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Soil Particle Prediction using Spatial Ordinary Logistic Regression

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Abstract

Purpose: The study aims to create a predictive model for soil texture, utilizing the Spatial Ordinary Logistic Regression model to accurately estimate soil particles in the topsoil. This involves employing Geographically Weighted Ordinary Logistic Regression to analyze and map the spatial distribution of these particles, based on primary data collected from the field.

Design/methodology/approach: This study gathers soil particulate and geospatial data from various random locations to address the complexity of modeling soil texture, which is crucial for soil management. Soil texture, a mix of sand, silt, and clay adding up to 100%, is analyzed using Digital Elevation Model (DEM) data. This research leverages topographical variations to predict soil texture, employing Geographically Weighted Ordinary Logistic Regression for areas without direct observations. The approach aims to enhance both understanding and prediction in soil science.

Findings: The proposed model will be cross-validated to ensure precision. Aimed at aiding land and resource management, this study focuses on spatial variations in topsoil particle sizes and their influencing factors. The Geographic Weighted Ordinary Logistic Regression model, designed for estimating soil particle sizes using a fixed bi-square weight, demonstrated superior effectiveness with a 90% accuracy rate compared to the standard model's 88%.

Practical Implications: In 2023, soil particle size data was gathered from the Kalikonto Watershed Area in Batu City, East Java, Indonesia. This data, divided into three categories, was analyzed using the Geographically Weighted Ordinal Logistic Regression method, incorporating spatial factors.

Originality/value: This study presents innovative methods, notably the Geographically Weighted Ordinary Logistic Regression technique, for enhanced spatial analysis. This approach improves the integration of spatial and statistical data for analyzing geographic information, offering insights into how spatial variables influence soil properties. Focusing on estimating particle-size fractions in soil's top layer, the research underscores the significance of soil attributes on plant growth and agricultural productivity. Furthermore, it provides new perspectives in the crucial field of soil property investigation.

Keywords: Soil, Spatial, Logistic Regression

JEL classification : C21, C31, R32, R12, Q15, Q24, R14

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