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Selection of Potential Sites for Promoting Small-Scale Irrigation across Mali Using Remote Sensing and GIS

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Abstract: Agricultural development across much of sub-Saharan Africa is constrained by the gap in knowledge on site suitability for sustainably expanding irrigable lands to new areas. This study aimed to identify the most suitable sites for promoting small-scale irrigation in Mali based on environmental and land use/land cover criteria. Six thematic layers were integrated to consider the water accessibility (distance from surface water and groundwater potential), soil, climate conditions, slope, and land use/land cover. Subjective scores and weights were assigned to each of the six layers, which were integrated to select the most suitable sites according to five categories ranging from 'very high' to 'very low'. Results indicated that 641,448 ha of land have a very high potential for small-scale irrigation expansion: these are mostly located in the central Segou region (53% of the total very high potential sites across the country) and around the capital district, Bamako, in southern Koulikoro (38% of the total very high potential sites across the country). Sites ranked second as having high potential are also distributed in southern Segou, central Koulikoro, and the western Kayes and Mopti regions, totaling 20.8 Mha. Moderate potential sites are generally located in the northwestern and southern parts accounting for 37.8 Mha of the country, whereas low and very low potential sites are concentrated in the northern and eastern parts of the country over a total area of 65 Mha. The present study demonstrates the usefulness of remote sensing and GIS techniques in agricultural development planning at large-scale; similar methodologies can be applied in other sub-Saharan African countries.

Keywords: small-scale irrigation; spatial modeling and computing; remote sensing and GIS; machine learning; mapping

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1. Introduction

Rapid population growth, the adverse effects of climate change, global pandemics, and political crises all increase the pressure on natural resources and food security, necessitating substantial attention to meet such challenges. Expanding irrigated agricultural areas could be considered one of the most important factors in addressing such issues and ensuring food security. Irrigated agriculture, which consumes approximately 70% of freshwater resources [1] and which accounts for about 40% of world crop production, is critical for global food security and the well-being of a large portion of the world's population [2]. Therefore, the selection of suitable sites for expanding irrigated agriculture can play a pivotal role in ensuring environmentally sustainable production systems and agricultural development [3,4].

Although there are inter-country agreements in sub-Saharan Africa for sharing water from large rivers, small-scale irrigation projects for soil and water conservation have historically received less attention. Mali is a sub-Saharan African country that suffers from land fragmentation and a limited contribution from small-scale irrigation to agricultural systems, necessitating special and urgent attention. The country made substantial progress in advancing its irrigation capacity through institutional and programmatic commitments. For example, the Program for Increasing Agricultural Productivity started in 2011 with the aim of developing an irrigation infrastructure able to cope with climate change-induced adverse impacts on crop production. Yet, only 7% of 43.7 million hectares (Mha) of arable land are being cultivated, of which only 14% are being irrigated, making it one of West Africa's most promising agricultural development destinations [5]. Irrigation can triple or even quadruple the yield of rainfed agriculture, while it can also increase cropping intensity. Investment in small-scale irrigation will not only improve household consumption and production but will also lead to an increase in assets and income. In addition, irrigation investment can enhance the socio-economic status of smallholders and reduce their vulnerability to economic challenges. Previous research showed that small-scale irrigation increases agricultural production [6], reduce farmer reliance on the unpredictable rainfall that characterizes the climatic conditions of sub-Saharan Africa, facilitate economic transactions, and improve community livelihood, wealth, and infrastructure [7]. Successful implementation of small-scale irrigation depends on several factors among which selecting the most suitable sites that consider various environmental and biophysical parameters for long-term sustainability is the most important [8–10].

Remote sensing and Geographical Information Systems (GIS) are powerful tools that can facilitate the identification and selection of potential sites for small-scale irrigation promotion. However, most studies focused on only one or two factors, such as groundwater accessibility and rainfall distribution [11–13]; further attention is required to integrate multiple factors to develop a robust and comprehensive approach. These factors vary in their relative importance and, therefore, assigning weights should be considered, using a robust decision-making approach, such as the Analytical Hierarchy Process (AHP) [14–18]. This approach has many advantages [19], including an easily reasonable system, usability, and quality assurance, because it has a strong mathematical foundation and is used in the process of evaluating and selecting alternatives.

Using machine learning algorithms in remote sensing solved many problems associated with mapping extensive and complex land use/land cover, and usually results in better overall classification accuracies [20]. Due to its simplicity, speed, and accuracy, Random Forests [21,22] is a very popular algorithm [23,24]. Random Forests is an ensemble learning algorithm that uses decision tree classifiers, bagging, and bootstrapping as its base learners. Decision trees are used as classifiers in the algorithm. Bootstrapping is used to train each tree, which uses different samples from the training data. A random subset of the predicting variables is also used to train each tree (in this case, the spectral bands of the satellite image). Random Forests employs many decision trees (500–2000), each of which casts a vote, with the majority vote determining the class prediction. In the present study, we applied the Random Forests classification algorithm to obtain a recent land use/land cover map, which was integrated with other parameters to determine the final potential site map across the country. To the best of our knowledge, no research was conducted so far on site suitability for irrigation development in Mali at the country level. Therefore, the main objectives of the study were to: (i) identify and process the most relevant parameters to site suitability for promoting small-scale irrigation; (ii) assign priority scores to classes in each thematic layer and the weight of each layer; and (iii) select the most suitable sites for promoting small-scale irrigation across Mali.

2. Materials and Methods

2.1. Study Area

This research was carried out in Mali (Figure 1), the largest country in West Africa. It is bounded to the north by Algeria, to the east by Niger, to the southeast by Burkina Faso, and to the southwest by Guinea (Figure 1). About 22% of the country is semi-arid, 7.2% is dry sub-humid, and the rest is arid [6]. During the rainy season (June to November), the Niger River floods frequently, washing away soil nutrients and causing soil erosion. The landscape in Mali is divided into four agroclimatic zones with a lower elevation in the northern and western regions and a higher elevation in the southern and eastern regions (Figure 1). The Sahara Zone is distinguished by its scarcity of water, hyper-aridity and desertification, low rainfall (0–100 mm), and erratic and unpredictable weather patterns. In addition, the soil in this zone is sandy and skeletal based on the origin of material, with poor water-holding capacity. The second zone is the Sahelian, which has long dry spells of 9–12 months. With rainfall ranging from 550 mm to 1100 mm, the Sudan zone is semi-arid to sub-humid. The major crops in Mali are pearl millet (*Cenchrus americanus* L.), sorghum (*Sorghum bicolor* L.), maize (*Zea mays* L.), rice (*Oryza sativa* L.), sugarcane (*Saccharum officinarum* L.), and cotton (*Gossypium hirsutum* L.).

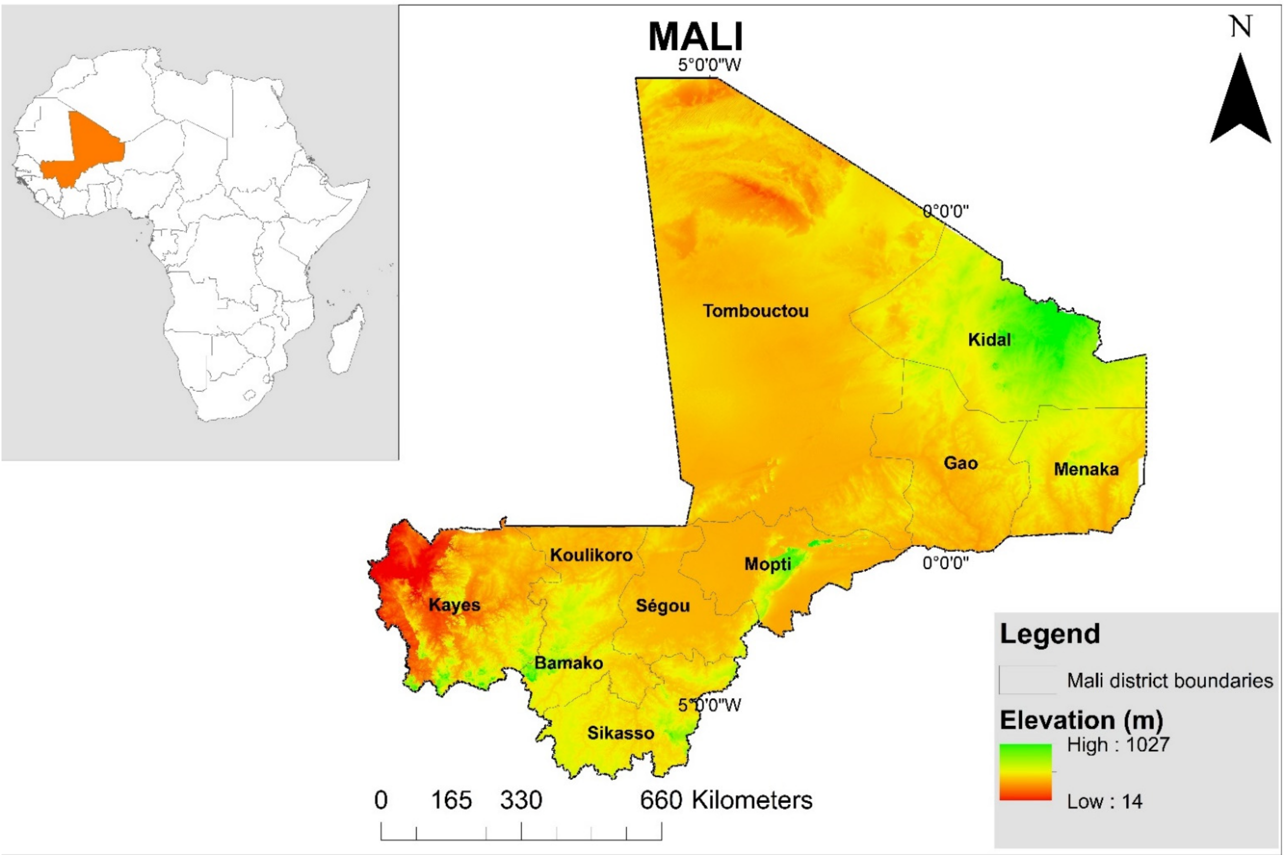

Figure 1. Regions and elevation of Mali and shapefile of Africa with Mali location in red.

Agricultural industry significantly contributes to over 40% of the gross domestic product and employs nearly 70% of the active population. Despite the significant groundwater and surface water resources from the Niger River, cultivated land accounts for only 7% of the country's 43.7 Mha because of the insufficient use of surface water and the insufficient harnessing of groundwater for farming. Nevertheless, Mali's irrigation capacities recently advanced substantially compared with other sub-Saharan countries, and it has high potential for expanding irrigable land.

2.2. Methods of Analysis

Identifying potential sites for promoting small-scale irrigation for agricultural development was achieved through the weighted integration of several thematic layers (Table 1). The process began by determining the most relevant layers suitable for the development of a small-scale irrigation system from the perspectives of the environment and land use/cover. Assigning scores and weightages were performed based on the AHP model, where the pairwise matrix of relevant importance was constructed corresponding to expert knowledge and the published literature (Table 2) [3,4,10,25,26]. Figure 2 describes the conceptual methodologies utilized in the present study.

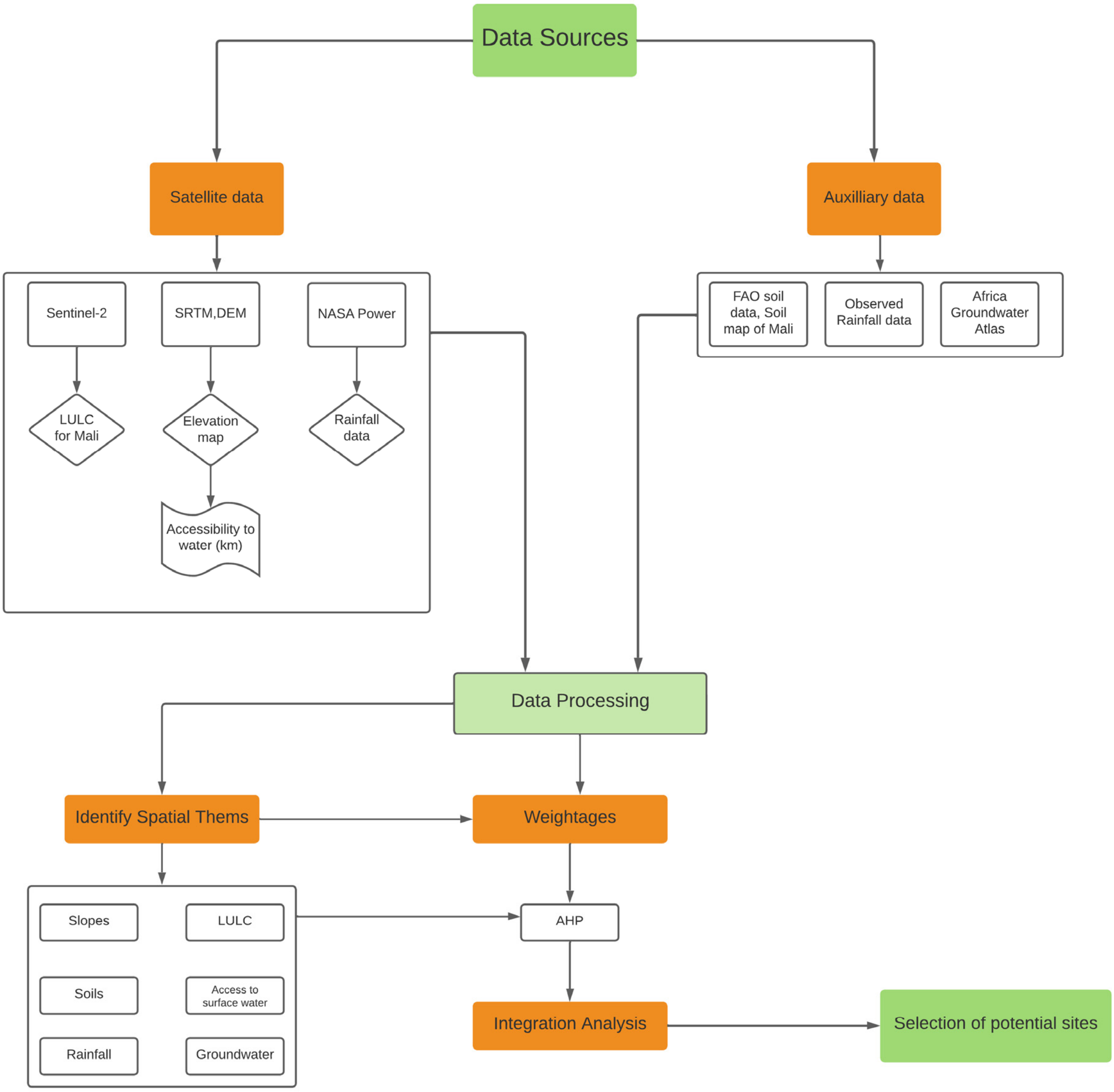

Figure 2. Conceptual framework implemented in the study.

2.2.1. Accessibility to Surface Water

Accessibility to surface water is an essential criterion for economically expanding irrigated crop lands to new areas [27]. The accessibility to surface water was determined by measuring the distance between the mainstream of the Niger River using the Euclidean distance method (Figure 3a). River streams for the country were derived from mosaicked ASTER GDEM image tiles applying the Fill function, Flow direction, and Flow accumulation tools from the Hydrology toolset in ESRI ArcGIS 10.6. For generating streams and creating stream order, the Strahler method within the Stream Order function in the Hydrology toolset was used. The function generated eight classes of stream order with the main streams having the highest value. The largest three classes were used to generate distance from streams. The Euclidean distance from the main streams (Figure 3a) needed a subjective judgment for classification. Several factors were considered in this judgment, such as cost of canal construction and maintenance, power capacity, and water loss from canals. Areas with a Euclidean distance <14 km were assigned a very high score, whereas areas with a Euclidian distance >60 km were assigned a low to very low score (Table 1). This classification is very similar to that reported by [28] who assigned areas within a 10 km distance from surface water as being a highly suitable class in surface-irrigation land suitability analysis.

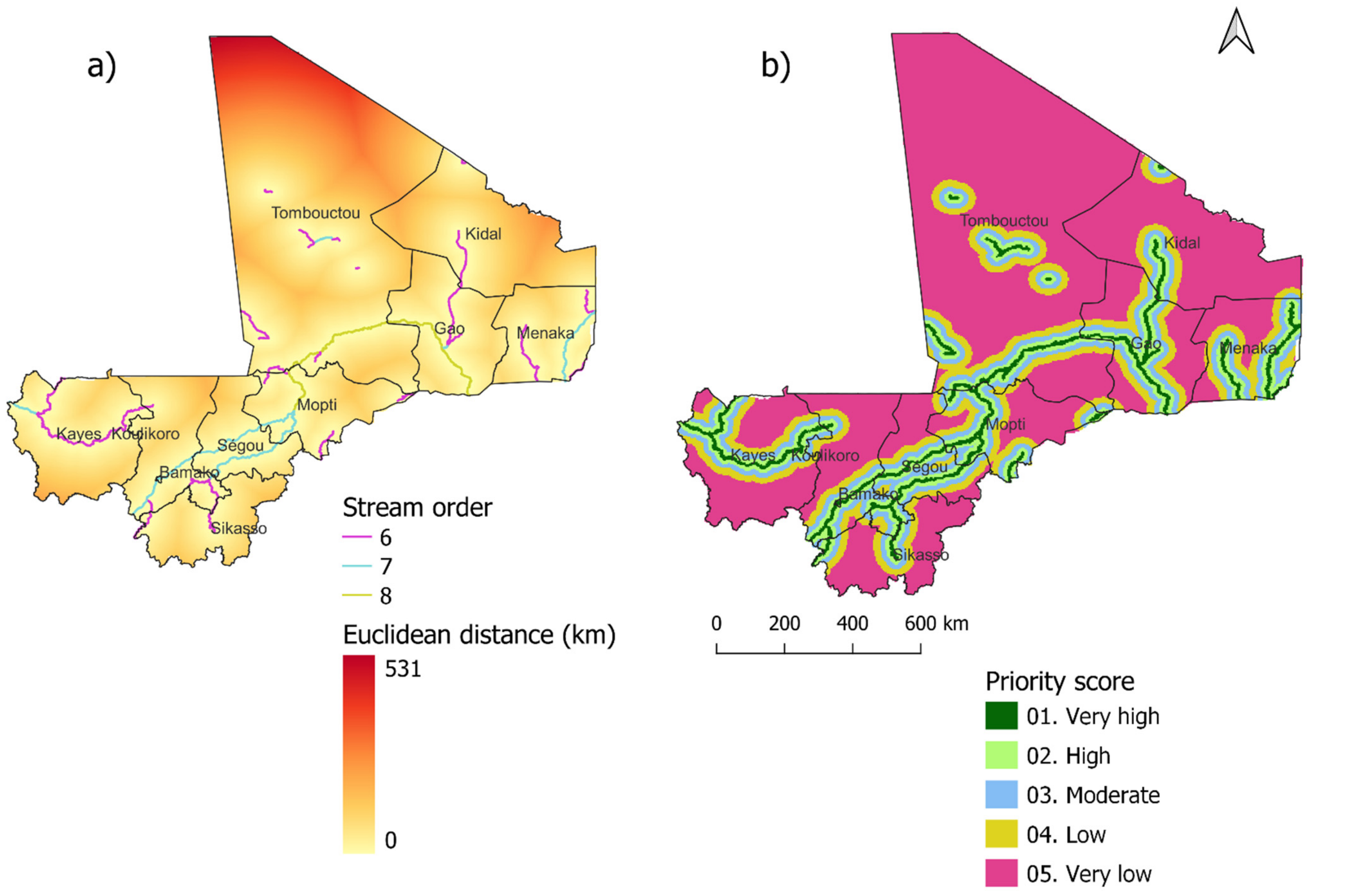

Figure 3. Euclidean distance from surface water Strahler stream order 6 to 8: (**a**) Euclidean distance and (**b**) priority score.

2.2.2. Land Use/Land Cover

Land use/land cover patterns were mapped by classifying Sentinel-2 10 m spatial resolution satellite imagery obtained during the rainy season of 2021, from 15 June to the end of September, utilizing the cloud-based platform Google Earth Engine for regional and planetary scale earth-observation data retrieval and processing. Google Earth Engine has the advantage of providing high-performance parallel computing resources to process large datasets, which facilitates computationally cumbersome geospatial analysis. The platform uses an application programming interface written in JavaScript or Python, which allows data processing and visualization at scale. The platform was used to obtain Sentinel-2 multi-spectral level-2A images that were processed in the present study. The processing of level-2A products includes atmospheric correction applied to Top-Of-Atmosphere (TOA) level-

1C orthoimage products to produce orthoimage Bottom-Of-Atmosphere (BOA) corrected reflectance products using the Sen2Cor processor algorithm [29]. Level-2A images were generated with spatial resolution of 10 m for bands 2, 3, 4, and 8, and 20 m resolution for bands 5–7, 8A, 11, and 12.

The retrieved images were mosaiced to produce one image for the whole country using R software v. 4.1.2 [30]. Nine land-use classes were classified using random forest supervised classification utilizing the Random Forest package in R software [31] (Figure 4). Random forests machine learning algorithms depend on a combination of tree predictors, such that each tree represents the values of a random vector sampled independently with a similar distribution for all trees in the forest [22]. The process started with the tuneRF function that searches for optimal mtry, which controls the size of a feature set to search the best split rules at each node of trees, and the values given in the input data. The mosaiced Sentinel-2 image was then classified by the Random Forest object produced with the optimal mtry. The nine classes were inferred from the ground truth data provided by local experts, GIS specialists, and Google Earth high resolution data totaling 700 polygons. The training data were then partitioned into 70% training and 30% validating using the createDataPartition function in the R package cart. Corresponding values of the mosaiced image at the location of the training data were extracted to create the predictor variables and the response vector for the tuneRF function.

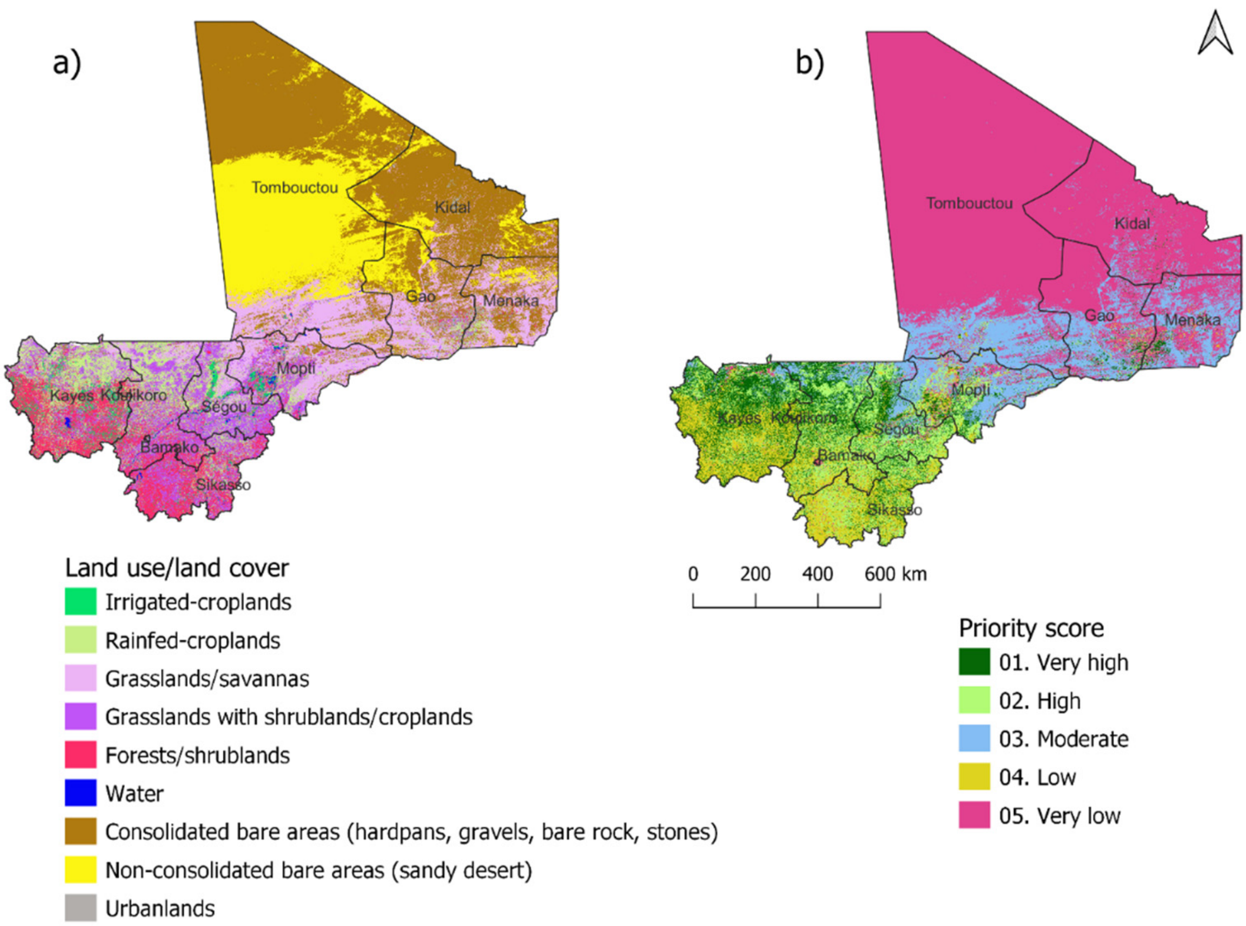

Figure 4. Land use/land cover during rainy season of 2021: (**a**) category and (**b**) priority score.

Table 1. Assigned score, priority class, and % of total area of various quantiles from six different themes used in the selection of most suitable sites for promoting small-scale irrigation across Mali.

Theme	Resolution	Quantile/Class	Area (ha)	% of Total Area (%)	Priority Class	Score Assigned	Source
Accessibility to surface water		Distance from surface water (km)					Equal intervals
	0.5 km	≤14	13,917,188	11.08	Very high	1	
		14–29	14,080,954	11.21	High	2	
		29–60	27,731,454	22.09	Moderate	3	
		60–100	28,277,453	22.52	Low	4	
		>100	41,493,350	33.06	Very low	5	
Land use/land cover		Land use/land cover classes					[25]
	30 m	Irrigated croplands	1,371,519	1.10	Very high	1	
		Rainfed croplands/rangelands	10,007,626	8.01	Very high	1	
		Grasslands/savannas	20,157,146	16.13	Moderate	3	
		Grasslands with shrublands/croplands	13,234,702	10.59	High	2	
		Forests/shrublands	10,855,254	8.69	Low	4	
		Water	342,684	0.27	Low	4	
		Consolidated bare areas (hardpans, gravels, bare rock, stones)	41,137,082	32.92	Very low	5	
		Non-consolidated bare areas (sandy desert)	26,393,019	21.12	Very low	5	
		Urban lands	1,470,857	1.18	Very low	5	
Groundwater		Groundwater type and quantity					[25,32]
	30 m	B-L: Basement-Low	887,891	0.727545	Low	4	
		B-M: Basement-Moderate	6,291,362	5.155194	Moderate	3	
		B-VL: Basement-Very low	3,050,316	2.499454	Very low	5	
		CSF-H: Consolidated Sedimentary Fracture-High	7,002,489	5.737897	High	2	
		CSF-M: Consolidated Sedimentary Fracture-Moderate	19,036,092	15.59833	Moderate	3	
		CSIF-H: Consolidated Sedimentary Intergranular/Fracture-High	15,797,166	12.94433	High	2	
		I-L: Igneous Intrusive-Low	674,418	0.552624	Very low	5	
		I-M: Igneous Intrusive-Moderate	2,669,599	2.187491	Low	4	
		U-H: Unconsolidated Sedimentary-High	19,716,021	16.15547	Very high	1	
		U-L: Unconsolidated Sedimentary-Low	2,845,219	2.331396	Low	4	
		U-LM: Unconsolidated Sedimentary-Low to Moderate	16,138,821	13.22428	Moderate	3	
		U-M: Unconsolidated Sedimentary-Moderate	24,654,245	20.20189	Moderate	3	
		U-VL: Unconsolidated Sedimentary-Very low	3,275,649	2.684094	Very low	5	
Soil		Soil type					[25,33]
	1 km	Haplic Acrisols	522,206	0.68	High	2	
		Plinthic Acrisols	173,842	0.23	High	2	
		Brunic Arenosols	4,616,834	6.03	Low	4	
		Hypoluvic Arenosols	5,974,861	7.80	Moderate	3	
		Eutric Cambisols	11,019,569	14.39	Low	4	
		Vetric Cambisols	410,884	0.54	High	2	
		FLUVISOLS	124,572	0.16	Very high	1	
		Eutric Fluvisols	40,139	0.05	Very high	1	
		GLEYSOLS	5,366,349	7.01	Moderate	3	
		Haplic Gypsisols	1,392,952	1.82	Moderate	3	
		LEPTOSOLS	6,897,030	9.01	Very low	5	
		Gleyic Luvisols	310,444	0.41	High	2	
		Haplic Lixisols	5,024,235	6.56	High	2	
		Dystric Nitisols	393,609	0.51	High	2	
		Eutric Nitisols	585,270	0.76	High	2	
		Solodic Planosols	17,878	0.02	Moderate	3	
		Petric Plinthosols	6,107,698	7.98	Very low	5	
		Pisoplinthic Plinthosols	1,226,930	1.60	High	2	
		Eutric Regosols	9,420,639	12.30	Moderate	3	
		SOLONCHAKS	291,929	0.38	Low	4	
		Haplic Vertisols	1,093,455	1.43	Moderate	3	
		Pellic Vertisols	7,977	0.01	Moderate	3	
		VERTISOLS	137,516	0.18	Very high	1	
		Ferric Luvisols	9,547,278	12.47	Very high	1	
		LITHOSOLS	5,868,606	7.66	Very low	5	

Table 1. *Cont.*

Theme	Resolution	Quantile/Class	Area (ha)	% of Total Area (%)	Priority Class	Score Assigned	Source
		Annual rainfall (mm)					[25]
Rainfall	1 km	0–200	77,432,500	61.67	Very low	5	
		200–400	10,054,300	8.01	Low	4	
		400–600	11,937,600	9.51	Moderate	3	
		600–800	12,136,400	9.67	High	2	
		≥800	14,003,800	11.15	Very high	1	
		Slope (%)					[3,4,25]
Slope	30 m	0–2	15,175,499	12.11	Very high	1	
		2–4	39,009,923	31.12	High	2	
		4–6	30,679,517	24.48	Moderate	3	
		6–8	17,416,586	13.9	Low	4	
		>9	23,070,395	18.41	Very low	5	

The land-use classes were subjectively categorized according to their importance in determining land suitability to promote the small-scale irrigation system. Irrigated land was given a score of one because it is generally associated with very high recharge zones of flood plains and buried channels, and is used to produce the target crops of the small-scale irrigation system. Rainfed croplands and grasslands/savannas were also given a high score because of possible high-water potential and water-holding capacity of the soil. In contrast, the forest/shrublands, urban lands, and consolidated bare areas were given low scores due to their influence on infiltration and runoff, and low water-holding capacity potential. The reclassified priority score layer was downscaled to 30 m resolution. As shown in Figure 4a, irrigated and rainfed croplands are mainly located in the Segou, Kouikoro, and Kayes regions, whereas the northern parts of Tombouctou and Kidal are desert areas.

2.2.3. Groundwater

Groundwater is another important source of water for irrigation. A GIS dataset of the country groundwater was obtained from the Africa Groundwater Atlas country hydrogeology maps (Version 1.1, 2019), created by the British Geological Survey [32]. This atlas summarizes the groundwater resources for 48 African countries, including Mali, with hydrogeology and geology attributes for each country. The hydrogeological categories combine aquifer type and productivity, which are essential criteria needed in the present analysis to determine groundwater potential for expanding irrigable land, whereas the geological categories reflect significant hydrogeological units. Aquifer type is categorized into four main categories based on the nature of groundwater flow and storage, e.g., flow through pores, fractures, or karstic, with subdivisions of some categories. Aquifer productivity was estimated based on borehole yield data as a proxy to relate the average yield of a single effective well-developed borehole to the appropriate depth of relevant aquifer (Table 1). Considering the hydrogeological characteristics of the groundwater, the priority classes were assigned in the present study (Figure 5). For example, the Igneous Intrusive-Low aquifer was assigned a very low score of five because it contains a low amount of water, commonly forms at depth, and has interlocking crystals with very low porosity, whereas the Unconsolidated-High aquifer was given a very high score of one because of the high amount of groundwater stored in relatively higher permeable materials, indicating easier extraction of water for irrigation purposes. The shapefile was then rasterized to obtain the groundwater score raster layer ranging from very high to very low scores.

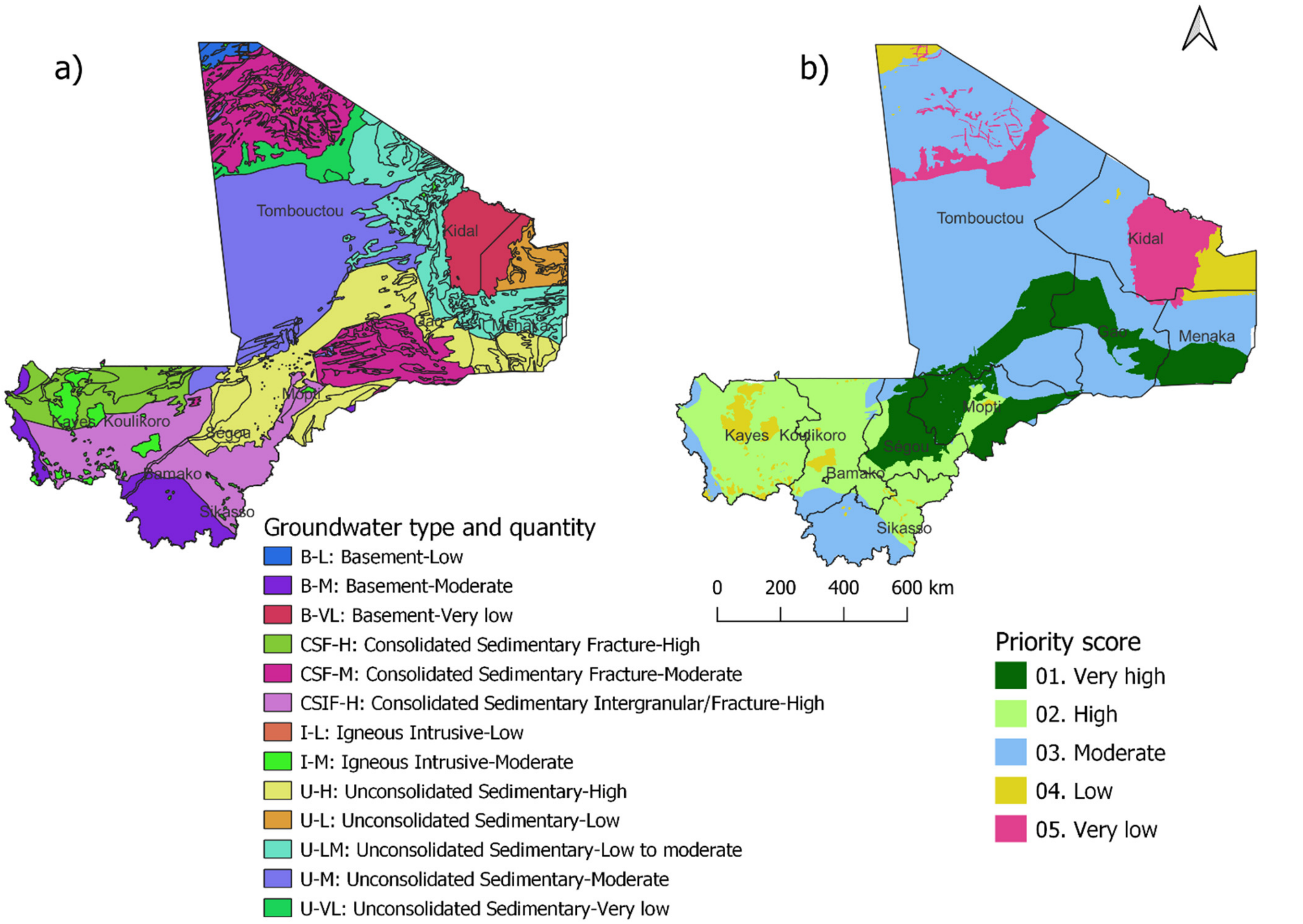

Figure 5. Groundwater type and quantity: (**a**) category and (**b**) priority score.

Table 2. Related studies on land suitability analysis in agriculture.

Objectives	Methods	Parameters	Reference
Determine the suitability of land for surface irrigation	GIS and AHP	LULC, soil, topography (slope and altitude), and distance from surface water	[3]
Map suitable land for surface irrigation development	GIS and AHP	LULC, soil, slope, distance from surface water	[4]
Evaluate land suitability for surface and drip irrigation	RS and GIS	Slope, soil texture, soil drainage, and soil chemical characteristics	[10]
Assess land suitability for surface irrigation	GIS and AHP	Slope, LULC, soil depth, soil drainage, soil type, and distance from surface water	[28]
Develop land suitability map of lowland sub-basin area for surface irrigation	GIS and AHP	slope, soil texture, depth, drainage characteristics, soil type and LULC	[9]
Identify suitable lands for agricultural development	GIS and AHP	Slope, elevation, LULC, soil moisture, distance from river, soil characteristics, geology, aspect, distance from road	[8]
Prioritize watersheds for productivity enhancement and livelihood improvement	RS and GIS	Population, slope, rainfall, LULC, and soil	[25]
Determine suitable lands for agricultural use	GIS and AHP	Parameters of great soil group, slope, aspect, elevation, and land use capability class	[34]

2.2.4. Soil

Soil type plays an important role in prioritizing areas suitable for promoting small-scale irrigation in reference to its water-holding capacity and other associated physicochemical characteristics. The Mali soil map was obtained from the Soil Atlas of Africa, created by the European Commission [33], where several maps were elaborated by the European Union, African Union, and the Food and Agriculture Organization of the United Nations available online at https://esdac.jrc.ec.europa.eu/content/soil-map-soil-atlas-africa (accessed on 2 January 2022). Scores were subjectively assigned to each soil type considering its characteristics of texture and organic matter content (Table 1). For example, loamy to clayey textures, such as the Fluvisols, were given the highest score of one as they indicate a high water-holding capacity content and balanced nutrient supply. In contrast, soils over hard rock or gravel, such as Leptosols, are usually low in organic matter and, therefore, were given a very low score (Figure 6a,b). The Mali soil-type map shown in Figure 6a indicates that fertile soils with a high water-holding capacity (Ferric Luvisols and Haplic Lixisols) are distributed in the central and southern parts of the country in the Segou, Sikasso, and Kouikoro regions (Figure 6a). Sandy soils with a low water-holding capacity (Brunic Arenosols) are concentrated in the northern regions of Tomboctou and Kidal.

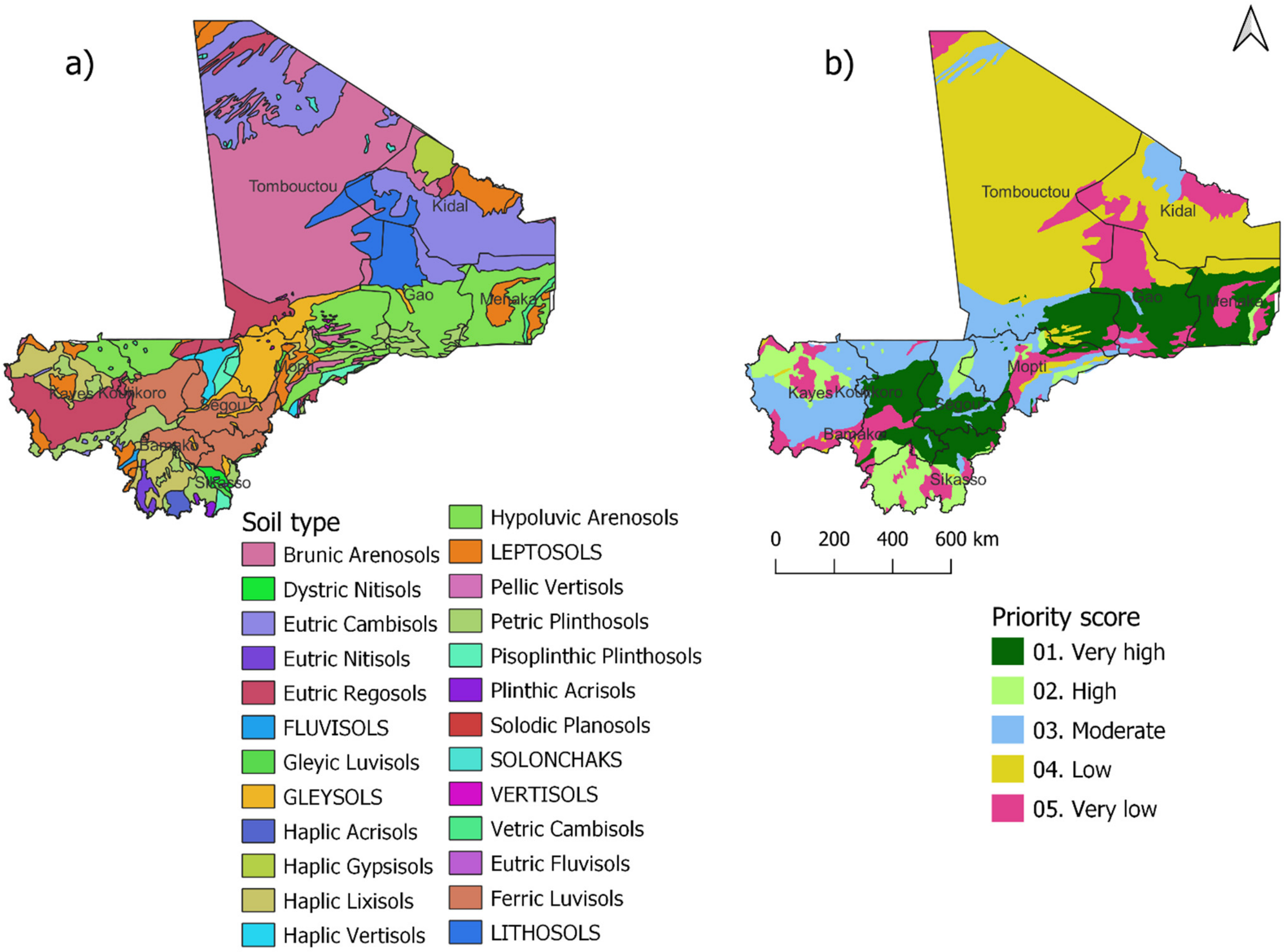

Figure 6. Soil type: (**a**) category and (**b**) priority score.

2.2.5. Rainfall

Mean annual rainfall data for several locations across Mali over the past five years from 2017 to 2021 were obtained from ground stations and the global meteorological network, NASA Power [35]. The obtained data were interpolated across the country at 1 km resolution using the kriging interpolation method in QGIS [36]. Areas receiving >800 mm annual rainfall were ranked as highly suitable, assuming a good water-availability zone, and mainly located in the southern region, while areas receiving <800 mm annual rainfall were equally partitioned into four quadrants at 200 mm intervals and gradually ranked (Table 1). Areas receiving <200 mm were assigned a very low score, assuming a poor water-availability zone, and mainly located in the northern Sahara region (Figure 7), similar to that assigned by [25]. This classification distinguished the driest areas in the northern regions, Tombouctou, Gao, Kidal, and Menaka, from the humid areas in the southern region, Sikasso, and the capital district, Bamaka (Figure 7).

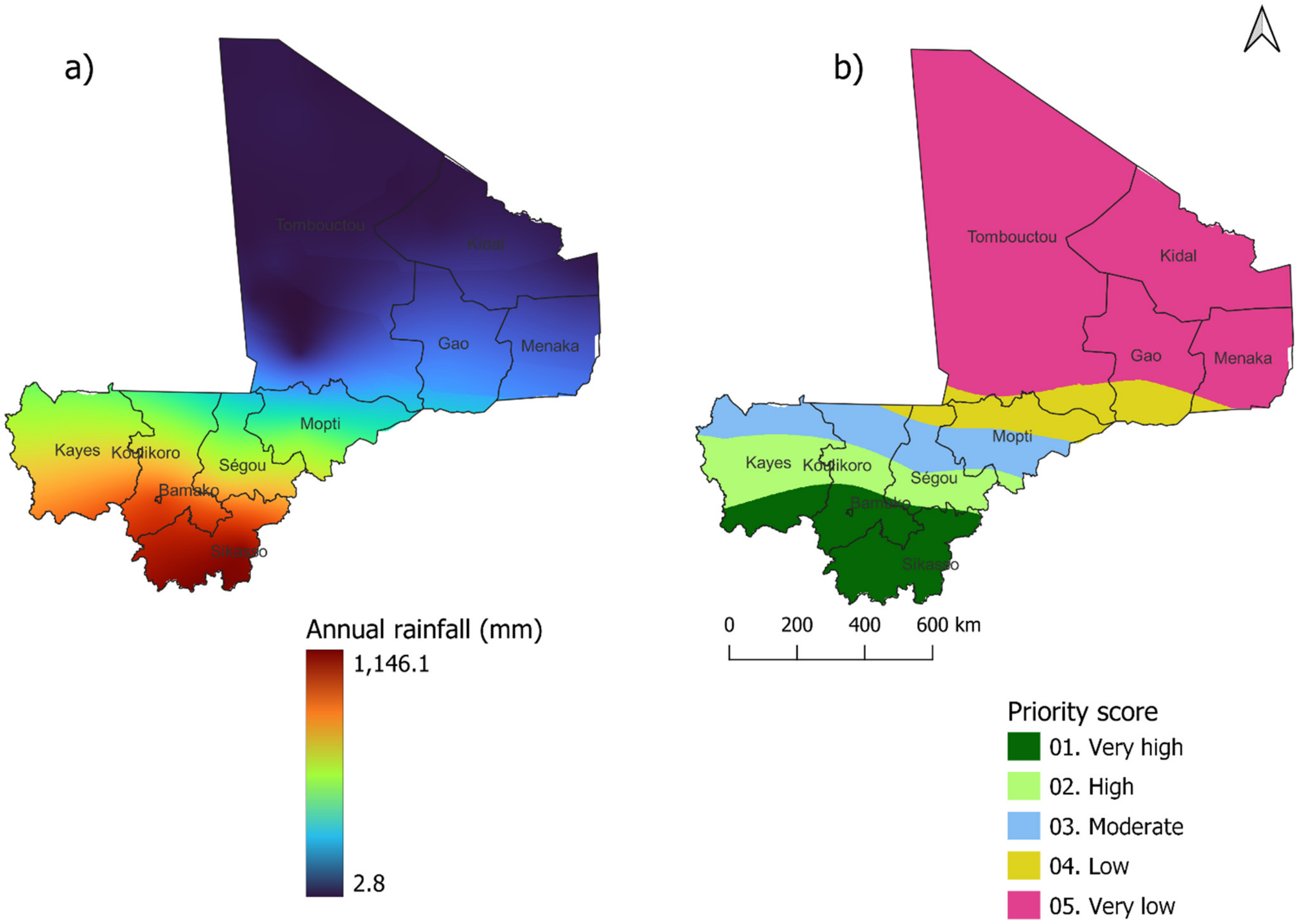

Figure 7. Annual rainfall: (**a**) distribution and (**b**) priority score.

2.2.6. Slope

The slope gradient directly influences the infiltration rate of rainfall, such that a steeper slope reduces the recharge rate as water runs rapidly off the surface, and vice versa. The Space Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) on a global scale at 30-m resolution by NASADEM was used to derive the slope in percentage. The SRTM DEM data by NASADEM are high resolution with wide coverage, and were obtained using Google Earth Engine. The resulting layer was then reclassified into 10 classes and scores were given accordingly (Table 1). The gentle slopes were given high priority and steep slopes were given low priority (Figure 8), similar to that assigned by [25] for watershed prioritization in Mali. Areas with slope <2% were classified as highly suitable because low runoff contributes to a higher recharge rate of groundwater. In contrast, areas with steep slope >9% were classified as highly unsuitable because of high runoff which does not allow sufficient time to infiltrate the surface and recharge the groundwater.

2.3. Integration of Thematic Layers

Suitable small-scale irrigation areas were implemented in QGIS using the raster calculator algorithm, which allows algebraic operations on raster layers to be performed. First, the weight of individual themes was determined based on the AHP as follows; first, the generation of a pairwise comparison matrix that included all the thematic layers based on the Saaty's scale [37] of relative importance. This was determined according to expert knowledge and the published literature [15,25–27,34]. Second, the consistancy ratio (CR) for checking the degree of consistency among the assigned ratings was calculated. This CR calculation included two steps; first, calcualting the consistency index (CI) as follows:

$$\mathrm{CI} = \frac{C(\lambda max - n)}{(n-1)} \quad (1)$$

where λ_{max} is the largest maximum eigenvalue of the comparative matrix and n is the rank of the matrix. Second, the CR is estimated by dividing the CI by the random index. The consistency ratio made up 5%, which is lower than the threshold of 10% [35], indicating an acceptable consistency value. Otherwise, if the consistency ratio is ≥10%, the subjective judgment must be revised. According to the analysis, accessibility to surface water had the highest weight of 23.8%, followed by LULC at 21.8% and groundwater at 16.5% (Table 3). The higher the weight of the layer, the greater importance it has in determining suitable areas for promoting SSI.

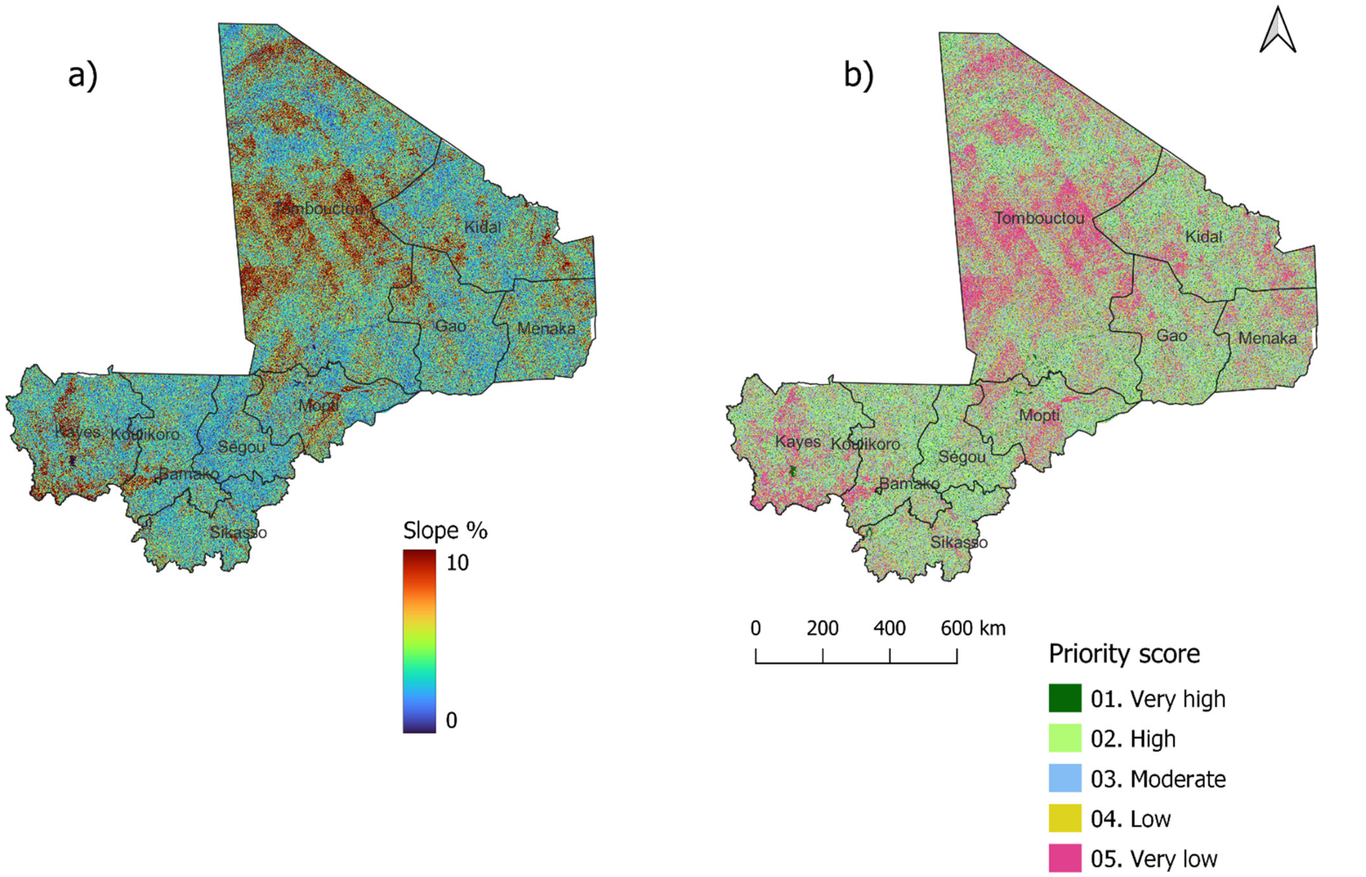

Figure 8. Slope in percentage: (**a**) Slope % and (**b**) priority score.

Table 3. The pairwise comparison matrix among the thematic layers for suitable small-scale irrigation areas.

	Accessibility to Surface Water	Land Use/Land Cover	Groundwater	Soil	Rainfall	Slope	Weightage	Weightage %
Accessibility to surface water	1						0.238	23.8
Land use/land cover	1	1					0.218	21.8
Groundwater	1	1	1				0.165	16.5
Soil	0.33	0.5	1	1			0.132	13.2
Rainfall	0.5	0.5	2	1	1		0.148	14.8
Slope	0.5	0.5	0.5	1	0.5	1	0.099	9.9
Consistency ratio			5 % (consistency is acceptable)					
Sum							1	100

Following the determination of each layer weight, the reclassified layers with scores ranging from one to five were integrated in weighted overlay analysis as follows:

$$SSPp = \sum Tss \times Fw \quad (2)$$

where *SSPp* is the SSI priority score for each pixel of the final integrated priority layer, *Tss* is the selected SSI priority layer, and *Fw* is the weightage factor of the layer.

3. Results and Discussion

3.1. Selection and Weight of Thematic Layers

Site selection is an essential step for agricultural development planning because it provides information about the constraints and opportunities of the area being investigated. The present study focuses on determining the most suitable sites for implementing irrigation projects for small-scale farmers. Therefore, selection of relevant thematic layers is a crucial component of this study and was achieved by reviewing the relevant literature on site suitability in agriculture (Table 2). Selection also took into account the knowledge of experts already working on implementing irrigation projects in Mali and co-authoring this article. Table 2 explores some of the previous research on site-suitability evaluation in agriculture and the methodologies used. Most of these studies used the AHP method [3,4,15,16,25,34], which is a multiple-criteria-making method that scores the selected layers relative to each other in a pairwise comparison matrix. By looking at previously conducted studies on suitability for irrigation development planning, selected layers mainly included accessibility to water sources and physical land features, such as soil and slope, and LULC [3,4]. Girma et al. [4] considered distance to the perennial rivers as the most important factor with a 35% weight for surface irrigation site-suitability selection. Similarly, Hagos et al. [3] assigned the highest score of 33% to distance from water sources, whereas they assigned the lowest score of 3.3% to LULC. Similar thematic layers were considered in the present study and included the groundwater potential in the access-to-water resources analysis. Agreeing with Girma et al. [4] and Hagos et al. [3], the highest weight was assigned to the accessibility-to-surface-water thematic layer, whereas the LULC layer was also indicated as an important layer due to the heterogeneity of the large land area investigated in the present study. Other important factors are rainfall and soil as they impact the vegetation cover and water resources. The last layer was the slope which influences the infiltration and runoff rates and, consequently, the groundwater recharge rate, agreeing with others [3,4,10,38] who considered the slope in site suitability for surface irrigation planning. Following the selection of thematic layers, priority scores within each thematic layer were assigned based on the available sources from the literature and expert judgement (Table 1). A similar approach was used for land-suitability mapping in other studies where expert opinions were used to determine the selected parameters, whereas the AHP method was used to obtain the weights [8].

3.2. Cross Validation of Introplated Layer and Land Use/Land Cover Map

The cross validation of the cumulative annual rainfall interpolation results indicated good agreement with the observed data as indicated by the R^2 value of 0.93 and RMSE value of 92.5 mm (Figure 9). The resulting interpolated thematic annual rainfall layer shows a wide range of annual rainfall variations with values ranging from <10 mm and >1000 mm, representing various agro-climatic zones across the country (Figure 7). This indicates satisfactory prediction by the kriging method, which is considered to be one of the best methods of interpolation. Abtew et al. [38] compared six methods of spatial interpolation for monthly rainfall and concluded that the kriging method is one of the best three methods with the advantage of providing estimates of the error interpolation. It uses a limited set of sampled data points to extend the value of the variable over a continuous spatial extent. The main difference from other methods, such as Inverse Distance Weighted Interpolation, Linear Regression, or Gaussian, is that it uses the spatial correlation between sampled points: the interpolation is, therefore, based on the spatial arrangement of the empirical observations rather than on the presumed model of spatial distribution. This means that a higher autocorrelation among the sample points is needed for kriging to outperform the other methods, which was the case in the present study.

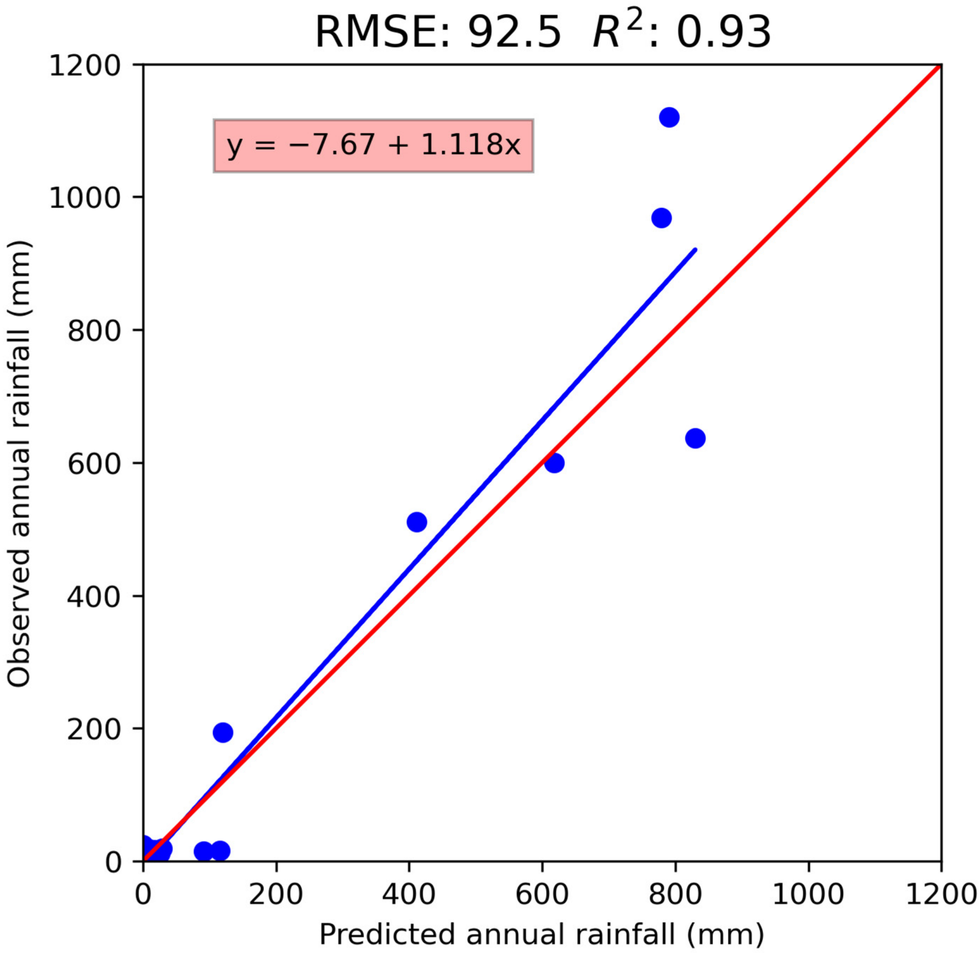

Figure 9. Cross validation of annual rainfall.

For the LULC validation, the ground truth data were partitioned into 70/30% for training and validating the classified Sentile-2 image. The classified nine classes were compared against 210 ground truth points provided by local experts and online resources, such as Google satellite maps for uncovered areas, particularly in northern sub-Saharan regions, to cover the spatial extent of the country. According to the error matrix, the accuracy assessment of users ranged from 50% to 100%, while the producer accuracy assessment ranged from 54.5% to 93.9%. The highest accuracy assessment of users related to consolidated and non-consolidated bare areas, followed by grasslands/savannas and forest/shrublands, and irrigated croplands. Interestingly, the accuracy assessment of producers for irrigated croplands was >90%. Out of the 210 validation points, 172 matched the derived classification results with an overall accuracy of 82% and a Kappa coefficient value of 0.79 (Table 4). These results indicate good performance of the random forest classification algorithm in large data classification, which is considered to be one of the most successful ensemble machine learning methods with several advantages. In the present study, the random forest algorithm outperformed other supervised-classification methods, such as support vector machine, due to its ability to deal with large data with fast model fitting and, therefore, producing accurate prediction for high-dimensional data [21].

Table 4. Accuracy assessment of land use/land cover map presented in Figure 4 using error matrix method.

	Classes	**Reference Data**										
		01	02	03	04	05	06	07	08	09	RT	UA
Derived classification	01. Irrigated croplands	32	2	0	0	4	2	0	0	0	40	80%
	02. Rainfed-croplands	1	12	1	8	2	0	0	0	0	24	50%
	03. Grasslands/savannas	0	0	20	0	0	0	2	1	0	23	87%
	04. Grasslands with shrublands/croplands	0	5	0	9	0	0	0	0	0	14	64.3%
	05. Forests/shrublands	2	2	0	1	24	0	0	0	0	29	82.8%
	06. Water	0	0	0	0	0	10	0	0	2	12	83.3%
	07. Consolidated bare areas (hardpans, gravels, bare rock, stones, boulders)	0	0	0	0	0	0	16	0	0	16	100%
	08. Non-consolidated bare areas (sandy desert)	0	0	0	0	0	0	0	14	0	14	100%
	09. Urban lands	0	1	0	0	1	0	0	0	31	33	93.9%
	Column total	35	22	21	18	31	12	18	15	33	205	
	Producers' accuracy	91.4%	54.5%	95.2%	50%	77.4%	83.3%	88.9%	93.3%	93.9%		

RT: Row totals; UA: Users accuracy; Overall classification accuracy = 82%; Kappa coefficient = 0.79.

3.3. Integration of Thematic Layers for Site Selection

Following the reclassification of the six thematic maps to five scores, the maps were integrated on the basis of the SSPp with five priority classes ranging from very high to very low (Figure 10). The assigned scores were used to standardize the priority classes for heterogeneous data by bringing them into a common domain of scaling. Results indicate that very high priority areas are located in central Segou and southern Koulikoro, with 340,384 ha in Segou and 243,512 ha in Koulikoro, accounting for 53% and 38% of the very high priority areas, respectively (Table 5). Within the very high priority sites of 641,448 ha, there is a high potential to expand irrigable land for sustainable agricultural development in the long term with an expected high internal rate of return. These results closely agree with the previously published report [39] on smart irrigation strategies in Mali that indicated about 0.3 Mha are very highly suitable for small-scale irrigation expansion. Areas of potentially irrigable land exceed 2.2 Mha for large or small-scale irrigation, as determined by the size of the installations [40]. Large-scale irrigation includes large areas over 100 ha which require large hydraulic structures, such as dams, whereas small-scale irrigation involves local irrigation managed by individual farmers or farmer organizations. Irrigation investment in Mali is long standing, with the creation of the Niger Office, a large irrigation scheme in the Segou region which includes 53% and 19% of the very high and high priority sites, respectively, in the present study (Table 5). These results demonstrate the efficacy of the implemented conceptual framework to select potential sites for expanding irrigable lands. High priority sites are distributed in the northern and southern Segou regions, in central to northwestern and southern Koulikoro, in northeastern Sikasso, northwestern Kayes, and in central and southwestern Mopti (Table 5). The Koulikoro and Kayes regions include about 42% of the total high potential sites, which indicates promising regions for irrigation project investments, particularly around the capital district, Bamako, in the Koulikoro region. In other words, investments in promoting small-scale irrigation are also possible to provide supplemental irrigation to rainfed croplands/rangelands to prevent dryland yield fluctuations due to prolonged drought events associated with a changing climate. The third class of moderate priority site is mainly located in the northeastern Kayes region, in eastern and southern Mopti and Sikasso, in southern and central parts of Goa, and in a small part of southern Tombouctou, giving a total area of 37.9 Mha (Figure 10, Table 5). Sites within the moderate priority regions can be devoted to grasslands/savannas where water scarcity is a major constraint for agricultural development. Central and northern parts of Tombouctou, most of Kidal, and northern Gao and Menaka are categorized as low and very low priority sites for a total area of 65 Mha due to the low rainfall, extreme weather, and infertile soil and, therefore, are not recommended for promoting irrigation projects.

The weight of each layer was determined based on the AHP method, which organizes the decision problem into several levels. Layers dealing with water availability and LULC, either surface or groundwater, were given a higher weight compared with other thematic layers as water scarcity is one of the main constraints to agricultural development in Mali. The next important layers were rainfall amount, soil, and slope. The northern parts of the country are generally categorized as a hyper-arid zone with <50 mm annual rainfall and, therefore, are not suitable for agricultural development. Areas far from surface water and areas with deep and low-yield groundwater are also unsuitable for irrigation installation investment. In contrast, areas near the Niger River, or those having groundwater in high quantities, are the most suitable for promoting small-scale irrigation as long-term investment for improving the livelihoods of smallholders. Irrigated crops may include cash crops, such as cotton and fodders or vegetables, which will indeed increase the sustainability of the system and the welfare of the farmers.

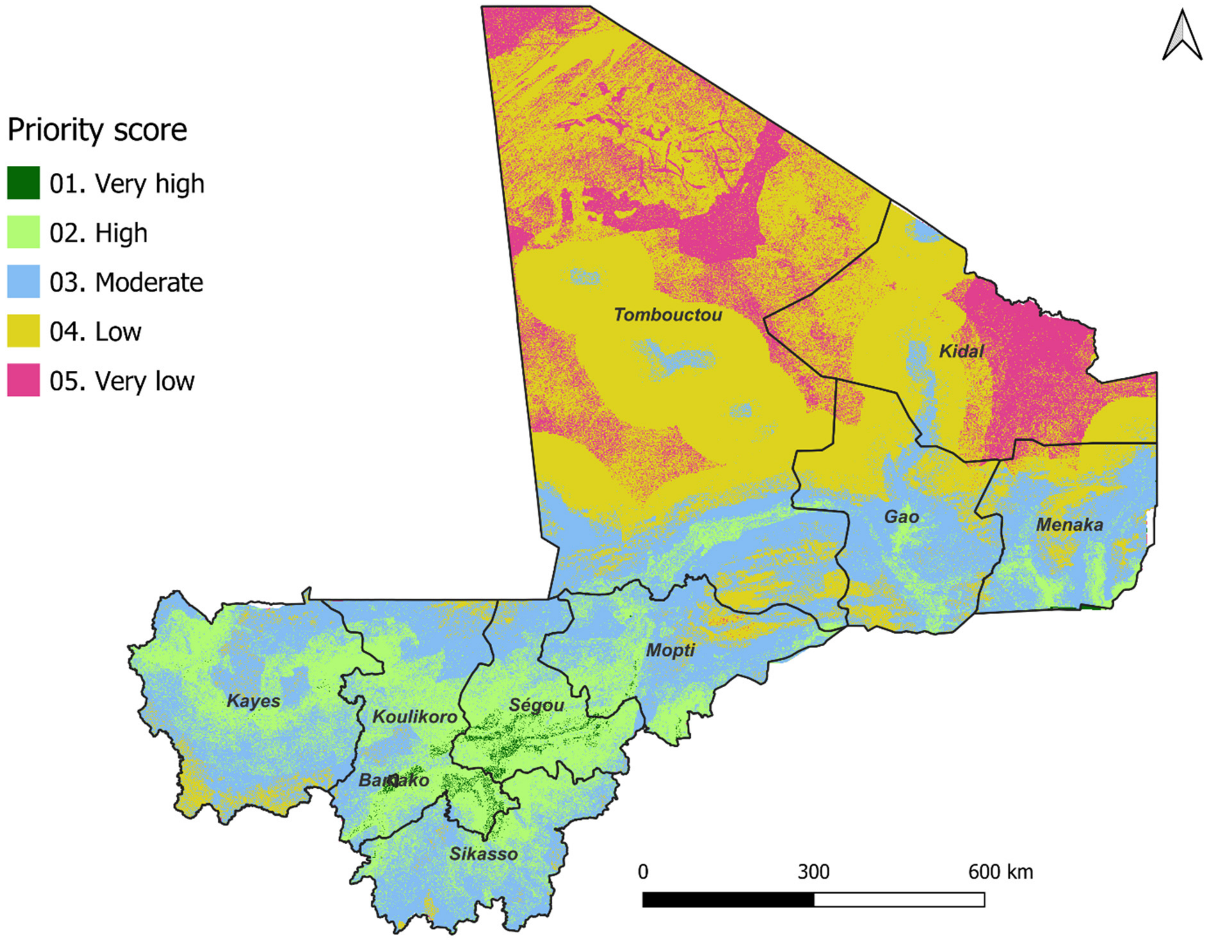

Figure 10. Site-suitability score for small-scale irrigation schemes across nine regions and one district of Mali.

Another important factor that was considered in this study is the percentage of slope as it influences the runoff and soil drainage, as well as vulnerability to erosion. In addition, developing a successful irrigation investment plan requires considering the land use/land cover to focus on irrigated crops and to determine potential areas for expanding irrigable land for crop production. Soil type is also important when considering suitability for expanding irrigable areas for agricultural development. Soil texture greatly impacts soil water-holding capacity, which enhances irrigation efficiency and the water productivity of crops. The detailed Mali soil map created by the European Commission was used and assigned scores, classifying the soil types from high to low according to their physical and organic matter properties. Therefore, considering all these factors, it was necessary to produce the final thematic layer that could determine the most suitable areas for promoting small-scale irrigation across the country.

Table 5. Area (ha) of each priority score shown in Figure 9 for nine regions and one capital district. Percentages in parentheses represent percentages from row sum and percentages from column sum, respectively.

Regions	Very High	High	Moderate	Low	Very Low	Row Sum
Bamako	1380 (5.6%, 0.21%)	23,159 (94.3%, 0.11%)	-	-	-	24,538
Koulikoro	243,512 (2.68%, 38%)	4,490,139 (49.4%,21.5%)	4,099,692 (45%,10.8%)	241,935 (2.6%, 0.48%)	98 (0.01%, 0.0062%)	9,075,377
Kayes	6504 (0.059%, 1%)	4,449,044 (36%, 21.3%)	6,752,207 (54.9%, 17.8%)	1,074,172 (8.7%, 2.1%)		12,281,927
Sikasso	26,509 (0.37%, 4.1%)	2,738,449 (38%, 13%)	4,150,247 (58.9%, 11%)	127,817 (1.8%, 0.2%)	-	7,043,022
Segou	340,384 (5.5%, 53%)	4,079,982 (66%, 19%)	1,639,147 (26.6%, 4.3%)	91,255 (1.4%, 0,18%)	-	6,150,769
Mopti	23,159 (0.29%, 3.6%)	2,369,782 (30%, 13%)	4,765,284 (60%, 12.5%)	712,403 (9%, 1.4%)	10,150 (0.12%, 0.64%)	7,880,777
Gao	-	858,648 (17%, 4%)	5,007,811 (49%, 13%)	4,066,777 (40%; 8%)	138,558 (1.3%; 0.8%)	10,071,793
Tombouctou	-	850,173 (17%, 4%)	6,461,097 (12.9%, 17%)	32,080,100 (64%; 64%)	10,353,740 (20.8%; 65%)	49,745,112
Kidal	-	-	676,531 (4.5%, 1.8%)	9,114,105 (61%, 18.3%)	5,120,353 (34%, 32%)	14,910,989
Menaka	-	1,001,740 (13%, 4.8%)	4,313,147 (56%, 11.4%)	2,222,945 (28.8%, 4%)	157,085 (2%, 0.9%)	7,694,917
Column sum	641,448	20,861,115	37,865,163	49,731,509	15,779,986	124,879,221

4. Conclusions

The results of the present study illustrate the efficacy of the spatial modeling approach in site selection for agricultural development and smallholder livelihoods and welfare. Remote sensing and GIS are powerful tools to process and obtain spatial data for agricultural development purposes. The process began with identifying the most relevant layers for promoting small-scale irrigation from the perspectives of water availability, climate and soil, and land use/land cover. Next, subjective scores for various distributions/classes were assigned within each layer for consistency. Finally, weights were allocated to spatial data to combine the layers and calculate the ranked sites map across the country. The obtained results provided the precise location of 'high' vs. 'low' potential sites and percentage areas of these sites. Overall, across Mali, the central regions in Segou and those near the capital district, Bamako, are more favorable for the promotion of small-scale irrigation infrastructure than the northern regions where the climate is very dry, and the soil has low fertility status. This also agrees with the land use/land cover map where irrigated and rainfed croplands and grassland with shrublands/croplands are mostly located in central and western regions, whereas northern regions are sandy desert or include hardpans, gravels, or bare rock/stones. The present methodologies can be implemented in other sub-Saharan African countries for agricultural development planning at large scale to enhance long-term sustainability of natural resources, increase crop production, and smallholder well-being.

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