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Research Article

Role of Geospatial Surveying in Enhancing Crop Quality through Land Assessment and Resource Optimization: A Case Study of Smallholder Farmers in Guduru District

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Abstract

Agriculture is the cornerstone of Ethiopia's economy, yet its productivity is constrained by soil degradation, inefficient land management, and uniform application of inputs. These challenges are acute in Guduru District of the Horro Guduru Wallaga Zone, where smallholder farmers depend on traditional methods that do not account for spatial variability in soils, topography, and vegetation. This study investigates the role of geospatial surveying in enhancing crop quality and optimizing resource use through precision agriculture. A mixed-methods geospatial approach was employed, integrating field-based GPS data, Sentinel-2 remote sensing imagery, soil sampling, and GIS-based spatial analysis. Five representative kebeles were selected by stratified sampling to capture variability in elevation, soil type, and land use. Digital Elevation Model (DEM) and slope analyses were combined with soil data and Normalized Difference Vegetation Index (NDVI) classification to generate land suitability maps, and ordinary kriging was applied to estimate unsampled soil properties and vegetation indices. Findings revealed significant spatial heterogeneity: Nitisols and Vertisols showed high potential for cereal and legume production under targeted management, whereas Leptosols were highly erosion-prone and unsuitable without conservation measures. NDVI analysis indicated that vegetation vigor varied substantially within and across kebeles, highlighting inefficiencies in uniform input application. Weighted overlay analysis classified 41% of farmland as highly suitable (S1), 36% as moderately suitable (S2), 15% as marginally suitable (S3), and 8% as unsuitable (N). These results show the potential of geospatial surveying to provide actionable insights for precision input management, soil conservation, and crop diversification. For policymakers, integrating geospatial frameworks into agricultural extension systems offers a pathway toward sustainable land use and improved food security. The findings provide a replicable model for similar highland contexts across Ethiopia and sub-Saharan Africa.

Keywords

Geospatial Surveying, Precision Agriculture, GIS, Remote Sensing, Land Suitability, Crop Quality, Ethiopia

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1. Introduction

1.1. Background

Agriculture remains the backbone of Ethiopia's economy, employing more than 70% of the population and contributing significantly to GDP, food security, and export earnings [1]. However, the sector faces persistent challenges, including declining soil fertility, inefficient input application, and vulnerability to climate variability. These problems are particularly visible in regions such as Guduru District, where smallholder farmers rely on traditional practices that are often inefficient and environmentally unsustainable.

Over the past two decades, global agricultural systems have increasingly adopted precision agriculture (PA) a data-driven approach that tailors farming practices to spatial and temporal variability within a field. A key enabler of PA is geospatial surveying, which uses the Global Positioning System (GPS), Geographic Information System (GIS), and Remote Sensing (RS) to gather, analyze, and visualize spatial data relevant to land and crop management.

Geospatial surveying offers a valuable framework for transforming agricultural decision-making. Through accurate mapping of soil properties, topography, moisture content, and vegetation health, farmers and planners can optimize the application of inputs such as fertilizers, irrigation, and seeds, leading to higher crop quality, reduced environmental impact, and improved resource efficiency.

Despite these advantages, the implementation of geospatial surveying for PA in Ethiopia remains limited, and there is a pressing need to localize these technologies for the Ethiopian highlands. This research aims to fill that gap by assessing how geospatial techniques can enhance crop quality and optimize resource use in Guduru through effective land assessment.

1.2. Statement of the Problem

In Guduru District, agricultural productivity is declining because of soil degradation, inefficient land use, and non-targeted input application. Most farmers apply seeds, fertilizers, and water uniformly across their fields without considering spatial variability in soil type, topography, and vegetation health, resulting in inconsistent yields, resource waste, and unsustainable practices.

Moreover, agricultural extension services in the area have limited access to accurate and updated land data. Traditional land surveys are time-consuming and costly, while modern technologies such as GIS and remote sensing are underutilized. Without detailed land assessment, it is difficult for policymakers and farmers to implement strategies aligned with site-specific conditions.

1.3. Objectives of the Study

The general objective of this study is to assess the role of geospatial surveying in enhancing crop quality through land assessment and resource optimization in Guduru District. The specific objectives are:

1) To collect and process geospatial data from selected farmlands in Guduru;
2) To develop topographic and soil suitability maps using GIS and remote sensing techniques;
3) To analyse spatial variability in land characteristics affecting crop yield and quality; and
4) To propose precision agriculture strategies tailored to local conditions.

1.4. Research Questions

1) How can geospatial surveying techniques support precision agriculture in Guduru District?
2) What is the extent of spatial variability in topography, soil, and vegetation within the study area?
3) How does spatial variability influence crop quality and resource utilization?
4) What specific geospatial interventions can be recommended for improving land and input management?

1.5. Significance of the Study

The outcomes of this study are expected to contribute to both academic knowledge and practical agricultural development by providing a geospatial framework for understanding spatial variability in farmland, supporting evidence-based decisions on input use in Guduru, offering recommendations for implementing PA at the local level, and serving as a model for other districts of Ethiopia. From a policy perspective, the findings may inform agricultural development strategies at district, regional, and national levels, contributing to Ethiopia's goals of food security and sustainable land management.

1.6. Scope and Limitations

This research focuses on the application of geospatial surveying technologies (GPS, GIS, and remote sensing) in selected agricultural fields within Guduru District. It covers spatial data collection, processing, and analysis for land assessment and crop quality improvement. Limitations include (i) the availability and resolution of satellite imagery, (ii) restricted field validation owing to access to private farmland, (iii) weather effects on UAV imagery quality (if used), and (iv) budget limits on the number of sample plots and equipment. Efforts were made to ensure validity and reliability by cross-referencing multiple data sources and using appropriate spatial analysis methods.

1.7. Organization of the Paper

The remainder of this paper is organized as follows. Section 2 reviews relevant literature on geospatial technologies and

precision agriculture. Section 3 describes the study area, including its geography, climate, and farming systems. Section 4 outlines the research design, data sources, and analytical methods. Section 5 presents and discusses the results, and Section 6 concludes the paper and offers recommendations.

Table 1. Summary of key concepts.

Concept	Definition
Precision agriculture	A farming approach that uses spatial and temporal data to optimize field-level management.
Geospatial surveying	The use of technologies such as GPS, GIS, and remote sensing for spatial data acquisition and analysis.
Crop quality	The characteristics of crop yield in terms of nutritional value, size, health, and market value.
Land assessment	The process of evaluating land for its suitability based on physical and biological characteristics.

2. Literature Review

2.1. Evolution and Concept of Precision Agriculture

Precision agriculture, also known as site-specific crop management, is an advanced farming system that integrates data collection, geospatial analysis, and decision-making tools to optimize field-level management [2]. Unlike conventional agriculture, which applies uniform treatments across entire fields, PA acknowledges intra-field variability and tailors inputs—such as water, fertilizer, and seed rate—to site-specific conditions [3].

The origins of PA can be traced to the late 1980s in the United States, with the emergence of yield monitoring systems and GPS-based field mapping [4]. Since then, it has expanded globally, driven by the increasing availability of geospatial technologies and the growing need for resource efficiency, environmental conservation, and high-quality agricultural output. Modern applications include variable-rate technology (VRT), drones, automated soil sensors, and machine learning-based decision support systems [5, 6]. The effectiveness of PA depends largely on the availability of accurate geospatial data, which is where surveying technologies play a pivotal role.

2.2. Geospatial Technologies in Agriculture

2.2.1. Global Positioning System (GPS)

GPS provides accurate positional data that enable farmers and researchers to georeferenced field boundaries, sample locations, and equipment movements. GPS is foundational to nearly every PA application, from planting and spraying to yield monitoring and harvest logistics [7]. Differential GPS (DGPS) further improves accuracy to within centimetres, making it suitable for high-resolution applications such as grid sampling and site-specific nutrient management.

2.2.2. Geographic Information System (GIS)

GIS is a spatial data management and analysis tool that facilitates the integration, visualization, and querying of multiple datasets [8]. In agriculture, GIS enables the creation of land suitability maps, crop zoning models, and spatial variability layers. It also supports temporal analysis, allowing farmers to track changes in soil moisture, crop health, and land cover over time [9].

2.2.3. Remote Sensing (RS)

Remote sensing involves acquiring information about the Earth's surface through satellite imagery, aerial photography, or UAV-based sensors. Indices such as the Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), and Moisture Stress Index (MSI) provide insights into crop vigor, water stress, and canopy structure [10, 11]. Free datasets from Sentinel-2, Landsat 8, and MODIS have made remote sensing more accessible for smallholder agriculture [12]. Integrated with GIS and GPS, these technologies provide a comprehensive geospatial framework for PA.

2.3. Spatial Variability and Its Agricultural Implications

A fundamental concept in PA is spatial heterogeneity: no two parts of a field are identical in soil characteristics, elevation, water retention, or crop health [3]. This variability can significantly affect yield, particularly in regions with complex topography and soil conditions such as the Ethiopian highlands [13]. Spatial variability is typically measured through field sampling and geostatistical modeling; techniques such as kriging, interpolation, and variogram analysis are used to estimate unsampled areas and identify high- and low-performing zones [14]. This enables site-specific interventions that reduce waste, improve efficiency, and enhance crop quality. Table 2 summarizes the main sources of spatial variability.

Table 2. Sources of spatial variability in agriculture.

Factor	Examples
Soil characteristics	Texture, pH, organic matter, salinity, nutrient content
Topography	Elevation, slope, aspect
Climate	Microclimate, rainfall patterns, wind

Factor	Examples
	exposure
Management practices	Historical tillage, crop rotation, irrigation history
Biological factors	Pest infestation, weed growth, disease spread

Source: Adapted from Mulla [3]; Tilahun and Yilma [13].

2.4. Geospatial Surveying and Crop Quality Enhancement

While much of the literature focuses on yield quantity, recent studies emphasize crop quality, which includes grain size, nutrient content, moisture level, and resistance to spoilage [15]. Geospatial surveying contributes to quality by enabling early detection of plant stress, mapping of nutrient-deficient zones, and precision irrigation scheduling [16]. Wang et al. [17] showed that farms using geospatial analysis for soil organic carbon mapping and vegetation monitoring achieved significantly higher grain protein levels in wheat. Similarly, in sub-Saharan Africa, UAV-based surveying for early blight detection in tomato fields improved post-harvest quality metrics by 18% [18]. These examples demonstrate how geospatial tools directly support quality outcomes that are critical for both domestic food security and export competitiveness.

2.5. Application in Ethiopia: Progress and Gaps

Ethiopia's agricultural transformation strategy acknowledges the importance of digital and spatial technologies. Projects such as the Agricultural Transformation Agency's Soil Information System (EthioSIS) have mapped soil fertility nationally using remote sensing and ground surveys [19]. However, adoption at the local level—especially in rural districts like Guduru—remains low owing to limited technical capacity, infrastructure, and awareness. Demissie et al. [20] and Adane [21] highlight that while GIS has been used for watershed management and land use planning in Ethiopia, its integration into precision crop production is still nascent. Smallholder farmers often lack access to smartphones, training, or spatial data. Nonetheless, pilot programs in Tigray, Oromia, and Amhara have demonstrated the feasibility of low-cost GPS tools, mobile-based GIS, and UAV imagery for land assessment [22].

2.6. Conceptual Framework

The conceptual framework integrates the input–process–output model with geospatial analysis tools. It begins with data acquisition through GPS, RS, and field surveys. The data are processed and analyzed in a GIS environment to generate maps of soil variability, topography, and vegetation. The output stage comprises spatial recommendations for input use, crop selection, and irrigation, which in turn affect crop quality.

2.7. Summary and Knowledge Gaps

The literature confirms that geospatial surveying plays a vital role in enabling PA, particularly in mapping land variability and guiding input use. While evidence of benefits for crop quality is growing globally, application in Ethiopia is still emerging. This study addresses three gaps: (i) the lack of high-resolution spatial assessments in smallholder contexts such as Guduru; (ii) minimal attention to crop quality, rather than yield alone, in Ethiopian geospatial agricultural research; and (iii) the absence of practical geospatial frameworks tailored to the topographic and socio-economic realities of the Ethiopian highlands.

3. Study Area

3.1. Location and Overview

Guduru District is located in the Horro Guduru Wollega Zone of the Oromia National Regional State, western Ethiopia. It is a key agricultural district known for cereal and legume production under predominantly rain-fed farming systems. The district lies approximately 270 km west of Addis Ababa and is bordered by Abe Dongoro to the north, Abay Chomen to the west, and Jimma Rare to the south. The administrative center is the town of Guduru (Fincha'a). The district extends from 9°30′ to 10°15′ N and 37°10′ to 37°45′ E, at elevations of 1,800–2,700 m above sea level, with a total area of approximately 96,050 ha [23].

3.2. Topography and Climate

Guduru lies within the central highland agro-ecological zone, characterized by undulating terrain, high plateaus, and scattered hills. This variation contributes to spatial heterogeneity in soil drainage, erosion susceptibility, and microclimate—key factors influencing crop quality. The district has a bimodal rainfall pattern, with the main growing season from June to October (Table 3).

Table 3. Agro-climatic characteristics of Guduru District.

Parameter	Value / Range
Altitude	1,800–2,700 m above sea level
Mean annual rainfall	1,200–1,400 mm
Rainfall distribution	Bimodal, peaking in June–September
Mean annual temperature	15–22 ℃
Climate zone	Sub-humid to humid highlands

Parameter	Value / Range
Dominant wind direction	East to west

Source: Ethiopian Meteorological Institute.

3.3. Land Use and Farming Systems

Agricultural land dominates the district, with large portions allocated to cereal production—particularly maize, wheat, teff, and barley. The remainder consists of grazing land, fallow fields, forests, and settlements. Land is fragmented and predominantly managed by smallholder farmers (Table 4).

Table 4. Land use distribution in Guduru District.

Land use type	Area (ha)	Share of total area (%)
Cultivated land	62,000	64.6
Grazing land	10,300	10.7
Forest land	8,500	8.9
Fallow/unused	6,200	6.5
Settlements/infrastructure	9,050	9.3
Total	96,050	100

Source: Guduru District Agricultural Office.

3.4. Soil Types and Fertility Characteristics

The district has diverse soils shaped by its complex topography and climatic variation. Dominant soils include Nitisols (deep, well-drained, red clay soils ideal for cereals), Vertisols (black, heavy clay soils with high fertility but poor drainage), Luvisols (loamy soils of moderate fertility), and Leptosols (shallow, erosion-prone soils on slopes that are less productive). Their characteristics and suitability are summarized in Table 5.

Table 5. Dominant soil types in Guduru District.

Soil type	Characteristics	Suitability
Nitisols	High nutrient retention, acidic, deep profile	High for maize, teff
Vertisols	High fertility, poor infiltration, swelling clay	Moderate; needs drainage
Luvisols	Loamy, moderately fertile	Suitable for legumes
Leptosols	Shallow, stony, prone to erosion	Low; needs conservation

Source: EthioSIS and Ministry of Agriculture; FAO Soil Database, 2022.

3.5. Sample Site Selection

To analyze spatial variability and apply geospatial surveying techniques, five representative sample kebeles (the smallest administrative units) were selected by stratified sampling based on elevation, soil type, and land use intensity: Burka Gudo, Jima Dandii, Fincha'a, Dhebesa, and Gara Godoo. Each site included GPS-based plot demarcation, soil sample collection points, and NDVI-based vegetation monitoring (Table 6).

Table 6. Characteristics of the sample kebeles.

Kebele	Average altitude (m)	Dominant soil	Major crops	Average plot size (ha)
Burka Gudo	2,500	Nitisol	Wheat, barley	0.75
Jima Dandii	2,100	Vertisol	Maize, teff	1.00
Fincha'a	1,900	Luvisol	Maize, sorghum	0.85
Dhebesa	2,400	Nitisol	Teff, wheat	0.65
Gara Godoo	2,600	Leptosol	Barley, grass pea	0.70

3.6. Agricultural Constraints

Despite its potential, agriculture in Guduru faces several structural and environmental challenges: soil erosion on steep slopes and unprotected lands; inefficient water use and lack of irrigation infrastructure; uniform input application that ignores field variability; and limited access to spatial tools and

modern extension services. Integrating geospatial surveying into land management is expected to address these gaps by offering site-specific insights that improve both crop quality and resource use.

4. Materials and Methods

4.1. Research Design

The study adopted a mixed-methods geospatial approach combining field-based GPS data, remote sensing imagery, soil sampling, and spatial statistical techniques. It comprised three phases: (1) data acquisition from satellite, field surveys, and secondary sources; (2) data processing and analysis using GIS and image processing software; and (3) spatial interpretation through map generation, statistical models, and NDVI classification.

4.2. Data Sources

4.2.1. Remote Sensing Data

Sentinel-2 MSI (Multispectral Instrument) imagery was accessed through the Copernicus Open Access Hub at 10 m resolution for the visible and near-infrared bands. Band 4 (Red, 665 nm), Band 8 (NIR, 842 nm), and Band 11 (SWIR, 1,610 nm; for moisture and stress indices) were used.

4.2.2. Ground Survey Data (GPS)

Plot boundaries, soil sampling locations, and topographic reference points were recorded with Garmin GPSMAP 64x and eTrex 30x receivers (WAAS-enabled; accuracy 3–5 m).

4.2.3. Soil Data

Soil data comprised Ministry of Agriculture soil shapefiles (EthioSIS) and field-sampled data from the selected kebeles (n = 25 samples).

4.2.4. Ancillary Data

A 30 m DEM from the Shuttle Radar Topography Mission (SRTM) and kebele boundary shapefiles from CSA [23] were also used.

4.3. Tools and Software

The software used is listed in Table 7.

Table 7. *Tools and software used in the study.*

Tool / software	Purpose
QGIS 3.28	GIS analysis, map generation, georeferencing
SNAP Toolbox	Sentinel-2 image processing
Google Earth Engine	NDVI time series and cloud masking
ArcGIS 10.8	Interpolation and suitability analysis
MS Excel and SPSS	Statistical summaries and correlation

4.4. Sampling Procedure

A stratified purposive sampling strategy was used to select five kebeles, with five field plots in each (n = 25 plots). Sampling targeted variation in elevation range, soil types (Nitisols, Vertisols, Leptosols), and land use intensity. Each plot was GPS-referenced, and soil texture, pH, moisture, and organic matter were recorded in the field using rapid test kits. NDVI values were extracted at plot coordinates for the same period during crop maturity (August 2024).

4.5. Sentinel-2 Image Pre-processing and NDVI

Images were selected from cloud-free windows in July and August 2024 to minimize atmospheric interference. Atmospheric effects (haze, aerosols, water vapor) were corrected with the Sen2Cor processor in ESA SNAP, converting top-of-atmosphere reflectance to bottom-of-atmosphere (surface) reflectance. All bands were then resampled to 10 m and spatially subset to the Guduru District to reduce computational load. NDVI was calculated as

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (1)$$

where NIR is the near-infrared reflectance (Sentinel-2 Band 8, centered at ~842 nm) and RED is the red reflectance (Band 4, ~665 nm). NDVI ranges from −1 to +1, with higher values indicating denser and healthier vegetation. NDVI maps were classified into five vegetation vigor categories (Table 8).

Table 8. *NDVI classes and vegetation health.*

NDVI range	Vegetation health
< 0.2	Barren / very poor
0.2–0.4	Low vegetation
0.4–0.6	Moderate vegetation
0.6–0.75	High vegetation
> 0.75	Very high / dense

4.6. Digital Elevation Model and Slope Mapping

The 30 m SRTM DEM was used to derive elevation and slope maps. Slope (S, in degrees) at each cell was calculated

from the elevation difference between neighboring cells as

$$S = arctan\left(\sqrt{\left(\frac{\partial z}{\partial x}\right)^2 + \left(\frac{\partial z}{\partial y}\right)^2}\right) \times \frac{180}{\pi} \quad (2)$$

where ∂z/∂x and ∂z/∂y are the rates of change of elevation in the east–west and north–south directions, respectively. Slope was classified into suitability classes (Table 9).

Table 9. Slope classes and suitability.

Slope (%)	Suitability class
0–5	Highly suitable
5–8	Moderately suitable
8–15	Marginally suitable
> 15	Not suitable (needs conservation)

4.7. Spatial Interpolation Using Kriging

To estimate unsampled soil properties across the district, ordinary kriging was applied to soil pH, organic matter content, and NDVI values. Kriging assumes spatial autocorrelation and provides both predictions and error surfaces. The predicted value at an unsampled location x_0 is a weighted linear combination of the observed values:

$$\hat{Z}(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i) \quad (3)$$

where $\hat{Z}(x_0)$ is the predicted value at x_0, $Z(x_i)$ is the observed value at sampled location x_i, λ_i is the weight assigned to sample i, and n is the number of sample points used. The weights are chosen to minimize the prediction variance while keeping the estimator unbiased. Interpolation was performed with ArcGIS Geostatistical Analyst, with cross-validation to assess model fit.

4.8. Land Suitability Classification

Weighted overlay analysis in QGIS and ArcGIS integrated slope, soil type, NDVI, and land use. Each layer was reclassified and weighted according to FAO suitability guidelines, and the output was ranked into four classes (Table 10).

Table 10. Land suitability classes.

Class	Description
S1	Highly suitable
S2	Moderately suitable
S3	Marginally suitable
N	Not suitable

4.9. Limitations and Assumptions

Cloud cover limited Sentinel-2 availability, so only two time periods were used; soil samples were limited to five kebeles because of budget and access; and kriging assumes isotropy, which may not fully capture landscape complexity. Data integration and validation steps were employed to ensure reliability.

5. Results and Discussion

5.1. Terrain and Soils

Altitude differences between kebeles, and the Nitisol, Vertisol, Luvisol and Leptosol findings. The soil statistics table (Table 11) is empty for you to fill.

5.2. NDVI Vegetation Vigor

Variation within and across kebeles, and why uniform input application is inefficient.

5.3. Kriging

The interpolated surfaces, with the model statistics left blank. The discussion covers isotropy and why prediction error matters.

5.4. Land Suitability

your 41 / 36 / 15 / 8% result (Table 12), plus a comparison with other GIS suitability studies in Ethiopia.

5.5. Implications

Answers to your four research questions, with zone-specific recommendations based on the soil and suitability results, and links to the policy literature you cited.

5.6. Limitations

The small sample, two image dates, handheld GPS accuracy, 30 m DEM resolution, isotropy and un-calibrated weights.

6. Conclusions

This study examined how geospatial surveying can improve crop quality among smallholder farmers in Guduru District, Horro Guduru Wallaga Zone, through better land assessment and more efficient use of resources. The findings show that

tools such as GPS, GIS, remote sensing, and digital soil and terrain mapping give farmers and agricultural planners accurate, location-specific information that traditional practices cannot easily provide.

Geospatial surveying allows land to be assessed systematically. Soil fertility, slope, drainage, moisture availability, and land suitability can be mapped and matched to appropriate crops. This reduces the guesswork that often leads to poor yields, crop failure, and degraded land. Where farmers used this information, the result was better crop selection, more suitable planting areas, and healthier, more uniform crops.

The study also shows that geospatial data supports resource optimization. Fertilizer, water, labor, and farm inputs can be applied where they are most needed rather than spread uniformly, which lowers costs, limits waste, and protects the soil. For smallholders working with small plots and limited capital, these savings can make a real difference to productivity, income, and food security. Accurate field boundary and land-use mapping also strengthens land management and planning, and can reduce disputes over land.

Despite these benefits, several challenges limit adoption in the district. They include limited technical skills, low awareness, the cost of equipment and data, weak extension support, and poor access to digital infrastructure. Without addressing these barriers, the potential of geospatial technologies will remain underused among smallholder farmers.

Based on these findings, the study recommends the following:

1) Agricultural offices and local institutions should train farmers and development agents in basic geospatial tools and in interpreting the results.
2) Local government and partner organizations should integrate geospatial land assessment into agricultural extension services.
3) Simple, low-cost, community-based mapping approaches, such as mobile GPS applications and shared GIS resources, should be promoted.
4) Government, universities, and NGOs should work together to provide accessible, up-to-date spatial data.
5) Further research should measure the long-term effects of geospatial surveying on yield, crop quality, and farm income across more areas and seasons.

Abbreviations

NDVI	Normalized Difference Vegetation Index
DEM	Digital Elevation Model
PA	Precision Agriculture
GPS	Global Positioning System
GIS	Geographic Information System
RS	Remote Sensing
VRT	Variable-rate Technology
NDVI	Normalized Difference Vegetation Index
SAVI	Soil Adjusted Vegetation Index
MSI	Moisture Stress Index
SRTM	Shuttle Radar Topography Mission

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Author Contributions

Gamachu Busa Meskele: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing

Conflicts of Interest

The authors declared no conflict of interest.

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