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ORIGINAL ARTICLE

A geo-approach to mechanized agricultural expansion in a tropical region: a case study in Rio de Janeiro

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Abstract:

Advances in geoprocessing techniques and geospatial data manipulation have optimized natural resources and enhanced environmental services globally. The agricultural sector, traditionally associated with intensive land use, is now benefiting from these technologies, leading to improved productivity aligned with better environmental conditions. Mechanization in agriculture is crucial for optimizing processes like soil preparation, planting, and harvesting. This study introduces a geoprocessing-based methodology to create a mechanization index for agricultural production by integrating land slope, land use, and soil classes using Digital Elevation Models (DEMs) and publicly available spatial data. Applied in Rio de Janeiro State, Brazil, a region with diverse altimetry and land use, this workflow uses open-source tools (QGIS) and Python. The results highlight the potential for expanding mechanizable areas and can guide public and private initiatives. Suitability for mechanization was determined for 7936.82 km², or 18.12%, and 5720.84 km², representing 13.06% of Rio de Janeiro's territory, depending on, respectively, SRTM and RJ25 data resolution and accuracy.

Keywords: Geoprocessing; Remote sensing; Slope; Agricultural mechanization.

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1. Introduction

Forecasts suggest the global population could reach 11 billion by the century's end, with tropical regions crucial in supporting this growth and maintaining the global food supply (Goldsmith and Cohn, 2017; Laurance et al., 2014; Marin et al., 2016). However, efforts to meet human needs often lead to environmental interventions that harm local biodiversity due to unsustainable production models (Brawn, 2017).

Agricultural land use has historically been crucial for the development of civilizations, supporting large populations (Mueller et al., 2010). Globally, more land has been allocated for agriculture, especially in tropical regions, which are key contributors to food production due to their favorable edaphoclimatic conditions.

Brazil's vast expanse, much of it in tropical zones, ranks it among the world's major food producers. Yet, daily challenges arise from agricultural expansion into ecologically crucial areas like the Amazon and Pantanal, affecting local wildlife due to poor planning (Gomes, 2019). Within this perspective, it is necessary to combine the optimization of land use for agricultural production and sustainable development, which is gaining more and more prominence, adding value to the production chain (Alves, D. de O. and Oliveira, L., 2022; Hu et al., 2022).

Agricultural machinery smartly improves efficiency and sustainability (Sims and Kienzle, 2017), enhancing crops, soil and harvest management. It increases rural labor productivity, being able to supply the lack of said labor in the most diverse locations (Silva, F. M. da et al., 2009). However, the sustainable development of the rural sector is a complex science of several influencing factors (Bacior and Prus, 2018), where mechanization and technology hold vital roles. Precision agriculture emerges as a sound approach, optimizing land use and productivity without further ecosystem intrusion (Laurance et al., 2014; Oliveira, A. J. de et al., 2020).

Geoprocessing tools offer methods to manipulate geospatial data, targeting specific outcomes. In modern agriculture, these tools find use in managing and advancing current and potential agricultural zones as for analyzing open-source data, such as digital elevation models (DEM) provided by the Shuttle Radar Topographic Mission (SRTM), become unavoidable in analyses. This supports ongoing technological progress, especially in expansive urban development areas (Kanga et al., 2022; Silva, J. L. B. da et al., 2022).

The selection of a Digital Elevation Model (DEM) hinges primarily on its intended application and the accessibility of data relevant to the targeted geographical area. Concerning resolution, the use of inappropriate models can lead to accuracy errors (Sampaio et al., 2021). An example is the Shuttle Radar Topography Mission (SRTM), a foundational dataset encompassing the entire globe with a 90-meter resolution. Widely adopted, the SRTM is particularly favored for conducting topographic analyses over extensive territorial expanses (Yamazaki et al., 2017).

As technology advances, terrain studies increasingly use higher-resolution models, requiring equipment capable of handling large data volumes (Vaze et al., 2010). When machine processing power is limited, preference is given to high-resolution images with finer grid spacing, especially for smaller regions, to ensure detailed results.

Safety in mechanized operations stands as a top priority when planning tasks and involving skilled professionals (Baesso, M. M. et al., 2018). The convergence of scientific and technological expertise involves geomatics and agricultural machinery. Here, terrain slope dictates operational feasibility, impacting stability and speed components ((Höfig and Araujo-Junior, 2015; Mueller et al., 2010).

Surveying slope classes within the action plan entails in-situ topographic practices with technical relevance in agricultural and environmental modeling, as well as the restoration of degraded areas (Cortijo et al., 2014; Minella and Merten, 2012). The process is simplified using elevation models, wherein a maximum terrain slope of 20% is set for operations, ensuring favorable conditions for both equipment and operators (Silva, F. M. da et al., 2009).

This study aimed to devise a geoprocessing workflow that integrates slope class, land use and cover, and soil class to pinpoint optimal zones for mechanized agricultural expansion within the study area. The state of Rio de

Janeiro was chosen due to its agricultural heritage and the scarcity of labor in rural regions, where only 3.29% of the state's population resides (IBGE, 2010). The analysis incorporated areas classified as pasture with soil classes suitable for both annual and perennial crop cultivation.

Despite its historical agricultural relevance, the study area plays a minor role in national agricultural production. According to data from the Municipal Agricultural Production (PAM), between 2018 and 2023, it contributed an average of only 0.1% of the harvested area and 0.23% of the production value. Given this context, the research aimed to assess the latent potential for agricultural expansion while ensuring alignment with the state's environmental preservation efforts.

By identifying regions where agricultural expansion is viable, this study provides scientific insights that can support land-use planning and public policies. The findings contribute to sustainable development strategies by balancing food production with environmental conservation, offering a framework that can be adapted to similar regions facing constraints in agricultural expansion.

2. Material and Methods

2.1 Region of Interest

The region of interest (ROI) can be defined as the geographical region of application of processes and data, to which layers and raster images are clipped and delimited (Kissling et al., 2022; Silva, R. F. et al., 2017; Weske et al., 1998). Highly significant in geoinformation, data extraction from these regions holds profound importance for subsequent analytical sequences. This influences not just physical-geographic data but also directly impacts the entire economic-cultural milieu within and surrounding it (Kuo et al., 2018).

The state of Rio de Janeiro in Brazil has an area of 43750.425 km², of which 6.47% is designated as urban. Situated along the Atlantic Ocean in the southeastern region, it carries an Aw climate classification as per Köppen-Geiger. This state encompasses the Atlantic Forest biome, recognized for its remarkable biodiversity but also in dire need of restoration. Despite ongoing economic growth, Rio de Janeiro has become a focal point for ecological preservation efforts. This context necessitates a delicate equilibrium between conservation and development, driving research endeavors in this domain (Siminski et al., 2016). Precisely demarcating zones ripe for agricultural activity demands meticulous data treatment to exclude urban areas and unsuitable land.

2.2 Workflow Process

To achieve the proposed aim, the workflow employs a simplified approach, offering diverse alternatives and utilizing methodologies that can enhance the accuracy and reliability of results. Being the workflow a process standardization tool, in the geoinformation environment, the tool gains value in the definition of parametric for establishing the analysis (Schäffer and Foerster, 2009).

In accordance with fundamental principles in agricultural sciences, the steps primarily focus on identifying and selecting regions with notable attributes, including fertile and high-quality soil, appropriate slopes for machinery operation safety, and available expanses for growth. This process was guided by precise data selection and utilization.

The employed workflow methodology enabled result generation across diverse settings, facilitating comparisons with past research. The significance of standardizing data manipulation via clear processes is evident, especially when handling extensive information. This not only streamlines result production but also fosters discussions and sets up adaptable working models for various input data. Such an approach stands as a proven reference for attaining dependable and uniform outcomes (Kissling et al., 2022; Silva, R. F. et al., 2017; Weske et al., 1998). The established flow may be observed as shown in Figure 1.

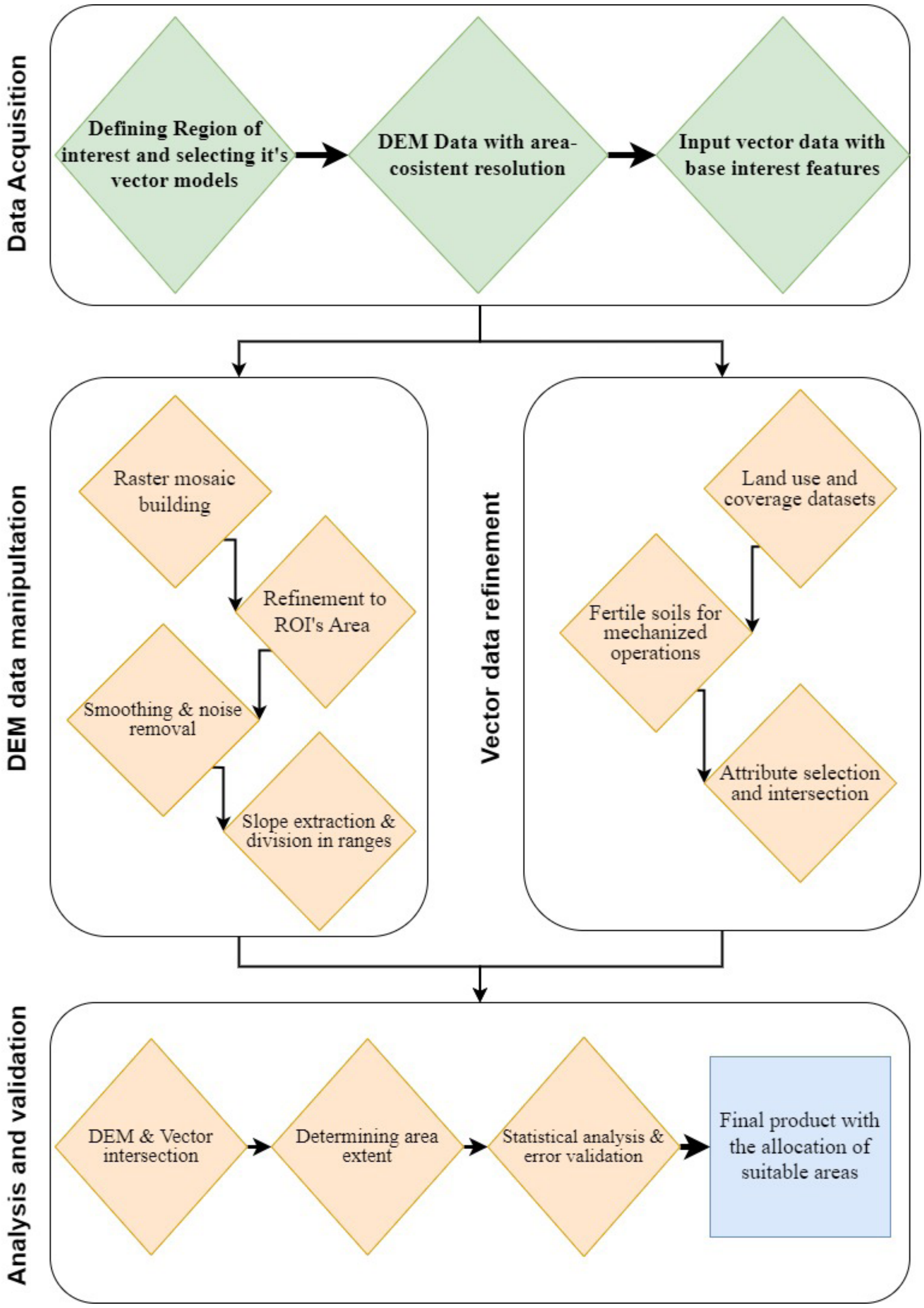

Figure 1: Applied workflow.

2.3 Data Acquisition and Refinement

Characterizing the targeted sites typically involves land use and cover geographical data, soil maps with corresponding classifications, and digital elevation models (DEMs), which provide topographic insights. Public administration sources, such as the Brazilian Institute of Geography and Statistics (IBGE) and Brazilian Agriculture and Livestock Company (EMBRAPA), supplied the land use, cover, and soil data.

For the ROI, the Low Intensity Soil Reconnaissance data from the State of Rio de Janeiro provides detailed characterization of local soils at a scale of 1:250,000, categorized up to the fourth level according to the Brazilian Soil Classification System (SiBCS) (EMBRAPA, 2017).

The land use and land cover data were collected and made available by the IBGE through the Land Cover and Land Use in Brazil project, at a scale of 1:250,000, within the ROI area. The vector data presents the results of the survey, analysis, and mapping of land cover and land use types, using Landsat 8 satellite images from 2015 as the primary input (IBGE, 2016). Both sets of vector data are based on the SIRGAS 2000 Datum.

Two DEM datasets were employed for this study: one obtained from NASA, SRTM data, and the other from local public agencies within our ROI. The inclusion of a local database aims to enhance the relevance of regional datasets in spatial analysis. Additionally, it serves to illustrate the behavior of data with resolutions distinct from the SRTM in focal scope analyses.

NASA's data originates from the Shuttle Radar Topography Mission (SRTM), carried out in collaboration with the National Imagery and Mapping Agency (NIMA). This mission aimed to compile a global Earth database, constructing digital elevation models (EMBRAPA, 2020). Conversely, the IBGE contributes to the ROI through Project RJ25, a vector cartographic resource containing DEMs segmented into sheets, aligning with Brazil's systematic mapping. This initiative serves as a fundamental topographic reference across various mapping activities.

Intersection tools in software like QGIS enable the required delimitation, while the geopandas library in Python offers an overlay function. This can be executed through both software-based methodologies and Python's geopandas library. Geopandas verifies intersecting values within a layer overlay through its overlay function and intersection method. In terms of elevation models, the intersection with vector layer data involves a straightforward process: clipping by a mask layer. This process binds the images to the pre-refined and optimized multi-polygon region.

By performing the attribute selection on vector layers, the Pasture class was chosen from land use and land cover data. For soil classifications catering to annual, perennial crops, as well as vegetables and fruit trees, the Brazilian Soil Classification System (SIBCS) guided the selection. The following classes were chosen: Dystrophic Red Argissolo; Eutrophic Red Argissolo; Dystrophic Red-Yellow Argissolo; Dystrophic Cambissolo Háplico Tb; Eutrophic Cambissolo Háplico Tb; Dystrophic Red-Yellow Latosol. These classes boast heightened fertility due to their formation processes and originating materials. Notably, they extensively span the ROI, marked by attributes such as fertility and beneficial physical traits like substantial depths, conducive to mechanized agriculture.

To smooth rasters, the "r.neighbors" function from the QGIS GRASS add-on was used, incorporating a smoothing factor—an odd value greater than 1. This factor adjusts the data to match the specified neighborhood. The choice of factor depends on model familiarity, application, and experience. For the analysis, the index was based on the ratio between the average rural area of the ROI and the pixel resolution of each DEM. Smoothing was applied only to the higher-resolution project, with a unitary index used for the lower-resolution base.

With the fusion of diverse raster images to create a mosaic, slope extraction becomes feasible—an essential factor in area suitability assessment. Terrain slope, expressed as a percentage, is segmented into bands that signify local undulations, leading to slope classes, as delineated by Ramalho Filho and Beek (1994) and presented in Table 1.

Table 1: Slope Classes.

Class Limits (%)	Slope Classes
0-3	Flat
3-6	Smoothly Flat
6-12	Moderately Flat
12-20	Undulating
20-40	Strong-Rounded
>40	Mountainous

According to Silva et al. (2009), to ensure the preservation and efficient operation of agricultural machinery, as well as the safety of operators, it is essential to establish pertinent slope thresholds. Thus, the authors introduced a novel classification system for slope ranges. This approach categorizes classes based on their suitability for the intended mechanical tasks, maintaining a slope limit under 20%. Suitability floats from highly suitable for classes between 0% and 5% slope to moderately suitable for a range of 15% to 20% slope.

Slope extraction takes place in the post-smoothing phase, where the projection of DEMs onto a UTM system with metric references is needed. By formulating a function to express slopes as percentages, images reflecting area-specific slopes can be obtained. Often, images have null-value neighborhoods around them, in line with their original resolution. To enhance visualization and mitigate potential data interference for future statistical analysis, it's recommended to repeat the refining process, delimiting images solely to the ROI. Given the extensive value range, pixels can be reorganized into ranges encompassing the identified outcomes. This task can be accomplished via the "r.reclass" function in the GRASS add-on. The classification brought by Ramalho Filho and Beek (1994) serves as a parameter for such action, exemplifying the presented product.

Data extraction and subsequent statistical analysis offer multiple approaches, with the Python environment standing out for its flexibility in data manipulation, often accomplished in just a few lines of code. For vector layer extraction, the ".area" complement can be employed, adjusting the layer projection to metric units for result clarity. Before procuring values, establishing a new index for observed data is necessary, optimizing their grouping. Using the ".dissolve(by="attribute")" command facilitates this grouping, leading to the summation of area values within each attribute column component.

Python was combined with QGIS for raster image processing. QGIS provides a "Raster Layer Unique Value Report" tool, generating an "html" file with pixel value details, pixel count per value, and corresponding total area in square meters. Alternatively, conversion to a "csv" table is achievable. The source file's columns align with the destination file's columns, enabling easy extraction of total area values for each slope class via straightforward code adjustment.

To ensure the reliability of the results, a comparison was made to identify any discrepancies between the original data and the data obtained after manipulation, refinement, and extraction. A maximum divergence of 2% was set as the acceptable limit, ensuring the accuracy of the analyzed data.

3. Results and Discussion

The results obtained demonstrate the versatility and effectiveness of the standardized approach across different scenarios, reinforcing its adaptability and applicability. The structured methodology ensured consistency in data processing, enabling robust comparisons with previous studies and facilitating the interpretation of spatial patterns.

This study specifically targeted the tropical region of the Brazilian state of Rio de Janeiro. Historically known for sugarcane and coffee cultivation, the region has shifted its economic focus towards non-sustainable options, particularly the oil and gas sector (Melo, H. P. and Oliveira, A. A., 2017; Santos, E. V. M. and Lima, 2015). Through overlaying diverse datasets, a visual comparison between two DEMs, SRTM and RJ25, was conducted. Since DEM accuracy is closely tied to satellite capabilities, it is crucial to compare outcomes across varying pixel resolutions to discuss potential results and their implications for rural planning.

The region was selected for its potential for agricultural expansion in tropical areas and the availability of relevant data. While this choice limits replicability in other regions, expanding the study would require accurate data collection and adaptation to the new area's characteristics. The broad applicability of the data supports the potential for replication across other tropical regions with similar environmental conditions.

Discrepancies in the acquired values between the two bases stem from their distinct resolutions. High-resolution databases offer a more precise portrayal of surface elements, thus yielding more accurate analysis and classification results across diverse classes (Amaral et al., 2009). The RJ25 database boasts a resolution of 20 meters, surpassing the 90-meter resolution of SRTM data. However, while higher resolution enhances accuracy, it also introduces challenges in terms of computational demand and processing time (Ivanov et al., 2021). These factors should be considered when selecting DEMs for specific applications.

When working with DEMs, diverse sources of noise—ranging from human structures like buildings to natural features like termite mounds in fields—can introduce distortions (Gallant, 2011). These disturbances in the data can lead to erroneous interpretations when analyzing slope values from these images. To yield more accurate outcomes, raster images need to undergo a smoothing process to eliminate such interference. This process was executed using a parameter derived from the average size of rural properties and the resolution of each model. Consequently, only the RJ25 project produced viable values, amplifying data quality and demonstrating the limitations of lower-resolution DEMs for fine-scale agricultural planning.

The construction of SRTM DEMs entails flaws, with its low resolution causing significant data loss and inaccurate terrain information (Cunha and Bacani, 2019). Research by Kasi et al. (2020) and Muthusamy et al. (2021) highlights how SRTM data inconsistencies lead to substantial information loss in analyses. These studies stress the need for higher-resolution DEMs to improve analysis accuracy. Discrepancies in SRTM data can directly affect slope extraction, crucial for the safe operation of agricultural machinery (Cunha and Bacani, 2019).

The original intent of the Shuttle Radar Topographic Mission was to perform image formation with a vertical accuracy of around 16 meters. Nevertheless, investigations have revealed that in regions such as South America, the mission experienced vertical inaccuracies surpassing the intended threshold (Mukul et al., 2015). This has spurred discussions and deliberations on data accuracy and the dispersion of associated errors, explored by several researchers (Mukul et al., 2017; Shortridge and Messina, 2011; Zhang et al., 2016).

The raw data produced by the mission contain gaps due to sparse sampling, which can lead to substantial information loss by misrepresenting features like water bodies, areas with steep slopes, dense vegetation, and atmospheric interference. To address this, techniques like interpolation, spatial filters, and data supplementation from alternative sources have been employed to complement and refine the available data characteristics (Costa, C. A. G. et al., 2010; Luana et al., 2015; Mukul et al., 2015).

Despite uncertainties, SRTM data are widely utilized in environmental and geoscientific studies for their scientific value. These models offer essential elevation parameters for applications like hydrological modeling, forest restoration, topography, agricultural expansion, and optimizing productive processes. SRTM models have resolutions ranging from 90 to 30 meters, lower than the higher-resolution RJ25 data. Nevertheless, SRTM data have found diverse applications, exemplified by studies conducted by Chen et al. (2018), Domeneghetti (2016), França et al. (2016), and Melo et al. (2020).

The significance of SRTM data should not be underestimated, even with their diverse resolutions. When analyzing extensive territories, higher resolution models could necessitate more intricate methodologies due to their numerous specifics. Furthermore, SRTM data offer a holistic viewpoint beneficial for comprehensive area observations (Chen et al., 2018; Mukul et al., 2015).

Analysis using the SRTM dataset indicated that 7936.82 km², or 18.12% of the state's territory, possessed a combination of favorable soil characteristics, free grazing areas, and slopes below 20%, making these locations ideal for agricultural machinery use and operation. The intersection of the RJ25 project data with the soil classes within the pasture areas resulted in a total area of interest of 5720.84 km², representing 13.06% of the territory, 2215.98 km² less than the SRTM base. The individual characteristics of each class of both DEM's are presented in Table 2, with percentages relative to the total state area.

Table 2: DEM slope classes extent in intersection with soils and pastures.

Slope (%)	**Area - RJ25**		**Area - SRTM**	
	Km²	**%**	**Km²**	**%**
0-3	1087.24	2.48	858.43	1.96
3-6	843.45	1.93	1258.08	2.87
6-12	1638.17	3.74	2650.62	6.05
12-20	2151.98	4.91	3169.69	7.24
Total	5720.84	13.06	7936.82	18.12

According to the distribution of suitable areas (Figure 2), the North and Northeast regions of the state have the highest concentration, making them important for future investments and public and private policies aimed at revitalizing agriculture. These investments and guidelines should follow an approach of resource efficiency and optimal planning, as reported by Sajjad et al. (2011) and Tsohou et al. (2012). Thus, this workflow can be useful for defining development policies in the region by presenting the ability to quickly manipulate data to obtain end products of interest.

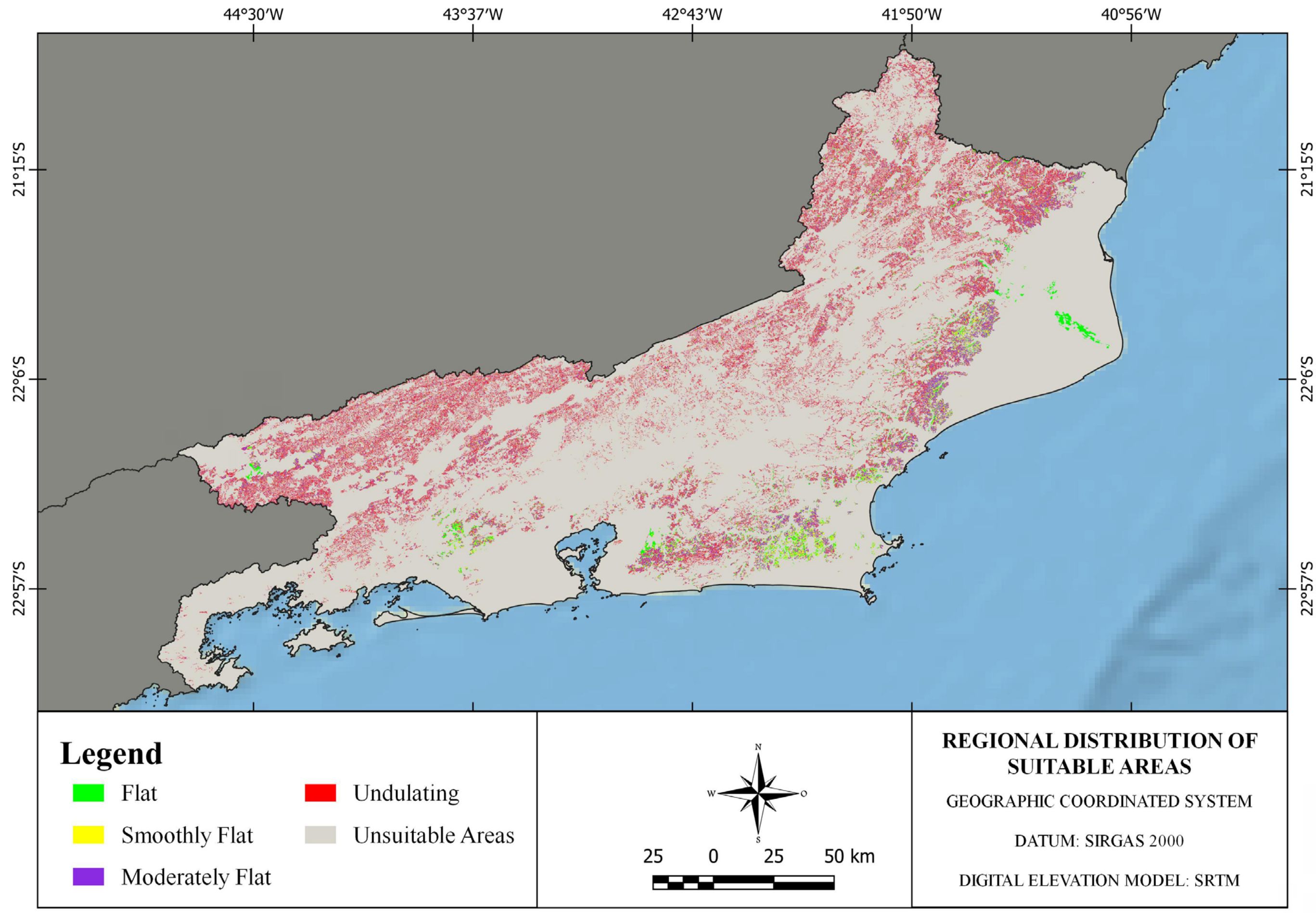

Figure 2: Distribution of suitable areas according to the SRTM DEM.

RJ25 provides high-resolution data that ensures accurate analyses of smaller areas. This data is valuable for localized assessments, such as the allocation of resources for mechanized agricultural expansion within each government region. However, for larger-scale analyses that require a more global perspective, lower resolution models like SRTM are often used in conjunction with other models (Robinson et al., 2014; Yamazaki et al., 2017).

By combining high and low-resolution models, researchers can achieve a more holistic grasp of the study area. Figure 3 highlights the city of Araruama, selected for having the highest ratio of suitable area to total municipal area within the ROI. With 33.01% of its territory classified as fit for mechanized agriculture, Araruama stands out as the municipality with the greatest relative potential for agricultural expansion in both approaches.

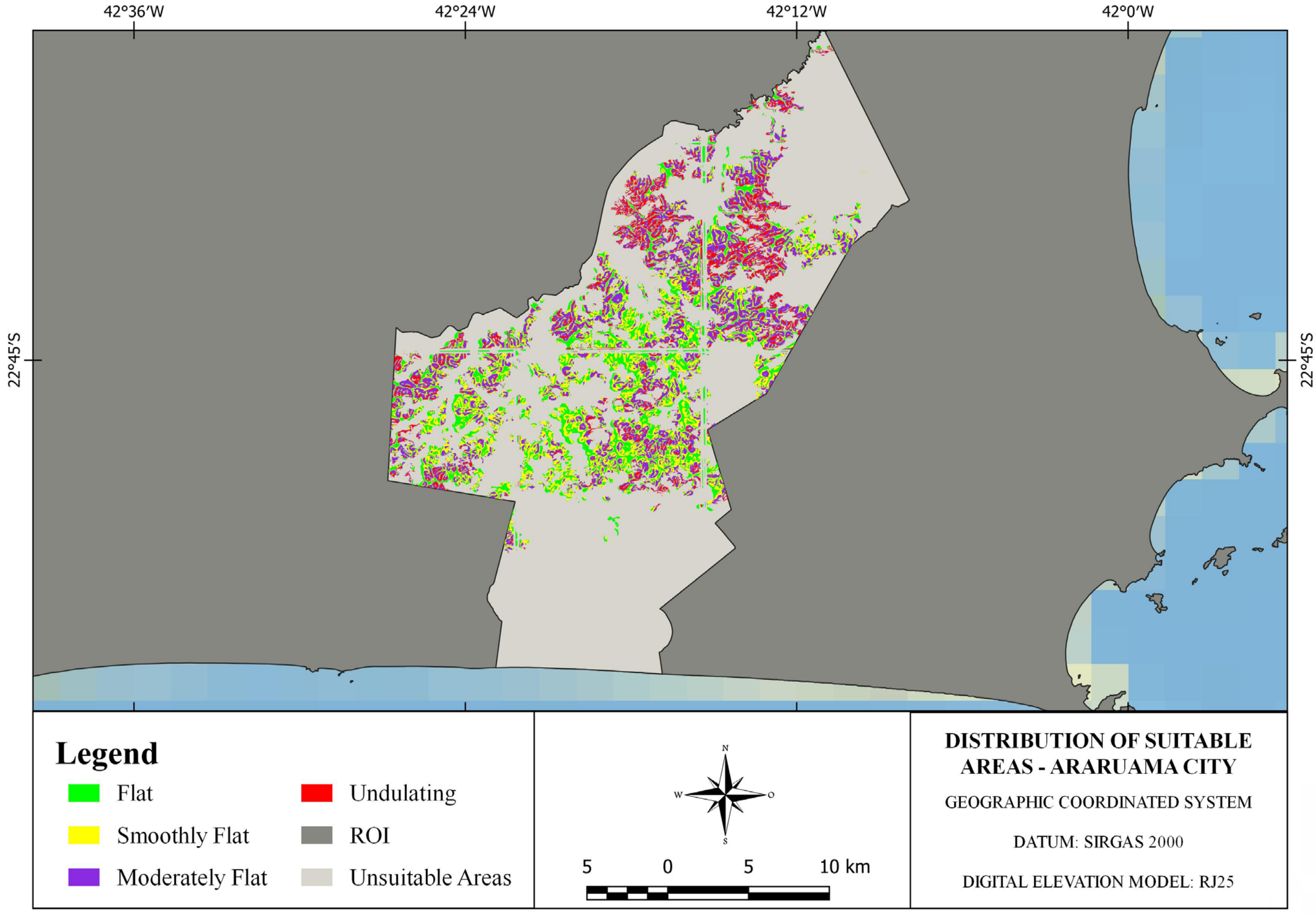

Figure 3: Suitable area distribution based on RJ25 DEM in Araruama City.

Mechanized operations are crucial in the evolving agricultural landscape, offering significant potential for advancing crops like coffee, corn, and sugarcane, which remain vital in local agribusiness. In 2021, about 2 million tons of sugarcane were produced in the Northeast region, highlighting the potential for mechanized expansion (IBGE, 2021). Horticulture, particularly tomato production, is also prominent in the state.

With around 17.5 million people, only 3.29% live in rural areas, contributing to local agriculture. As urban centers grow, so does the demand for food, often requiring imports from nearby regions when local production falls short. Family farming, which produces 80% of global food (FAO, 2018), is significant in Rio de Janeiro, with 43,726 establishments making up 67.04% of local agribusiness.

Due to limited rural labor in family farming, agricultural machinery plays a key role in boosting productivity. These farms, often with limited investment, rely on cooperatives and associations to access resources, support property development, and acquire equipment.

To analyze machinery distribution on rural properties, it’s crucial to understand the current situation. The state has a machinery-to-farm ratio of 1:3 for conventional farms and 1:8 for family farms. The machinery-to-area ratio is 1:253 hectares for conventional farms and 1:95 hectares for family farms, highlighting the need for more equitable machinery allocation to boost efficiency and productivity in family farming. These findings suggest significant potential for expanding mechanized cultivation in both unused and currently cultivated areas. Further research is needed to explore this potential and introduce innovative farming methods.

Comparing the outcomes from both databases with the original land use and soil data validated the process’s efficiency. Data loss was minimal—0.02% for SRTM and 0.05% for RJ25—well below the study’s 2% threshold, confirming the data’s robustness despite extensive manipulation.

4. Conclusions

Effective agricultural planning requires selecting relevant variables to achieve accurate and actionable results. This study demonstrated that using a standardized workflow methodology is crucial for managing large datasets, optimizing analytical processes, and facilitating discussions in land use planning.

Focusing on the state of Rio de Janeiro, the research evaluated multiple digital elevation models to identify areas suitable for agricultural mechanization. The findings underscore the importance of using high-resolution models tailored to the analysis scale, as well as the necessity of accounting for data interference sources to enhance reliability.

The comparison between datasets revealed that RJ25 data, with its 20-meter spatial resolution, provided a more accurate representation of the terrain, identifying 5,720.84 km² (13.06%) of the state's territory as suitable for mechanized agriculture. In contrast, SRTM data estimated 7,936.82 km² (18.12%), highlighting its broader applicability but also its limitations in terrain representation.

Beyond identifying soil and slope conditions for the proposed application, this study emphasizes the broader application of geospatial analysis in agricultural planning. While topographic and soil characteristics are critical, sustainable agricultural expansion also depends on cultural, economic, and ecological factors. Therefore, integrating these dimensions into future studies is essential for developing strategies that balance productivity with environmental conservation, ensuring long-term viability in land-use decision-making.

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AUTHOR´S CONTRIBUTION

G.B.S. Silva, F.C. Silva and A.L. Belem conceptualized and designed the research as well as drafted the manuscript. G.B.S. Silva carried out data analyses, as well as visualization and interpretation of results supervised by F.C. Silva and A.L. Belem. All authors read revised and approved the final manuscript.

Additional Information

A preliminary version of this manuscript was previously made available as a preprint on SSRN - Social Science Research Network (06th October 2023), DOI: 10.2139/ssrn.4594420.

Data Availability

The code used to convert tables type and extract the area information in it, and the vector data used may be found under the repository: https://github.com/gabrielbrazo/geo-approach

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