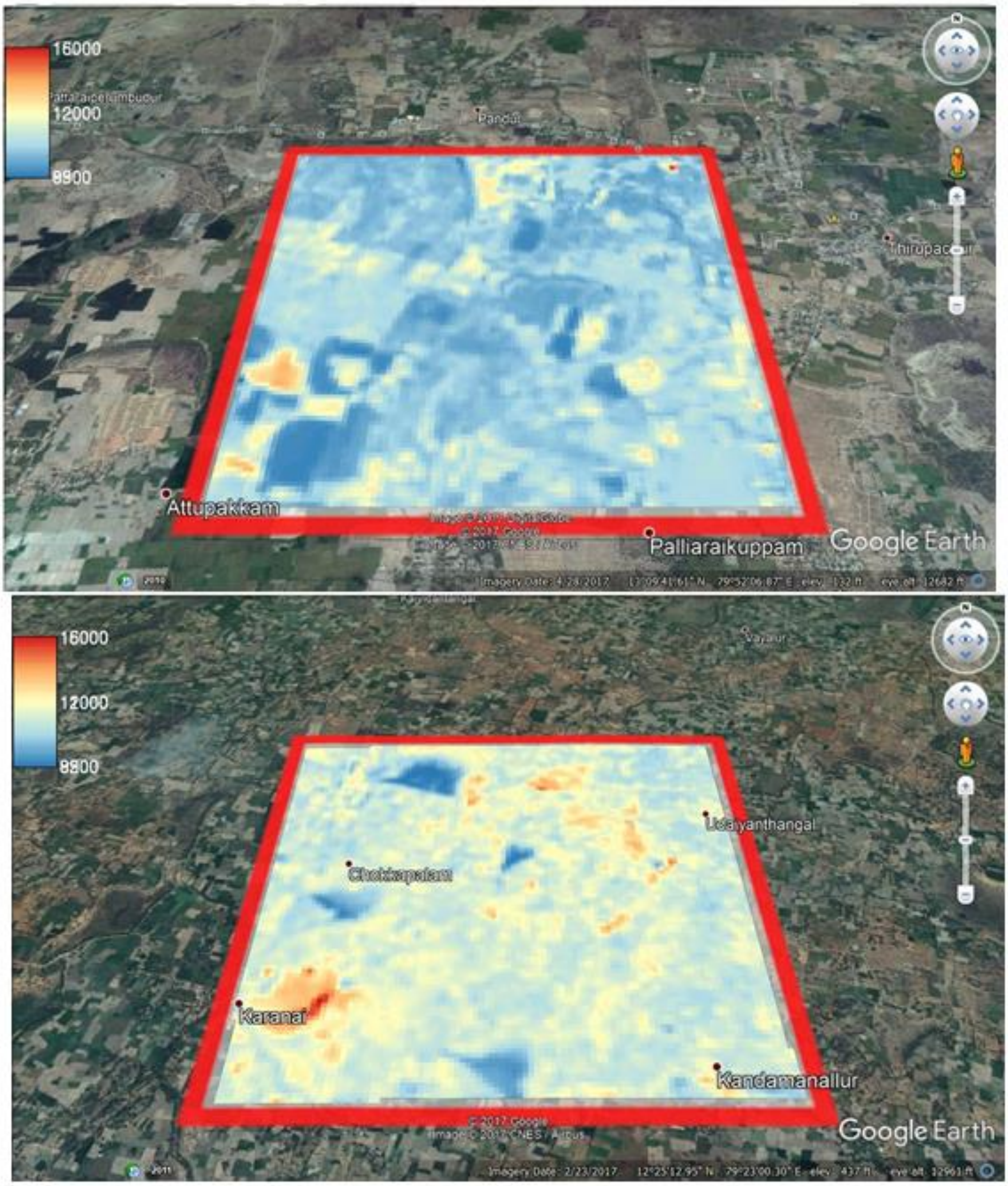

Figure 10: Region 3 and Region 4: Area of Interest (superimposed on Google Earth)

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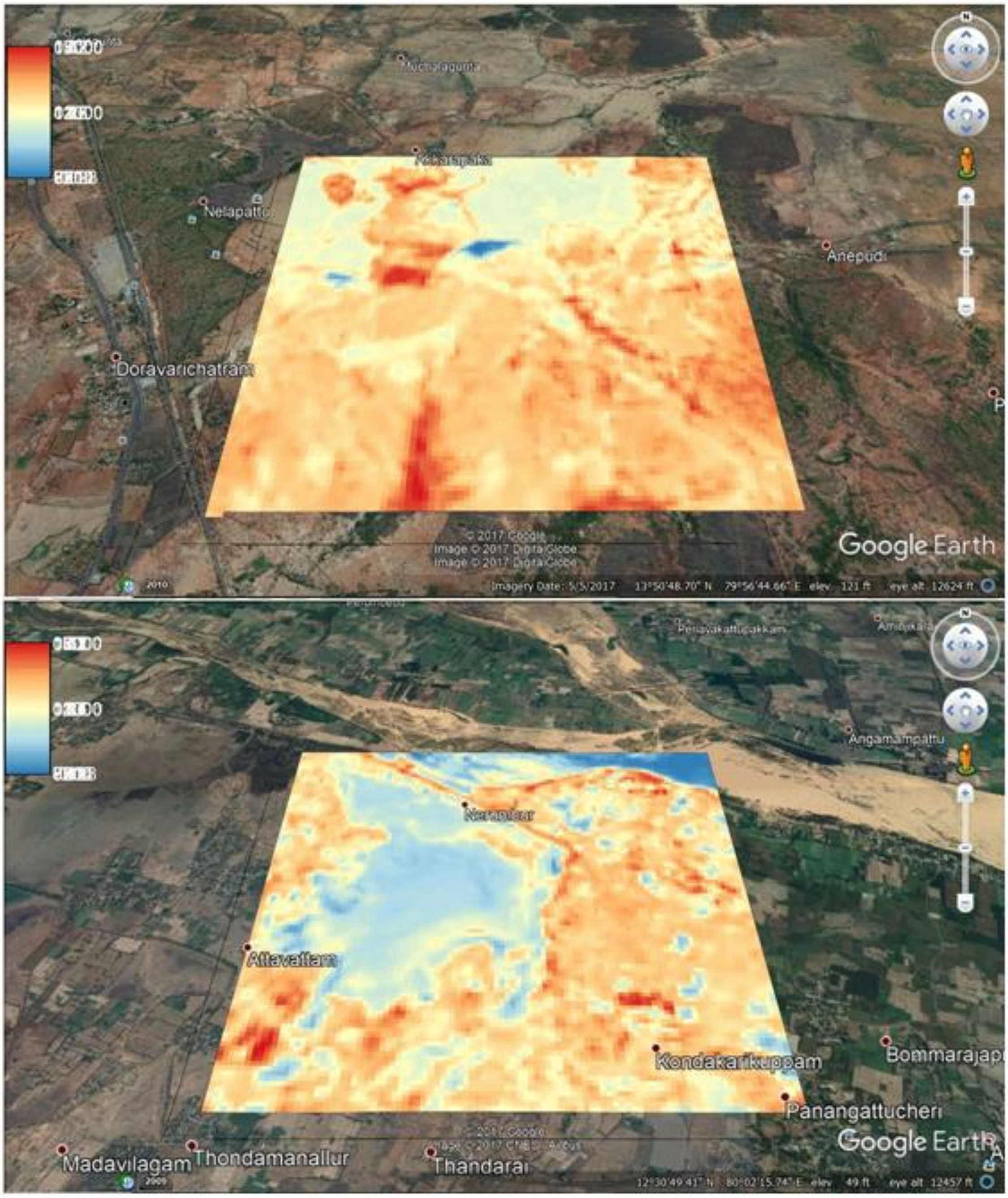

Figure 11: Normalized Difference Vegetation Index (NDVI) From Region 1 and Region 2

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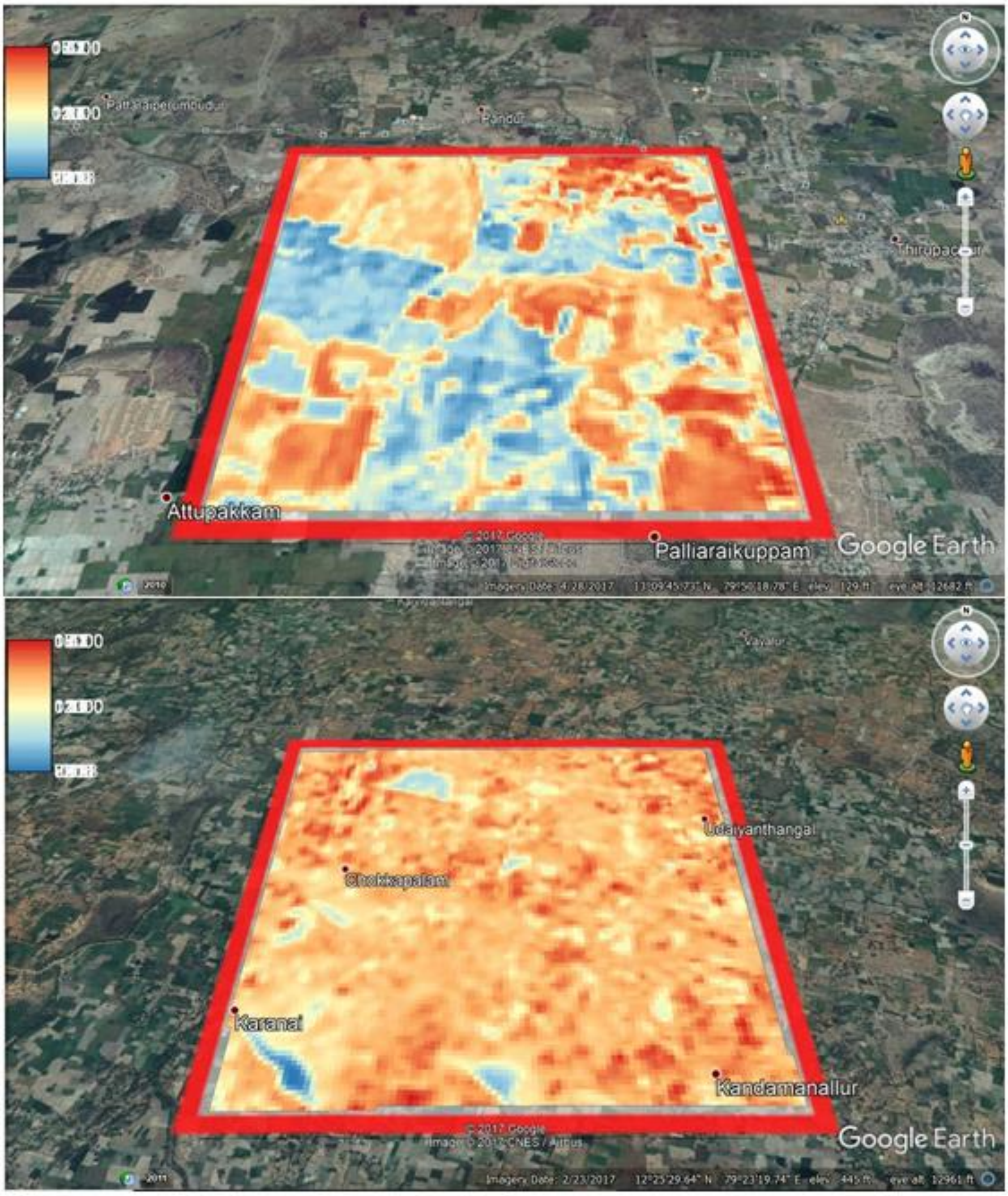

Figure 12: Normalized Difference Vegetation Index (NDVI) from Region3 and Region 4

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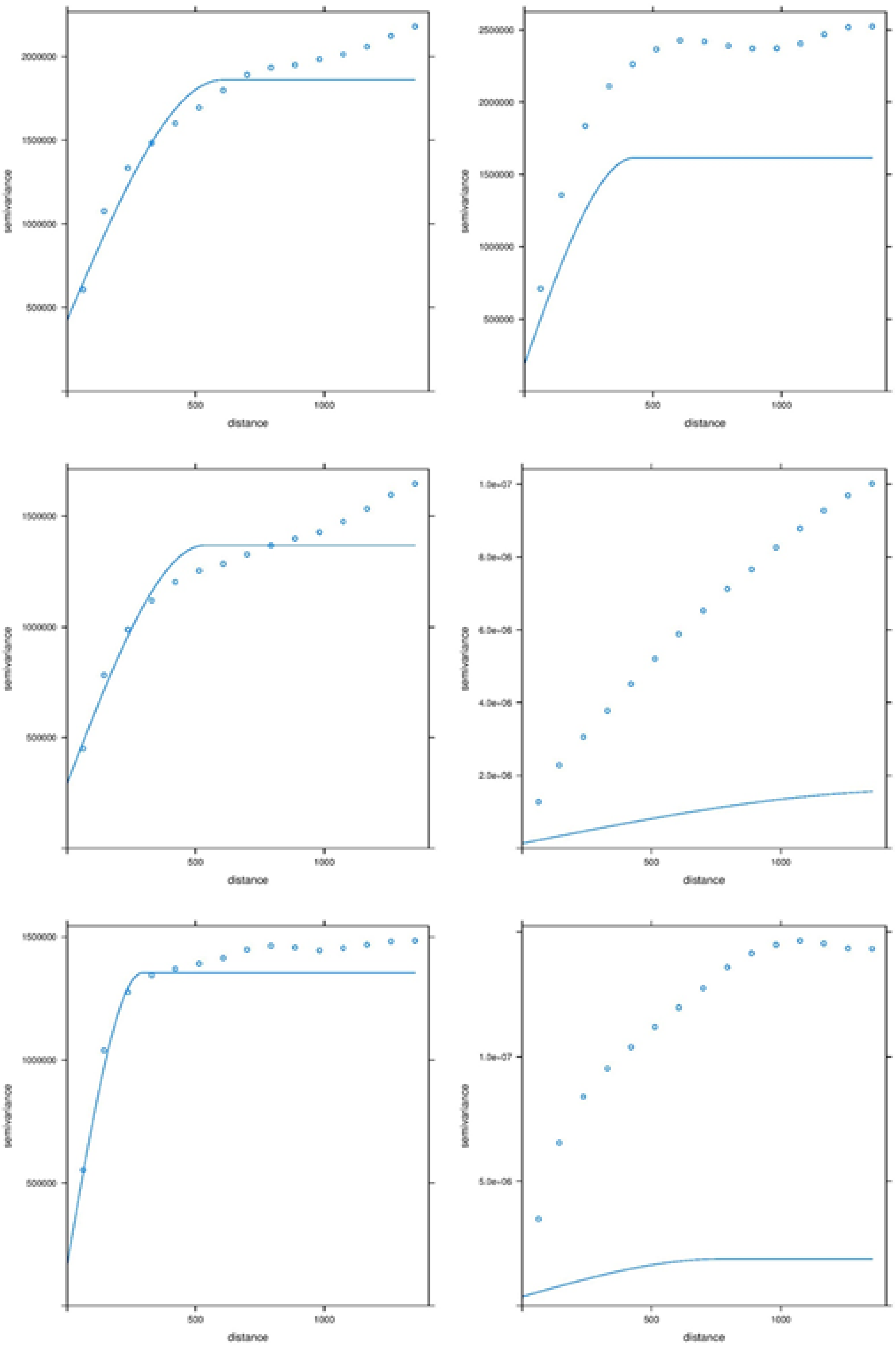

Figure 13: Semivariogram Plots from Landsat-8 Band4 and Band5 of Regions

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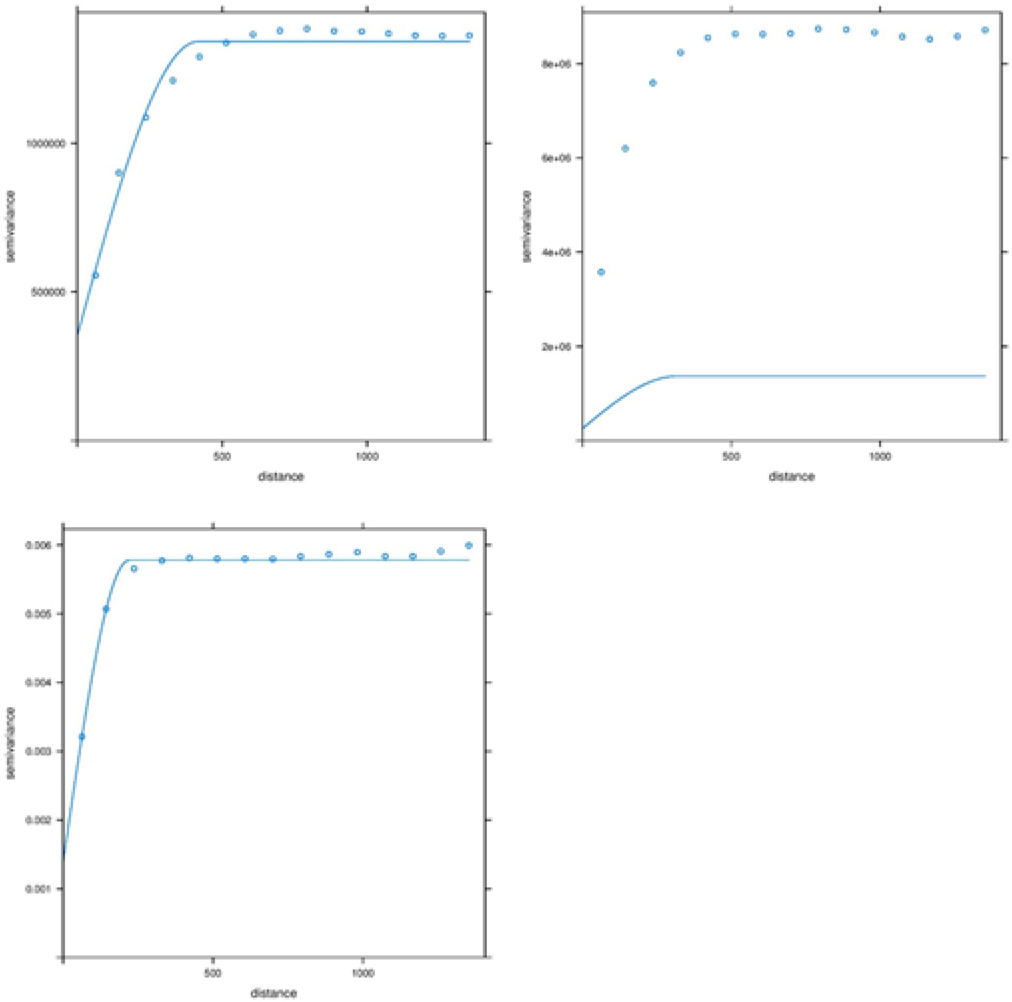

Figure 14: Semivariogram plots from NDVI of Region 4.

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