sustainability

Article

Analytic Hierarchy Process Based Land Suitability for Organic Farming in the Arid Region

Pandian Mangan [1,*], Dinagarapandi Pandi [2], Mohd Anul Haq [3], Aniruddha Sinha [4], Rajagopal Nagarajan [1], Twinkle Dasani [4], Ismail Keshta [5] and Mohammed Alshehri [6]

1 AmnexInfotechnologies Pvt. Ltd., Ahmadabad 380052, Gujarat, India; rajmtech1989@hotmail.com
2 School of Civil Engineering, Vellore Institute of Technology, Chennai 600127, Tamil Nadu, India; dinagarapandi@gmail.com
3 Department of Computer Science, College of Computer and Information Sciences, Majmaah University, Al-Majmaah 11952, Saudi Arabia; m.anul@mu.edu.sa
4 Symbiosis Institute of Geoinformatics, Pune 411016, Maharashtra, India; aniruddhasinha2995@gmail.com (A.S.); tdasani13@gmail.com (T.D.)
5 Computer Science and Information Systems Department, College of Applied Sciences, AlMaarefa University, Ad Diriyah, Riyadh 13713, Saudi Arabia; imohamed@mcst.edu.sa
6 Department of Information Technology, College of Computer and Information Sciences, Majmaah University, Al-Majmaah 11952, Saudi Arabia; ma.alshehri@mu.edu.sa
* Correspondence: pandiangeotechm@gmail.com

Abstract: The use of organic farming in the Thar desert region (great Indian desert) is extremely low due to the low humidity and high temperatures across India. As a result, the desert area faces significant challenges in agricultural production and in meeting the demand for high-quality food. Thus, the farming community in this area needs to expand to meet the required demands. Geospatial technologies are capable of recommending suitable farming areas in desert regions and, specifically, to increase organic farming. However, the prevalence of organic farming is very low in developing countries. In this study, a multi-criteria decision-making process was used to determine land suitability for organic crops and to increase organic food production. This study attempted to identify suitable land for reliable organic farming in Rajasthan's Barmer district. The analytical hierarchy process (AHP) technique combined with the geographic information system approach showed that, in the Barmer district, the highly suitable area for organic farming comprises about 832 sq. km and the moderately suitable area covers about 8524 sq. km. Monthly Gravity Recovery and Climate Experiment (GRACE) and precipitation data were used to identify the impact of organic farming in the Barmer district for the period from January 2017 to December 2020. Finally, this study investigated the quality of land and its application so that it can be used effectively to solve social and economic problems.

Keywords: Thar desert; Barmer district; analytical hierarchy process (AHP); organic farming; gravity recovery and climate experiment (GRACE)

check for updates

Citation: Mangan, P.; Pandi, D.; Haq, M.A.; Sinha, A.; Nagarajan, R.; Dasani, T.; Keshta, I.; Alshehri, M. Analytic Hierarchy Process Based Land Suitability for Organic Farming in the Arid Region. *Sustainability* **2022**, *14*, 4542. https://doi.org/10.3390/su14084542

Academic Editor: Sara Bosi

Received: 3 February 2022
Accepted: 25 March 2022
Published: 11 April 2022

1. Introduction

Desertification is the most serious environmental problem globally in terms of biodiversity and land productivity [1,2]. Desertification promotes land degradation in all climate zones, including humid, semi-arid, and arid zones [3]. Desertification is expected to continue in flat areas of Africa, North America, northern China, and India [4]. In India, the process of land degradation affects roughly one-third of the total geographical area [3]. The Thar desert, located in northwestern India, is well known for its desert landscape [5]. The Thar desert encompasses nine districts in Rajasthan, India (Bikaner, Jaisalmer, Barmer, Jodhpur, Churu, Nagaur, Sikar, Jhunjhunu, and Jalore). Varghese and Singh [5] proposed a policy to control desertification in the state of Rajasthan. Thar desert districts are confronted with challenges due to decreased rainfall and increased food consumption [6].

Organic farming has the potential to significantly contribute to preventing desertification and land degradation [7]. Desertification has necessitated the use of sustainable agricultural practices, such as organic farming, in recent decades. In the arid zone, organic farming has significant potential for sustaining climatic and environmental conditions. It is environmentally friendly because it avoids the use of external synthetic fertilizers and pesticides [8]. Eco-friendly farming necessitates inputs that are subject to various climatic, topological, and geophysical constraints [9]. As a result, thematic criteria maps based on geographic information systems (GIS) and other supplementary data can be created to assess the potential for organic farming in arid areas [10]. Geospatial tools can identify suitable lands for organic farming based on various criteria, such as soil quality, geology, drainage, and topography [11]. Thematic criteria are used to identify and prioritize potential organic farming sites [12]. One of the decision-making tools for identifying potential organic farming sites is the analytical hierarchical process (AHP) method [13,14]. Saaty [15] first developed the AHP method, which is a hierarchical modeling approach, based on thematic criteria, used to solve complex problems [16]. AHP is a multi-criteria decision-making method that has been used to solve a wide range of problems involving multiple criteria and their constraints [17]. AHP allows weighted overlay analysis, and can result in very positive outcomes for potential organic farming sites. Themes and their subclasses can be used to create a multi-level hierarchical structure based on various criteria and constraints [18]. Before determining the final score, the hierarchical structure is designed to regulate the relative importance of weights for each criterion [19]. To rank the individual criteria, a pair-wise comparison method is used. A decision support system was previously used to define potential site maps by integrating AHP and GIS [20]. Xu et al. [21] used the integration of AHP and GIS to identify potential organic farming sites.

Le Campion et al. (2020) [22] compared the implementation of organic farming with that of conventional farming, finding that organic farming is relatively easy because it defines the natural soil fertility. The authors forcefully adapted organic farming to improve agro-ecosystem management. Thar desert districts encourage a variety of organic farming activities using bio-fertilizers [23], which increase food production. Overall, Thar desert districts have fewer agriculture operations, resulting in less water consumption for organic farming [6]. The decline in water resources in desert areas is the result of various parameters, including low precipitation, and high air and soil temperatures, which result in low soil moisture. Therefore, water demand has risen in various fields, such as for municipal, agricultural, and industrial purposes [2]. To successfully implement organic farming, it is essential to determine the water equivalent thickness of the land and the precipitation in the desert area [6]. The state of Rajasthan can benefit from increased land productivity and socio-economic activity as a result of this organic farming implementation. The productivity, net profit, and total labor cost are all important factors in organic farming [24]. As a result, it is critical to identify suitable land with minimal input using geospatial techniques [7]. Based on the minimal parameters revealed from remote sensing and other secondary data sources, suitability maps can be drawn using geospatial tools [25].

The prevalence of organic farming is low in desert areas. Areas in the Thar desert districts have limited water supplies and high dunes [7]. Alsharif et al. (2020) [23] conducted a detailed review of the importance of bacteria to perform organic farming in desert regions. In this study, geospatial tools were used to map possible organic farming sites. Barmer is noted for its arid western zone and drier environment. Desertification is a problem in this district, and artificial agricultural practices, such as organic farming, must be improved [23]. Gravity recovery and climate experiment (GRACE) data were used to determine the water equivalent thickness in land and compare it with the precipitation in the Barmer district. The goal of this project was to employ AHP and GIS-based methodologies to discover prospective organic agricultural areas in the Barmer district of India's Thar desert.

2. Study Area

One of the Thar desert districts was chosen as the study area. There are nine districts in the Thar desert that are located in Rajasthan's western region. One of the Thar desert districts in Barmer. It is Rajasthan's third-largest district by area and India's fifth-largest district. The area is estimated to be around 28,341 sq. km (Figure 1). The area is located between 260 30′ N and 240 38′ N latitude and 700 5′ E and 720 51′ E longitude. The research region is located at heights ranging from 25 to 250 m above sea level. This district shares borders with Jaisalmer to the north, Pali and Jodhpur to the east, Jalore to the south, and Pakistan to the west. River Luni flows about 480 km until meeting the Gulf of Kutch in Jalore. The Barmer region receives about 277 mm of yearly rainfall on average.

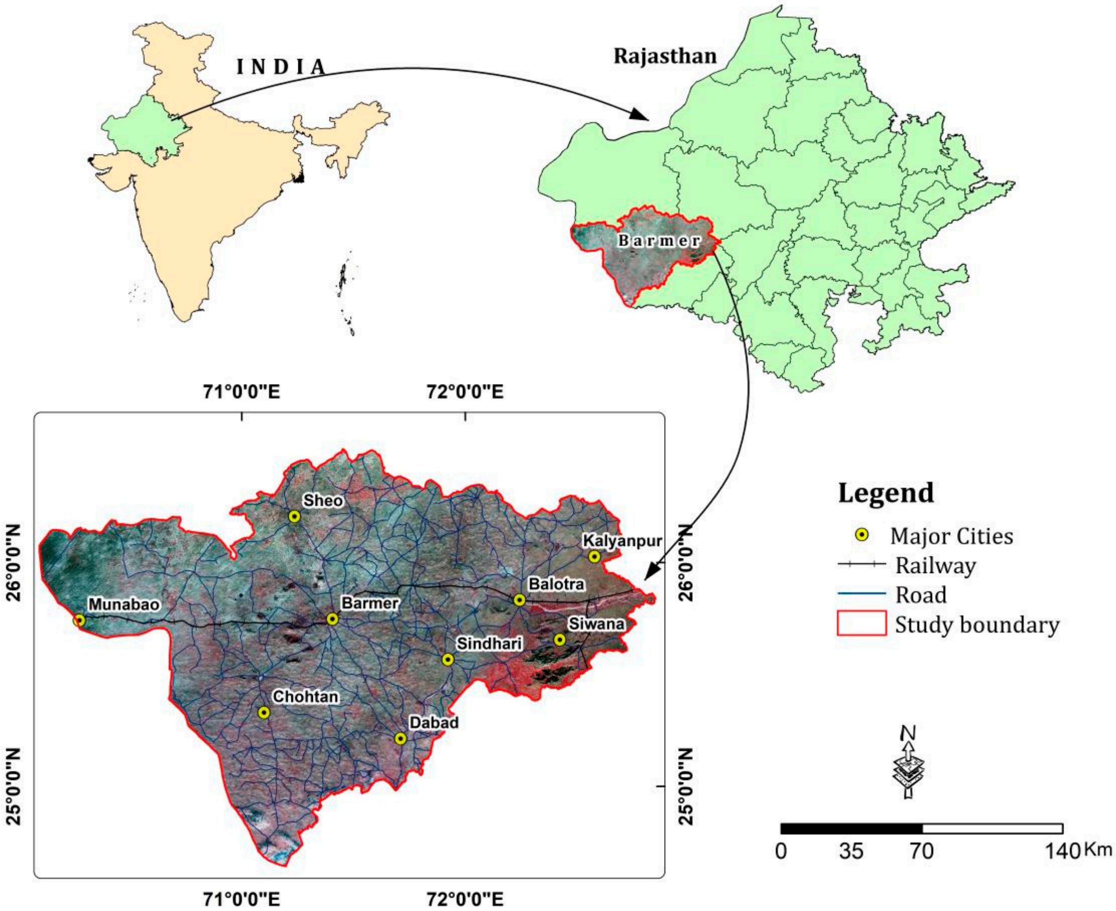

Figure 1. Location map of the study area.

3. Materials and Methods

Multi-criteria decision making (MCDM), i.e., AHP was used in this study to find optimal places for organic farming using a multi-criteria approach [10]. AHP was used to determine the weights for each criterion, and then a weighted overlay was performed to construct the suitability map. The process is shown in detail (Figures 2 and 3).

3.1. Preparation of Multi-Criteria Maps

To develop the multi-criteria using GIS platforms, primary and secondary data were collected from diverse sources. Geology, soil pH, soil texture, land use/land cover (LULC), land surface temperature (LST), drainage density, availability of roads, slope, soil organic carbon, soil salinity, normalized difference weight index (NDVI), and rainfall were chosen as multi-criteria based on their importance and significance in organic farming (Figures 4–9). These parameters were used to identify prospective organic farming locations [26].

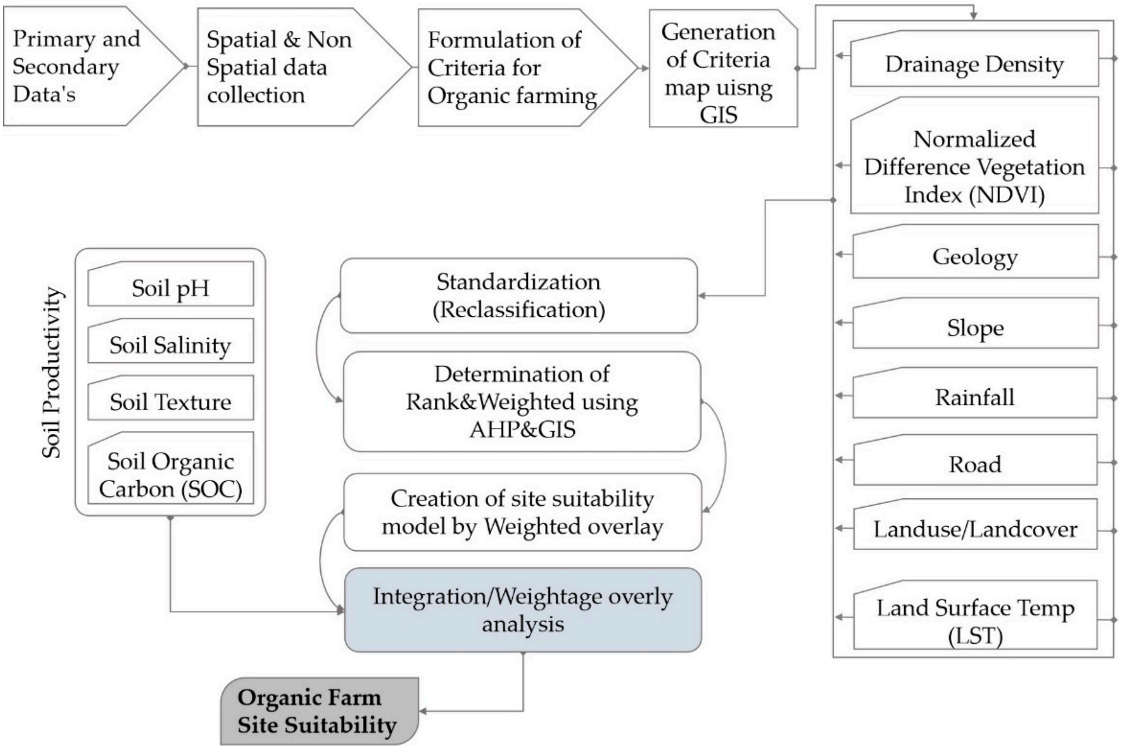

Figure 2. Flow chart briefly explaining the methods for organic farming site suitability.

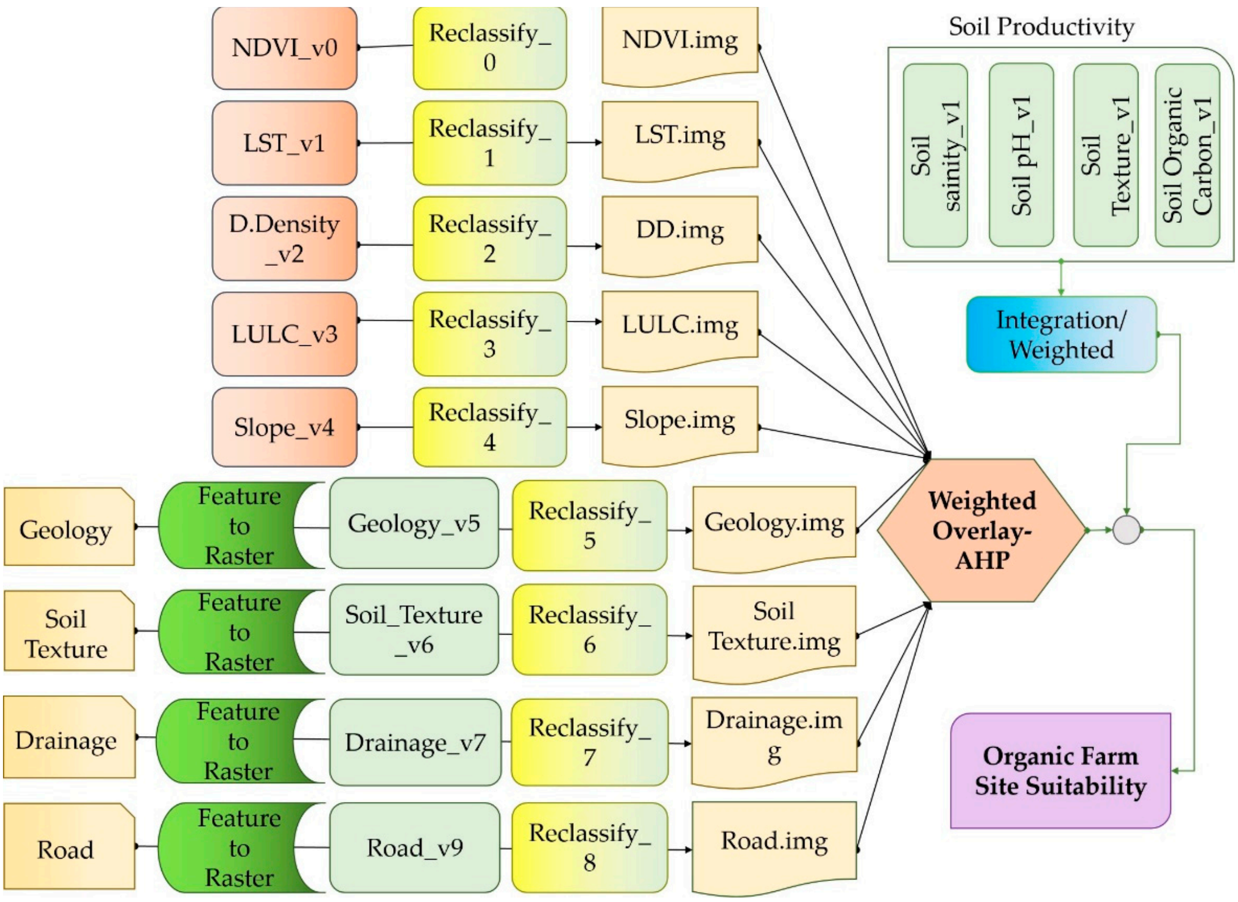

Figure 3. The appropriateness of land for organic farming is depicted in this model.

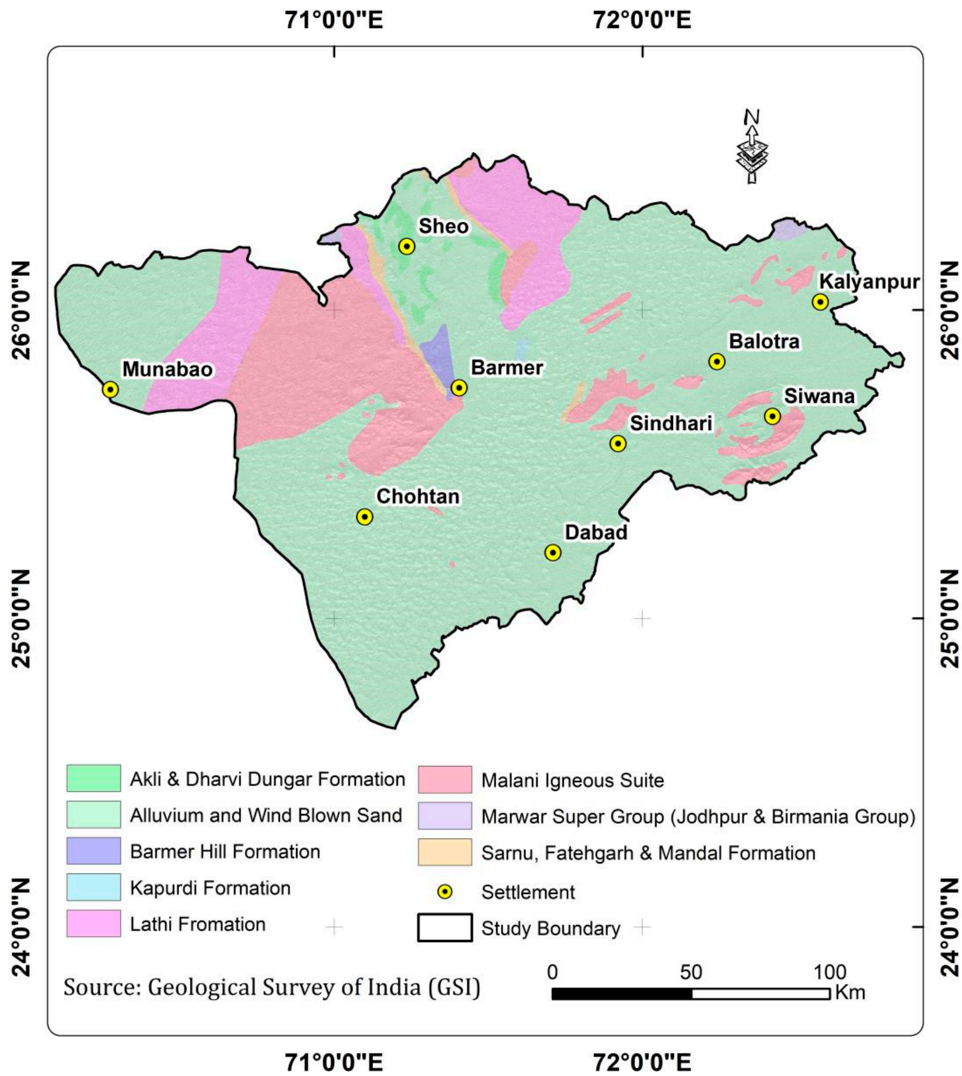

Figure 4. Geology map of the study area.

The open roadway data were used to create the drainage. The density slices approach was used to create drainage density from the drainage lines. There are four sub-criteria for drainage density. There are four levels of difficulty: poor, moderate, high, and extremely high. The geology map is provided by the Geological Survey of India (Figure 4). In the Barmer district, geological landforms, such as the Akli and Dharavi Dungar formations, the Barmer Hill formation, the Kapurdi formation, the Lathi formation, the Samu, Fatehgarh, and Mandal formations, the Marwar supergroup, and alluvium/wind-blown sand are spread and mapped. Land use/land cover (LULC) maps were created using Landsat data for the years 2017, 2018, 2019, and 2020. LULC was broken down into 11 sub-criteria. Settlements, cropland, deciduous forest, dunes, open forest, plantation, river, industry/wasteland, shrubland, and sand dunes+shrubland are the different types of land (Figure 5). The USGS earth explorer provided SRTM-DEM data with a resolution of 30 m (https://earthexplorer.usgs.gov/ (accessed on 23 September 2014). Slope can be expressed as a percentage or as a degree. The range of high to low was used to calculate the slope. The normalized difference vegetation index (NDVI) was calculated using Landsat series data in the near-infrared and red bands. For the years 2017, 2018, 2019, and 2020, NDVI was calculated (Figure 6). The NDVI is divided into five categories. They are extremely poor, very poor, poor, moderate, high, and extremely high. Landsat 8 is used to calculate land surface temperature (LST) (Figure 7). It calculated the temperature in Celsius between the years 2017, 2018, 2019, and 2020, with a minimum temperature of 31 °C and a maximum temperature of 46 °C. Rainfall data for the year was gathered from the Indian

Meteorological Department. It was divided into five categories. They are extremely low, very low, low, moderate, high, and extremely high. The road was built using an open street map. It was divided into five categories: buffer zones of >5 km, 6–10 km, 11–20 km, 21–30 km, 31–40 km, and 40 km.

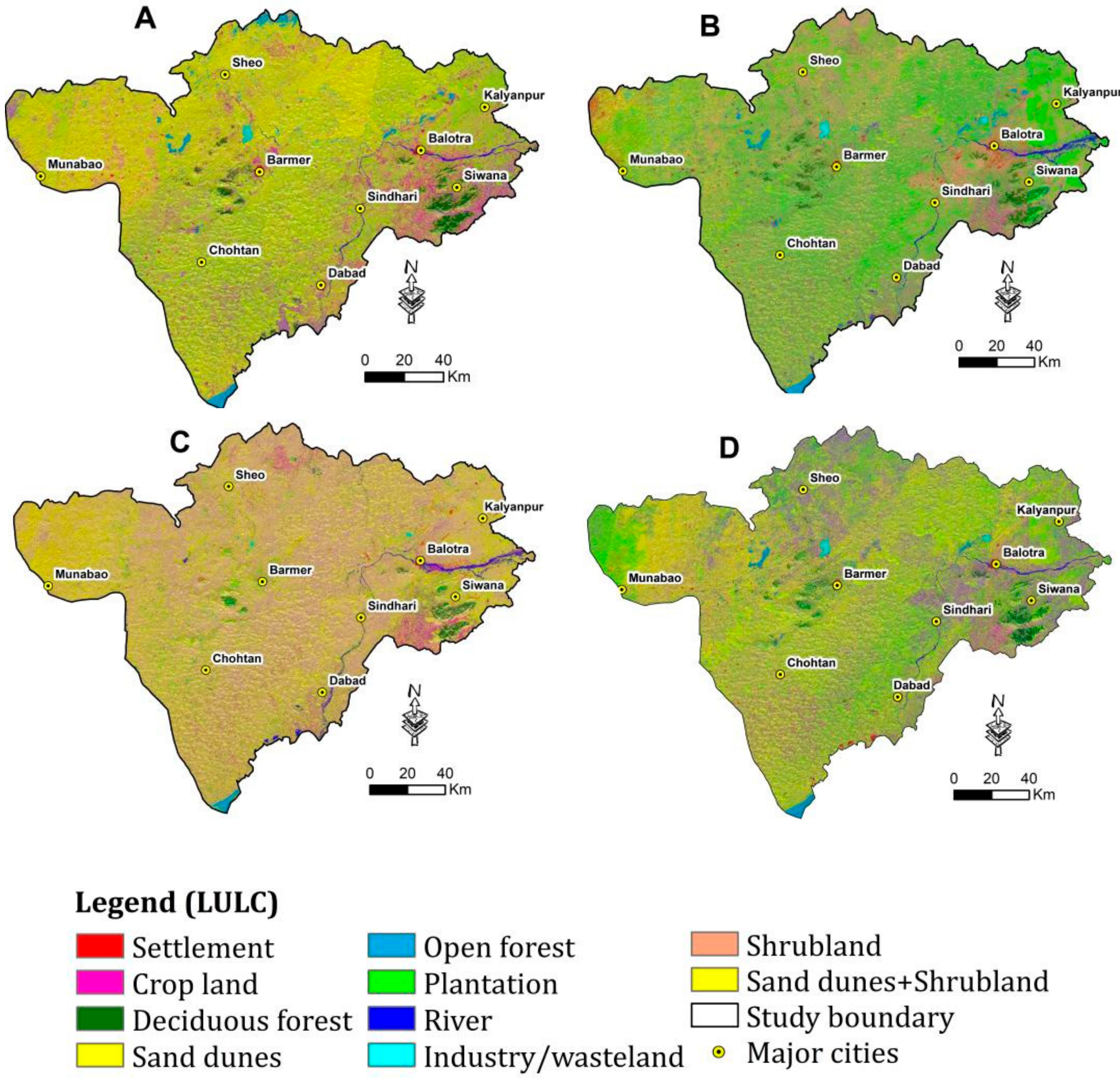

Figure 5. The land use/land cover map of the study area is represented for the year 2017 (**A**), 2018 (**B**), 2019 (**C**), and 2020 (**D**).

The soil maps are published by the National Bureau of Soil Survey and Land Use Planning. In the Barmer district, the soil texture is yellowish-brown loamy soil, yellowish-brown sandy soil, gravelly loam hilly soil, gravelly sand soil, and gravelly loam soil. Soil productivity includes sub-criteria, such as soil pH, soil nitrogen, soil salinity, and soil organic carbon (Figure 8), all of which are derived from the International Soil Reference and Information Centre's database. Three sub-criteria were used to prepare the pH of the soil. Acid, neutral, and alkaline are the three types. The nitrogen content of the soil ranged from 0.026 to 9.9 mg/kg. For the years 2017, 2018, 2019, and 2020, soil salinity is categorized into five sub-categories: non-salinity, low salinity, medium salinity, high salinity, and additional salinity. The amount of organic carbon in the soil varied from 1 to 147 gm/cm^2. To determine the best organic farming, sub-criteria are created.

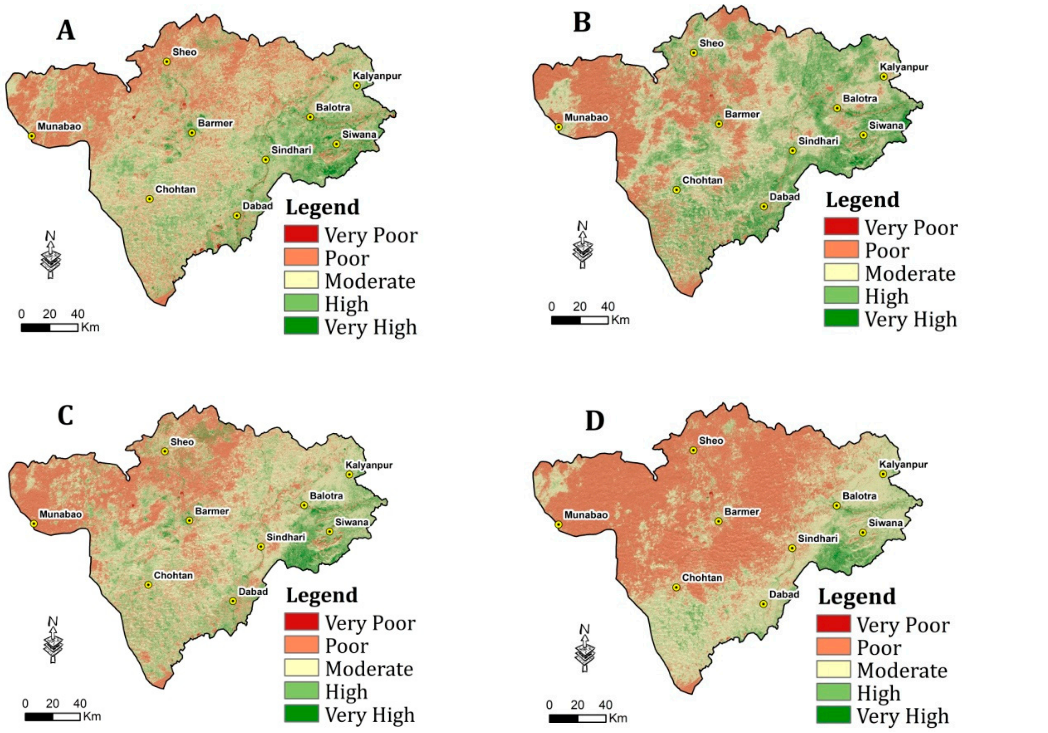

Figure 6. The year 2017 (**A**), 2018 (**B**), 2019 (**C**), and 2020 (**D**) show the average normalized difference vegetation index.

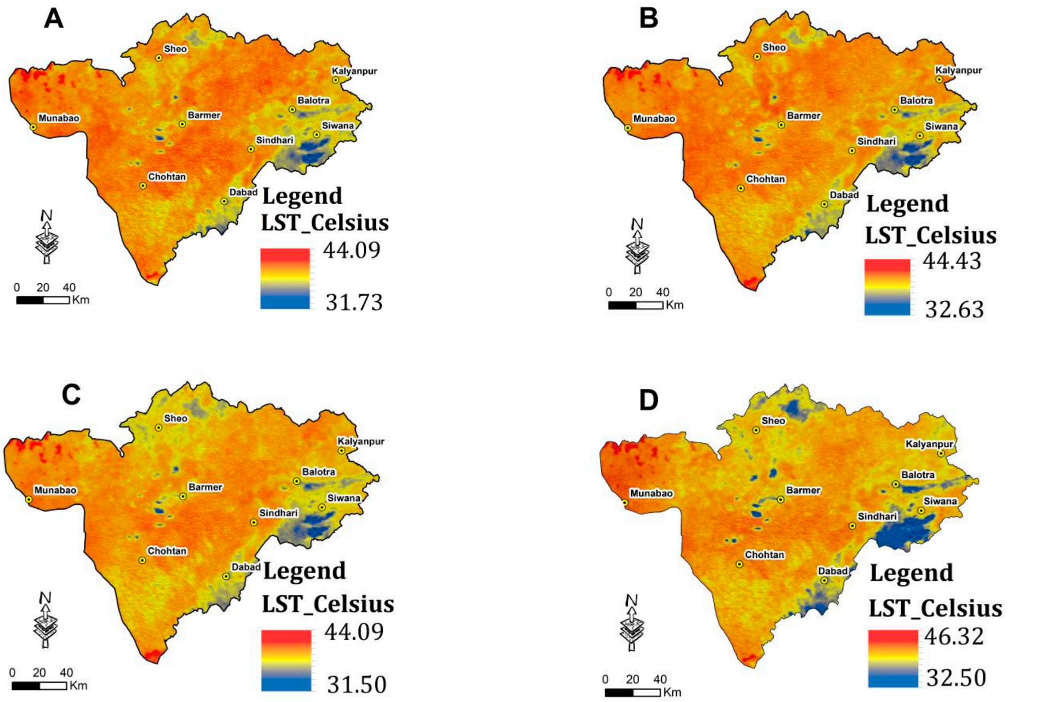

Figure 7. The year 2017 (**A**), 2018 (**B**), 2019 (**C**), and 2020 (**D**) represent the average land surface temperature.

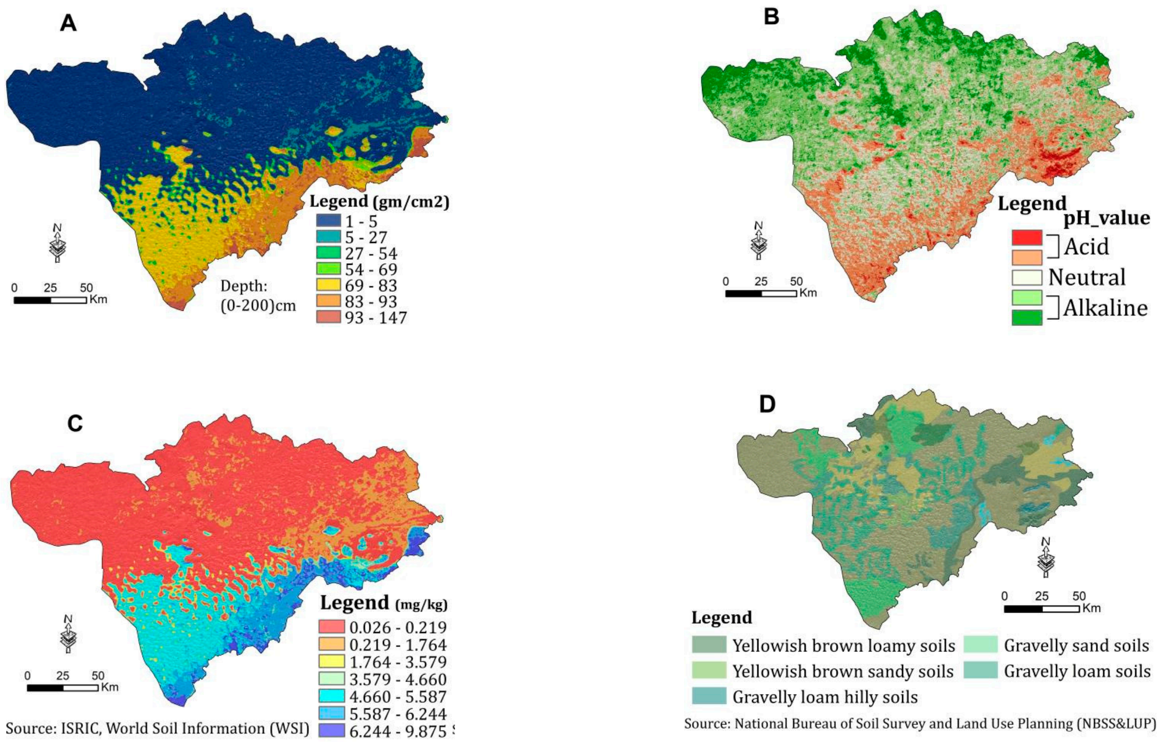

Figure 8. (**A**) Soil organic carbon: This figure depicts soil organic carbon, which is an essential indicator of soil fertility; (**B**) Soil pH: The acidity or alkalinity of soils is measured by their pH; (**C**) Soil nitrogen: The majority of the nitrogen in these inputs is organic nitrogen, which is converted to mineral form for plant uptake by microbial transformations. In other words, soil bacteria play a role in the N mineralization process; (**D**) Soil texture: The quantity of sand, silt, and clay particles in the soil determine the texture.

3.2. Determination of Weights Using AHP

Multi-criteria decision-making (MCDM) provides better decisions that can be employed for these factors while choosing an acceptable area for suitable organic farming. The multi-dimensional aim of MCDM is to suggest acceptable organic farming based on 11 criteria that are explicit, transparent, logical, and efficient decision procedures [27]. For site selection GIS techniques, MCDM techniques, such as analytical hierarchy process (AHP), analytic network process, elimination and (Et) choice translating reality, multi-objective programming, goal programming, a technique for order performance by similarity to an ideal solution, and others are available.

AHP uses all of the criteria and their sub-criteria to create a hierarchical structure by determining the weighting of each criterion throughout the decision-making process. The weights assign a relative priority to each criterion and must, thus, be carefully chosen. AHP can be used to do pairwise comparisons between criteria, which simplifies the process [15]. It calculates the weights by evaluating the relative relevance of criteria pairwise on a scale of 1–9, with 1 denoting equal value and 9 denoting excessive importance of all criteria [13]. The AHP derives the ranking for each criterion by first taking the eigenvector equivalent to the eigenvalue in this matrix, and then normalizing the total weight in each criterion [13,17]. In each column criteria, the lower diagonal of a pairwise comparison matrix has the property of reciprocity. The value of the row criterion in a pairwise comparison matrix is divided by the sum of the column criteria to obtain a normalized comparison matrix. In the AHP method, the sum of the rows in the normalized comparison matrix is utilized as the normalized weight for each criterion. One of the strengths of AHP is that it recognizes and considers the inconsistencies of decision-makers [20,28]. As a result, AHP efficiency criteria are assessed using the consistency relationship (*CR*), which is calculated using Equation (1).

$$CR = \frac{CI}{RI} \tag{1}$$

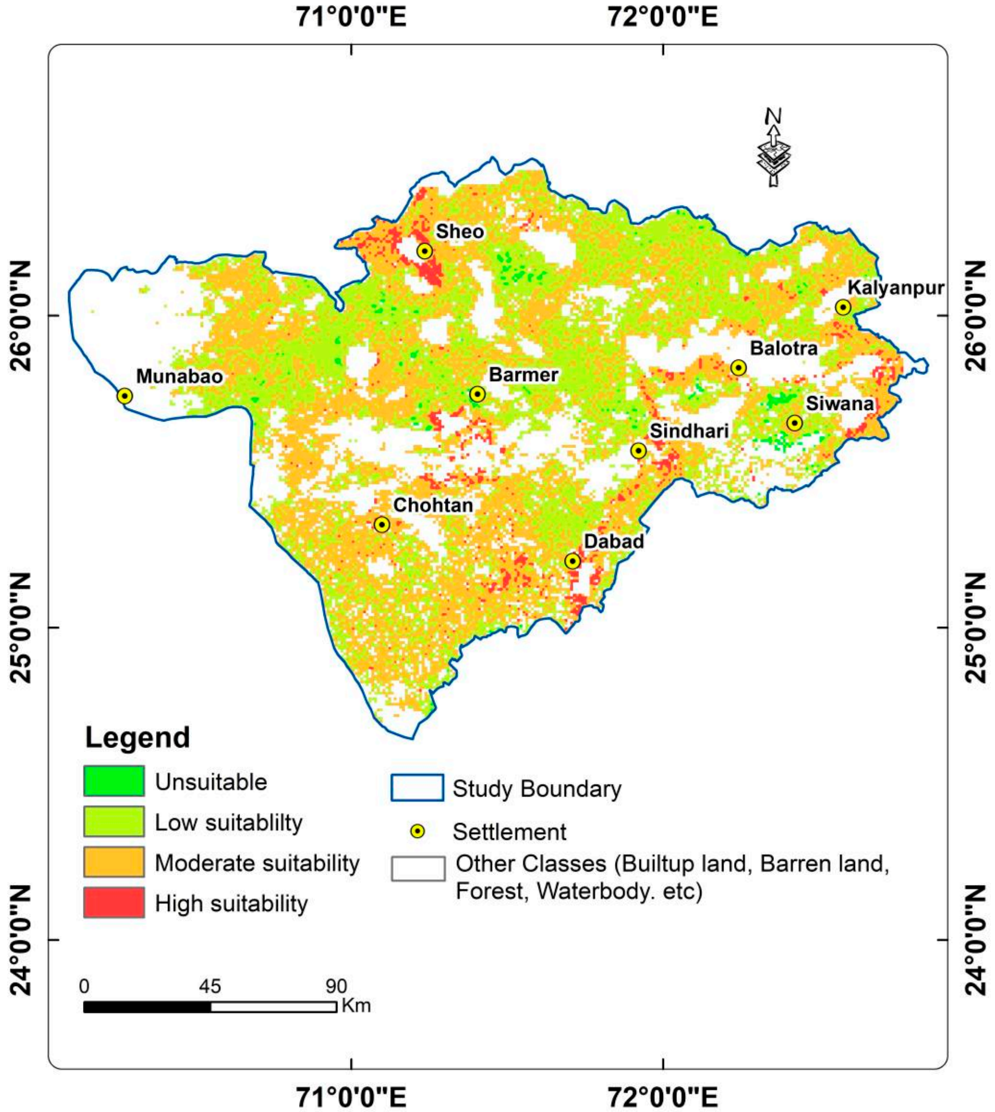

Figure 9. Site suitability map for organic farming in the Barmer district.

CR represents a measure of the degree of consistency or inconsistency in the decision-making process [29]. The *CR* depends on the consistency index (*CI*) and random index (*RI*).

$$CI = \frac{\lambda_{max-n}}{n-1} \tag{2}$$

where *max* is the summation normalized weight matrix of individual criteria and *n* is the number of criteria employed, Equation (2) reflects the *CI*. Depending on the number of criteria utilized, *RI* is the average of the resulting consistency index [15]. The pairwise comparison matrix is acceptable if the *CR* is less than 0.10. The normalized weight values are validated, and sub-criteria might be given additional weight. The *CR* in our case was 0.097, which is within acceptable standards. Finally, AHP weight overlay analysis is a basic notion for assigning a judgmental weight to each sub-criteria. The total weight of each sub-criteria is split, and the normalized weight of each sub-criteria is multiplied for each sub-criteria.

3.3. Generating Suitability Organic Farming Using Geospatial Model

By merging all of the criteria and overlaying the weights of separate criteria, the organic farming model was created using ArcGIS 10.3 modeler. To perform AHP weighted overlay analysis, all of the criteria in this model have various sub-criteria. This study must have the same spatial resolution as other multi-criteria analyses so that it can be standardized. Standardization uniformizes measurement units, causing scores to lose dimension as a result of the uniformization [30]. Geology and soil were generated as vector layers for these standards, whereas the other 12 criteria were prepared as raster layers. The vector layers were rasterized with a spatial resolution of 30 m. AHP weighted values of sub-criteria presented in their characteristics were used to reclassify additional raster layers. For the suitability map to be created, an overlay analysis was performed.

3.4. Gravity Recovery and Climate Experiment (GRACE) and Precipitation Data in An Arid Region

A joint mission organized by NASA and the German Aerospace Center (DLR) provides the Gravity Recovery and Climate Experiment (GRACE) data. GRACE/GRACE-FO information was obtained at 0.5m spatial resolution and monthly temporal resolutions. Jet Propulsion Laboratories (JPL) acquired from the GRACE release 06 (RL06) V 2.0 global mass concentration blocks or mascon products [2,31]. The Prediction of Worldwide Energy Resources (POWER) Project provides free access to the climatic data organized by NASA. In the POWER project, Modern Era Retrospective-Analysis for Research and Applications (MERRA-2) is given accessibility for the precipitation data. Here, GRACE-JPL and precipitation data were used as a monthly comparison from January 2017 to December 2020. Finally, the time variation of water equivalent thickness and precipitation deals with the anomaly of soil moisture and the climatic impact of a desert region. This reveals the impact of organic farming on the Barmer district.

4. Results and Discussion

The MCDM technique is commonly used in geospatial technology for locating possible groundwater locations, landslide hazards, and rainfall harvesting, among other things [11,12,14,32]. Geology, soil pH, soil texture, land use/land cover (LULC), land surface temperature (LST), drainage density, availability of roads, slope, soil organic carbon, soil salinity, normalized difference weight index (NDVI), and rainfall are among the 12 criteria used in this study to determine whether organic farming is suitable. The AHP process was used to apply the twelve criteria, which were followed by three steps: pairwise comparison matrix, normalized comparison matrix, and weighted overlay analysis. These are the three types of comparison matrices.

4.1. Thematic Criteria Contribution

Thematic criteria play an important part in geospatial site appropriateness studies using remote sensing and GIS technology. For finding the potential zone of organic farming over the Barmer district, probable criteria, such as geology, soil pH, soil texture, land use/land cover (LULC), land surface temperature (LST), drainage density, availability of roads, slope, soil organic carbon, soil salinity, normalized difference weight index (NDVI), and rainfall are used. Physical and chemical weathering sediment is provided by geology as a soil deposit above the surface. Physical weathering eroded the granite outcrop due to high pressure and wind blowing in the Barmer district, which is a desert location. This aids in locating alluvium or comparable regions (Figure 4). As a result, it provides excellent organic agricultural concepts. LULC is also important for comprehending farming activities and terrain kinds. LULCs vary in length; here, LULCs are developed for the years 2017 through 2020 (Figure 5). However, the Luni river continues to flow in the northwestern part of the Barmer district from 2017 to 2020. Its surroundings are used to cultivate the crop, resulting in more soil moisture [13]. As a result, it determines if the site is suitable for organic farming. LULC has a comparable impact on NDVI. Both data were utilized to observe the plant cover or biomass content in the Barmer district's northwestern corner. Even the NDVI shows some changes in vegetation from 2017 to 2020 (Figure 6). However, the average NDVI was used to determine the viability of a site for organic farming. For NDVI and LULC, LST is the inverse because it only produces a negative impression. Lower LST is located in the Barmer district's northwestern corner (Figure 7). The north section of the LST in 2019 and 2020 is lower than in 2017 and 2018. It discusses the advantages of organic farming. Drainage density indicates the moisture content of the soil [31] and helps to optimize organic agricultural activities. In the north and northwest of the Barmer district, there is a high density of drainage. Slope with a flat surface provides the most soil depth, and organic farming is intertwined with it. In the south and northwest of the Barmer district, there is a flat and gently sloping terrain. The deeper the soil, the more organic carbon it contains. The amount of organic carbon in the soil is higher in the Barmer district's south. It reduces the amount of land that may be used for organic farming. Loamy soil texture in the north and northwest of the Barmer district (Figure 8). Loamy soil provides more soil nutrients, which aids organic farming. Soil pH in the acid range (5.5 to 7.5) is better for agriculture crops, as well as organic farming. The acidity area may be seen towards the south and northwest (Figure 8). Rainfall intensity also identifies organic farming sites, and high rainfall contributes to the center region. The study used the MCDM technique to propose a site suitability region for organic farming, based on the geospatial viewpoints.

4.2. Pairwise Comparison Matrix

Initially, the AHP process is based on the AHP hierarchical scale, with 1 representing equal importance, 3 representing moderate importance, 5 representing strong importance, 7 representing very strong importance, 9 representing extreme importance, and 2, 4, 6, and 8 representing intermediate values [33]. In the 12 criteria of the AHP hierarchical scale geology is given equal weight, soil texture is given moderate weight, LST is given strong weight, slope, and SOC are given very strong weight, and rainfall is given extreme weight. Soil pH, LULC, drainage density, road, salinity, and NDVI are the intermediate values assigned to the criterion. As a result, the higher scales 7, 8, and 9 are assigned to SOC, salinity, NDVI, and rainfall. Because of their biochemical and biophysical features, these criteria play a significant role in organic farming. SOC is a direct input that refers to the amount of organic content in the soil. The biochemical salts that promote soil fertility are dealt with by salinity. The biomass in a given area is determined by the NDVI. Rainfall has an important role in farming activities because it is a natural source of water. The lower scale of 1–6 was then applied to geology, soil pH, soil texture, LULC, LST, drainage density, and road. These qualities are less important when looking for potential organic farming locations. In the present investigation, it was observed that air temperature does not have much influence on soil moisture and other organic farming activities compared to soil temperature. In every agricultural activity, some criteria, such as soil pH and LST, will play a negative influence. As a result, for optimal organic farming, a minimum LST and a maximum soil pH can be used. Alternative inputs, such as geology, drainage density, road, soil texture, and LULC, are used to improve the results. The top diagonal of the pairwise comparison matrix is determined by the AHP hierarchical scale.

The inverse of the respective condition is the lower diagonal matrix (>1). It denotes a matrix having an equal distribution. For example, the top diagonal matrix for geology vs. rainfall has a larger scale of 9 than the bottom diagonal matrix, which has a minimum value of 0.11. In geology, the sum of column requirements yields a minimum value of 3.3 and a maximum value of 66. In the normalized comparison matrix, these values are used.

4.3. Normalized Comparison Matrix

A normalized comparison matrix was created from the pairwise comparison matrix. The normalized weight was extracted from the matrix for each criterion.The lowest hierarchical scale of the pairwise comparison matrix produces a value of 0.31. Using a higher AHP hierarchical scale, the value of 0.14 is attained. The bottom diagonal matrix is used to achieve the 0.15 to 0.01 range. The total row criteria produce a minimum value of 0.14 in rainfall and a maximum value of 0.02 in geology. This normalized weight is used in weight overlay analysis.

4.4. Weight Overlay Analysis for Sub-Criteria

The weights for individual criteria and their sub-criteria were determined using the weight overlay analysis. This analysis is solely based on a judgmental approach and the application of the AHP principle. The AHP technique is a numerical approach for calculating decimal values. Each individual criterion is divided into 3 to 10 sub-criteria in this study, with a minimum of three and a maximum of 10 sub-criteria. So, for sub-criterion, 1 to 10 weights were assumed. Eachindividual criterion has a maximum weight of 55 and a minimum weight of 6. The total weight of each individual criterion is divided by their sub-criteria. Weight overlay analysis for sub-criteria is performed, and the normalized weight of individual criteria is multiplied. The outcome is a maximum weight in rainfall of 22 and a minimum weight in a slope of 0.47. The greatest weights assigned to rainfall in comparison to other criteria are shown in Table 1.

Table 1. Weightage overlay analysis.

Parameters	Classes	Weights
Geology	Akli&DharviDungar Formation	0.56
	Alluvium and windbl sand	2.26
	Kapurdi formation	0.56
	Lathi formation	1.13
	Malani Igneous suite	0.56
	Marwar supergroup	0.56
	Srnu, Fetehgarh& Mandal formation	1.69
Soil pH	Acid	4.13
	Neutral	2.75
	Alkaline	1.38
Soil Texture	Loamy	2.91
	Sandy	0.97
	Gravelly Loam hilly soil	1.46
	Gravelly sand	0.97
	Gravelly loamy	1.94
LULC	Settlement	0.57
	Agriculture land	2.29
	Rocky outcrop	0.57
	Sand dunes	0.57
	Open Forest	0.57
	Plantation	0.57
	River	0.57
	Industry/wasteland	0.86
	Shrubland	1.14
	Sand dunes + shrub land	1.71
LST	High	1.57
	Moderate	3.14
	Low	4.71
DD	Very low	0.73
	Low	1.47
	Moderate	2.20
	High	2.93
	Very high	3.67

Table 1. *Cont.*

Parameters	Classes	Weights
Road	<5 km 5–10 km 11–20 km 21–40 km >40	3.67 2.93 2.20 1.47 0.73
Slope	Nearly Level Gently sloping Moderately sloping Strongly sloping Moderately steep Steep Very steep	3.30 2.83 2.36 1.89 1.41 0.94 0.47
SOC	Very low Low Moderate High Very high	1.10 2.20 3.30 4.40 5.50
Salinity	Non salinity Low salinity Medium salinity High salinity Extra salinity	7.33 5.87 4.40 2.93 1.47
Rainfall	very low Low Moderate High Very high	4.40 8.80 13.20 17.60 22.00
NDVI	Very low Low Moderate High Very high	2.20 4.40 6.60 8.80 11.00

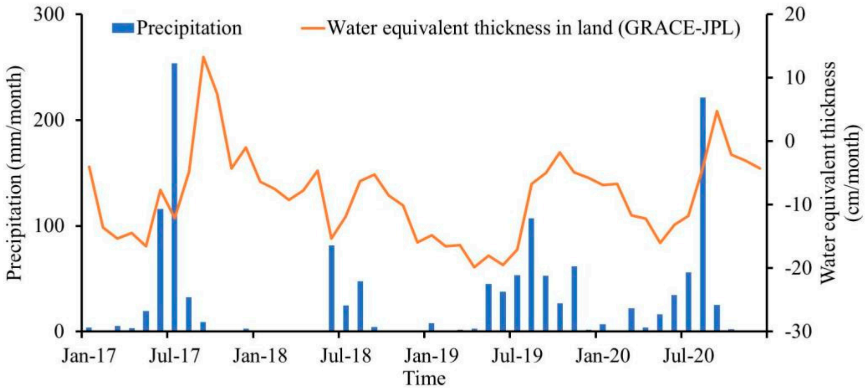

Figure 10. The water equivalent thickness and precipitation level in the research region are compared in this chart.

4.5. Suitability of Organic Farming

In a GIS setting, the MCDM and geographic perspectives of each criterion were used to overlay with the model developer. The final suitability map for organic farming in the Barmer district was created using an AHP weight overlay analysis for sub-criteria(Figure 9). The organic agricultural suitability map is classified into two main categories viz. agriculture (19, 564 sq. km) and other classes (8777 sq. km). Then, agricultural land is divided into four categories. They are high suitability (831 sq. km), moderate suitability (9614 sq. km), low suitability (8870 sq. km), and unsuitable (249 sq. km). The dunes, as well as the uneven height (steady slope), appear to be unsuitable. In the south and northwest, the high vegetated area and river bedside are designated as highlysuitable.. AHP identifies the regions that are the most appropriate in terms of the criteria. The dark red patches denote areas that are ideal for organic farming, while the orange and light green patches denote areas that have made significant contributions to the Barmer district (Figure 9). Additionally, other classes are also taken into consideration in this organic agricultural suitability map where it denotes white patches in Figure 9. The other classes, such as waterbody, barren land, built-up land, etc., are also cover the Barmer district and it could not control organic farming.

Geospatial techniques help to find out the suitable area for natural fertility in Barmer district, Rajasthan, based on the results of the suitability map for organic farming. The red-colored region of 831 sq.km is likely to be used to research organic farming with food crops. This exposes the study's goal: to carry out sustainable organic farming. Bio-fertilizers will improve moderately sustainable organic farming in the future, according to Alsharif et al. 2020 [23], who have already identified suitable bio-fertilizers for sustainable organic farming. In the future, we plan to further research field-based organic farming, soil study, crop types suitable for natural agriculture, and crop-health monitoring.

4.6. Comparison of Water Equivalent Thickness and Precipitation Data

After finding the suitability of organic farming, water storage capacity needs to be interpreted in the arid region. Vary time denotes the change in water storage capacity in an arid region. The main input of water resources is precipitation and, alternatively, water equivalent thickness in land observed from the GRACE satellites. A comparison of precipitation and water equivalent thickness inland was performed (Figure 10). The Barmer district receives the precipitation from June to September. The maximum precipitation is about 250 mm/month. Water equivalent thickness varies from −20 to 12 cm/month. The monsoon period of June to September provides water to the land. Simultaneously, after the monsoon, the increase in water equivalent thickness lasts from August to October. Both data show similar trends. Similarly, organic farming alsotrended towards increasing. Thereby, water equivalent thickness inland gives rise to agriculture activities, as well as organic farming in the field [2], while forecasts from GRACE-JPL data are used to increase the suitability of organic farming in the Barmer district over time.

5. Conclusions

The agricultural operations in the Thar desert, which includes the Barmer district, are usually minimal. In the Barmer district, a case study was imposed to produce organic crops. Geospatial viewpoints were employed to locate potential places. The weighted overlay analysis of the AHP was employed in MCDM. A site appropriateness map was created by ranking and weighing the 12 criteria and their sub-criteria. Some of the multi-criteria were applied over four years, from 2017 to 2020. As a result, the suitability of organic farming was analyzed. The criteria for multi-purpose studies were employed, which increased the significance of this study in terms of finding suitable organic farming areas. The area appropriate for organic farming is very small and it accounts for 2% (832 sq. km) of the Barmer district. Organic farming and other conservative agricultural methods are possible to implement in the most suitable organic farming areas (832 sq. km). Barmer district receives maximum precipitation in monsoon and Barmer district has high water equivalent thickness. Therefore, this supports agricultural activities, as well as organic farming. Overall, this study enhances the susceptibility of land improvement and the dependable quality of farming activities in arid climates. The future scope of the present investigation is to utilize the advanced deep learning models, including [2,34–36] for sustainable agriculture in another semi-arid region of the world [13,37].

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/su14084542/s1, Table S1: Pairwise Comparison matrix; Table S2: Normalized Comparison matrix.

Author Contributions: P.M. designed this study, performed the main analysis. P.M., D.P. and M.A.H. wrote the paper. P.M., D.P. and M.A.H. contributed to the revising of the manuscript. R.N., A.S., M.A., I.K. and T.D. contributed to formal analysis, resources, data collection, and validation. P.M. and M.A. edited the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by Researchers Supporting Program (TUMA-Project-2021-14), AlMaarefa University, Riyadh, Saudi Arabia. Mohd Anul Haq would like to thank the Deanship of Scientific Research at Majmaah University for supporting this work under Project No. R-2022-100.

Data Availability Statement: In this research, satellite data are generated and provided by Google Earth Engine https://code.earthengine.google.com/ (accessed on 1 January 2022). This datasets is freely available in the Google Earth Engine platform. The provider of these datasets is the Landsat 8 satellite payload, which consists of two science instruments—the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). These two sensors provide seasonal coverage of the global landmass at a spatial resolution of 30 m (visible, NIR, SWIR); 100 m (thermal); and 15 m (panchromatic) https://earthexplorer.usgs.gov/ (accessed on 10 April 2013) Rainfall data, soil map, Geology provided by ISRIC, World Soil Information (WSI), National Bureau of Soil Survey and Land Use Planning (NBSS&LUP), Geological Survey of India (GSI), and the Indian Meteorological Department (IMD).

Acknowledgments: Mohd Anul Haq would like to acknowledge the Deanship of Scientific Research at Majmaah University for supporting this work under Project No. R-2022-100. The authors deeply acknowledge the Researchers Supporting Program (TUMA-Project-2021-14), AlMaarefa University, Riyadh, Saudi Arabia for supporting steps of this work. The authors are also very grateful to thank AmnexInfotechnologies Pvt Ltd. for providing the opportunity and facility for the entire research work, as well as my colleagues in Amnexinfotechnologies Pvt Ltd. for sharing their pearls of wisdom with us during the study process. We thank ISRIC, World Soil Information (WSI), National Bureau of Soil Survey and Land Use Planning (NBSS&LUP), Geological Survey of India (GSI), and Indian Meteorological Department (IMD) for providing data. We would like special thanks to Prashant Baral for supporting all document work, and we thank "anonymous" reviewers for their so-called insights.

Conflicts of Interest: No potential competing interest was reported by the authors.

References

1. Albalawi, E.K.; Kumar, L. Using Remote Sensing Technology to Detect, Model and Map Desertification: A Review. *J. Food Agric. Environ.* **2013**, *11*, 791–797.
2. Haq, M.A.; Khadar Jilani, A.; Prabu, P. Deep Learning Based Modeling of Groundwater Storage Change. *Comput. Mater. Contin.* **2022**, *70*, 4599–4617. [CrossRef]
3. Ajai, R.R.; Arya, A.S.; Dhinwa, P.S.; Pathan, S.K.; Ganesh Raj, K. Desertification/Land Degradation Status Mapping of India. *Curr. Sci.* **2009**, *97*, 1478–1483.
4. Huang, J.; Zhang, G.; Zhang, Y.; Guan, X.; Wei, Y.; Guo, R. Global Desertification Vulnerability to Climate Change and Human Activities. *Land Degrad. Dev.* **2020**, *31*, 1380–1391. [CrossRef]
5. Varghese, N.; Singh, N.P. Linkages between Land Use Changes, Desertification and Human Development in the Thar Desert Region of India. *Land Use Policy* **2016**, *51*, 18–25. [CrossRef]
6. Kumar, M.; Santra, P.; Singh, S.K.; Raina, P.; Kar, A.; Ram, B.; Moharana, P.C. Identifying Sensitive Soil Properties as a Function of Land Use Change in Thar Desert of India. *Agric. Res.* **2018**, *7*, 187–199. [CrossRef]
7. Salunkhe, S.S.; Bera, A.K.; Rao, S.S.; Venkataraman, V.R.; Raj, U.; Murthy, Y.V.N.K. Evaluation of Indicators for Desertification Risk Assessment in Part of Thar Desert Region of Rajasthan Using Geospatial Techniques. *J. Earth Syst. Sci.* **2018**, *127*, 116. [CrossRef]
8. Leifeld, J. How Sustainable Is Organic Farming? *Agric. Ecosyst. Environ.* **2012**, *150*, 121–122. [CrossRef]
9. Kamkar, B.; Dorri, M.A.; Da Silva, J.A.T. Assessment of Land Suitability and the Possibility and Performance of a Canola (*Brassica Napus* L.)—Soybean (*Glycine Max* L.) Rotation in Four Basins of Golestan Province, Iran. *Egypt. J. Remote Sens. Space Sci.* **2014**, *17*, 95–104. [CrossRef]
10. Keshtkar, A.R.; Oros, Z.; Mohammadkhan, S.; Eagdari, S.; Paktinat, H. Multi-Criteria Analysis in Artemia Farming Site Selection for Sustainable Desert Ecosystems Planning and Management (Case Study: Siahkouh Playa, Iran). *Environ. Earth Sci.* **2016**, *75*, 1195. [CrossRef]
11. Karimi, F.; Sultana, S.; Shirzadi Babakan, A.; Royall, D. Land Suitability Evaluation for Organic Agriculture of Wheat Using GIS and Multicriteria Analysis. *Pap. Appl. Geogr.* **2018**, *4*, 326–342. [CrossRef]
12. Rajasekhar, M.; Sudarsana, R.G.; Nanabhau, K.; Ramachandra, M.; Pradeep, K.B. Multi-Criteria Land Suitability Analysis for Agriculture in Semi-Arid Region of Kadapa District, Southern India: Geospatial Approaches. *Remote Sens. Land* **2021**, *5*, 59–72. [CrossRef]

13. Haq, M.A. Intellligent Sustainable Agricultural Water Practice Using Multi Sensor Spatiotemporal Evolution. *Environ. Technol.* **2021**, 1–14. [CrossRef] [PubMed]
14. Zolekar, R.B.; Bhagat, V.S. Multi-Criteria Land Suitability Analysis for Agriculture in Hilly Zone: Remote Sensing and GIS Approach. *Comput. Electron. Agric.* **2015**, *118*, 300–321. [CrossRef]
15. Saaty, T.L. A Scaling Method for Priorities in Hierarchical Structures. *J. Math. Psychol.* **1977**, *15*, 234–281. [CrossRef]
16. Roig-Tierno, N.; Baviera-Puig, A.; Buitrago-Vera, J.; Mas-Verdu, F. The Retail Site Location Decision Process Using GIS and the Analytical Hierarchy Process. *Appl. Geogr.* **2013**, *40*, 191–198. [CrossRef]
17. Feizizadeh, B.; Jankowski, P.; Blaschke, T. A GIS Based Spatially-Explicit Sensitivity and Uncertainty Analysis Approach for Multi-Criteria Decision Analysis. *Comput. Geosci.* **2014**, *64*, 81–95. [CrossRef]
18. Boroushaki, S.; Malczewski, J. Implementing an Extension of the Analytical Hierarchy Process Using Ordered Weighted Averaging Operators with Fuzzy Quantifiers in ArcGIS. *Comput. Geosci.* **2008**, *34*, 399–410. [CrossRef]
19. Bunruamkaew, K.; Murayama, Y. Site Suitability Evaluation for Ecotourism Using GIS & AHP: A Case Study of Surat Thani Province, Thailand. *Procedia Soc. Behav. Sci.* **2011**, *21*, 269–278. [CrossRef]
20. Khahro, S.H.; Matori, A.N.; Chandio, I.A.; Talpur, M.A.H. Land Suitability Analysis for Installing New Petrol Filling Stations Using GIS. *Procedia Eng.* **2014**, *77*, 28–36. [CrossRef]
21. Xu, Y.; Sun, J.; Zhang, J.; Xu, Y.; Zhang, M.; Liao, X. Combining AHP with GIS in Synthetic Evaluation of Environmental Suitability for Living in China's 35 Major Cities. *Int. J. Geogr. Inf. Sci.* **2012**, *26*, 1603–1623. [CrossRef]
22. Le Campion, A.; Oury, F.X.; Heumez, E.; Rolland, B. Conventional versus Organic Farming Systems: Dissecting Comparisons to Improve Cereal Organic Breeding Strategies. *Org. Agric.* **2020**, *10*, 63–74. [CrossRef]
23. Alsharif, W.; Saad, M.M.; Hirt, H. Desert Microbes for Boosting Sustainable Agriculture in Extreme Environments. *Front. Microbiol.* **2020**, *11*, 1666. [CrossRef] [PubMed]
24. Thapa, G.B.; Rattanasuteerakul, K. Adoption and Extent of Organic Vegetable Farming in Mahasarakham Province, Thailand. *Appl. Geogr.* **2011**, *31*, 201–209. [CrossRef]
25. Mishra, A.K.; Deep, S.; Choudhary, A. Identification of Suitable Sites for Organic Farming Using AHP & GIS. *Egypt. J. Remote Sens. Space Sci.* **2015**, *18*, 181–193. [CrossRef]
26. Zolekar, R.B. Integrative Approach of RS and GIS in Characterization of Land Suitability for Agriculture: A Case Study of Darna Catchment. *Arab. J. Geosci.* **2018**, *11*, 780. [CrossRef]
27. Sadeghiravesh, M.H.; Zehtabian, G.; Khosravi, H. Application of AHP and ELECTRE Models for Assessment of Dedesertification Alternatives. *Desert* **2014**, *19*, 141–153. [CrossRef]
28. Saaty, T.L. How to Make a Decision: The Analytic Hierarchy Process. *Eur. J. Oper. Res.* **1990**, *48*, 9–26. [CrossRef]
29. Chen, Y.; Yu, J.; Khan, S. Spatial Sensitivity Analysis of Multi-Criteria Weights in GIS-Based Land Suitability Evaluation. *Environ. Model. Softw.* **2010**, *25*, 1582–1591. [CrossRef]
30. Effat, H.A.; Hassan, O.A. Designing and Evaluation of Three Alternatives Highway Routes Using the Analytical Hierarchy Process and the Least-Cost Path Analysis, Application in Sinai Peninsula, Egypt. *Egypt. J. Remote Sens. Space Sci.* **2013**, *16*, 141–151. [CrossRef]
31. Haq, M.A.; Jain, K.; Shoab, M.; Menon, K.P.R. Estimation of Terrestrial Water Storage Change in the Bhagirathi Ganga and Vishnu Ganga Basins Using Satellite Gravimetry. In Proceedings of the 2013 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Melbourne, Australia, 21–26 July 2013; pp. 1817–1820. [CrossRef]
32. Nefeslioglu, H.A.; Sezer, E.A.; Gokceoglu, C.; Ayas, Z. A Modified Analytical Hierarchy Process (M-AHP) Approach for Decision Support Systems in Natural Hazard Assessments. *Comput. Geosci.* **2013**, *59*, 1–8. [CrossRef]
33. García, J.L.; Alvarado, A.; Blanco, J.; Jiménez, E.; Maldonado, A.A.; Cortés, G. Multi-Attribute Evaluation and Selection of Sites for Agricultural Product Warehouses Based on an Analytic Hierarchy Process. *Comput. Electron. Agric.* **2014**, *100*, 60–69. [CrossRef]
34. Haq, M.A. CDLSTM: A Novel Model for Climate Change Forecasting. *Comput. Mater. Contin.* **2022**, *71*, 2363–2381. [CrossRef]
35. Antzoulatos, G.; Kouloglou, I.-O.; Bakratsas, M.; Moumtzidou, A.; Gialampoukidis, I.; Karakostas, A.; Lombardo, F.; Fiorin, R.; Norbiato, D.; Ferri, M.; et al. Flood Hazard and Risk Mapping by Applying an Explainable Machine Learning Framework Using Satellite Imagery and GIS Data. *Sustainability* **2022**, *14*, 3251. [CrossRef]
36. Chen, L.; Ren, C.; Li, L.; Wang, Y.; Zhang, B.; Wang, Z.; Li, L. A comparative assessment of geostatistical, machine learning, and hybrid approaches for mapping topsoil organic carbon content. *ISPRS Int. J. Geo-Inf.* **2019**, *8*, 174. [CrossRef]
37. Rukhovich, D.I.; Koroleva, P.V.; Rukhovich, D.D.; Kalinina, N.V. The Use of Deep Machine Learning for the Automated Selection of Remote Sensing Data for the Determination of Areas of Arable Land Degradation Processes Distribution. *Remote Sens.* **2021**, *13*, 155. [CrossRef]