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Optimizing Sericea Lespedeza Fodder Production in the Southeastern US: A Climate-Informed Geospatial Engineering Approach

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Abstract: Lack of attention to rural healthcare for livestock in the southeastern United States has led to a focus on small ruminant farming, mainly using sericea lespedeza [SL; *Lespedeza cuneata* (Dum-Cours) G. Don], a drought-resistant forage species with nutraceutical benefits. Climate change has increased land availability for SL cultivation, further expanding the potential of this bioactive (anti-parasitic) legume. This study aims to create a geospatial engineering and technology-assisted model for identifying suitable SL production areas for supporting profitable small ruminant farming. The cultivation of SL depends on specific weather conditions and soil properties, with minimum requirements for temperature and rainfall, non-clay soil with reduced bulk density, and open land cover. The main objective was to develop an automated geospatial model using ArcGIS Pro Model-Builder to assess SL production suitability. This model also aimed to identify appropriate locations for small ruminant production in Georgia in the southeastern United States, characterized by increasing temperature fluctuations. A web-based geographic information system (webGIS) platform was developed using the ArcGIS Online dashboard interface, allowing agriculturalists to access decision support for SL production suitability tailored to their land. This forage production suitability analysis, conducted in the context of climate change, offers valuable guidance for pasture managers in other nations with similar environmental attributes, promoting global adaptability and resilience.

Keywords: bioactive forage; ArcGIS Pro ModelBuilder; production suitability model; climate change

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1. Introduction

Undiagnosed and untreated health issues in animals, particularly infection with internal parasites, can significantly impact the financial success of livestock farming operations. This is particularly true for small ruminants (sheep and goats) because of their high susceptibility to infection with gastrointestinal parasites [1]. Failure to identify and treat afflicted animals can lead to the rapid spread of diseases, causing a decline in overall herd or flock health and a decrease in the economic value of individual animals. The successful management of the health of small ruminants (sheep and goats) infected with internal parasites necessitates a comprehensive approach, including incorporating anti-parasitic nutraceutical plants such as the tannin-rich perennial legume sericea lespedeza [SL; *Lespedeza cuneata* (Dum-Cours) G. Don] into their diet [2,3].

Sericea lespedeza is well adapted to the various soil types and environmental conditions of the southeastern United States (U.S.), making it an ideal forage option for both large (cattle) [4], and small ruminant farmers in this region [1,2]. Although considered an invasive weed species in some midwestern states such as Kansas [5], it is recognized as an important forage and conservation crop in the southeastern US. In addition to its environmental adaptability, SL contains significant levels of condensed tannins. These bioactive compounds have been shown to possess anthelmintic properties, effectively combating gastrointestinal parasites that commonly afflict grazing livestock [6,7]. Sericea lespedeza has demonstrated excellent bioactivity against gastrointestinal nematode [8] and coccidia infections in both sheep and goats [9,10], and it has other reported bioactivity as well, including rumen methane suppression [11], rumen protein bypass [12], depression of *Musca domestica* L. (common housefly) larvae in manure [13], and anti-bloat properties [14]. Determining the geographical suitability for growing SL is vital to harnessing its full potential as a nutraceutical forage, which includes enhancing the sustainability and profitability of livestock farming, particularly promoting sustainable rearing practices for small ruminant populations [6,15–17].

To achieve this, several factors must be considered, such as soil composition, temperature, precipitation patterns, and land use. Soil composition plays an essential role in determining the success of SL cultivation. The growth of SL depends on various soil types. Analyzing current land use patterns, such as cropland, pasture, or urban areas, can reveal opportunities to integrate SL into existing agricultural systems or identify underutilized land resources. This plant prefers well-drained soils, including loamy, sandy, and clay soils [18]. Assessing the pH, nutrient content, and soil texture of potential cultivation sites is essential in determining the compatibility of SL with local soil conditions [18,19].

Temperature is another crucial factor, as SL is known to be adaptable to a wide range of temperatures, from warm to cool climates [4]. However, its optimal growth occurs in areas with moderate temperatures. Analyzing historical temperature data and climate trends can help identify regions with suitable temperature ranges for SL cultivation [18,20]. Precipitation patterns are also essential since SL exhibits drought tolerance, making it an ideal forage plant in regions prone to water scarcity [18]. Understanding the average annual rainfall, seasonal variations, and potential changes due to climate change can help determine if a location is suitable for growing SL. Additionally, the plant's drought-tolerant nature can be beneficial in regions where water conservation is a priority. Land use is a crucial consideration, as the availability of suitable land for SL cultivation may be limited by competing agricultural or industrial demands. Analyzing current land use patterns, such as cropland, pasture, or urban areas, can reveal opportunities to integrate SL into existing agricultural systems or identify underutilized land resources.

By carefully examining these factors, suitable areas for SL cultivation can be identified, facilitating the development of targeted agricultural strategies.

Precision agriculture encompasses monitoring, evaluation, and timely strategic intervention in response to small fluctuations in crop production, intending to optimize crop yields through the judicious use of external resources. This approach has been widely employed across various agricultural practices [21,22]. Site-specific crop management (SSCM), an essential component of precision agriculture, combines various technologies and methodologies to optimize crop production while minimizing resource wastage. By incorporating spatial referencing, crop and climate monitoring, attribute mapping, soil analysis, topography, and land cover evaluation, SSCM provides a comprehensive approach to agricultural management [21], while allowing producers to allocate resources like water, fertilizers, and pesticides more precisely, reducing waste and environmental impact. Additionally, decision support systems guide targeted management actions to address the specific needs of crops grown in different regions [21,22]. Geospatial technologies (including remote sensing (RS), geographic information systems (GIS), global positioning systems (GPS), and information technology (IT) or data management) and robust decision support systems [21–23] enable a higher degree of precision in SSCM practices.

Applying SSCM to SL production could enable farmers to increase animal production while limiting inputs, ultimately enhancing profitability. Machine learning can further improve SSCM in row and field crop management [4]. By leveraging geospatial technology and analyzing land cover data, researchers can thus obtain additional information for pasture management decision support, including biomass yield estimation, fertilizer application scheduling, irrigation planning, and pest and disease management using pesticides [24].

We previously devised an automated geospatial model that used low-spatial-resolution data pertaining to soil, land cover, and topography to pinpoint optimal locations for SL production in Swaziland (now Eswatini) in southern Africa, which predominantly exhibited favorable natural climatic conditions for SL growth, such as suitable minimum and maximum temperature ranges and rainfall patterns [4]. The present study constitutes a progression toward developing Site-Specific Forage Management (SSFM) to enhance the production of high-quality forage and bolster animal production in arid or semi-arid regions in the U.S. where climate change could lead to improved temperature conditions supporting SL production. The primary goal of this study was to develop a geospatial engineering and technology-based SL production suitability model to identify potential areas conducive to profitable SL production in the southeastern U.S., with a case study of the State of Georgia only, using ultra-high resolution soil, land cover, topography, and climatic spatial data. The specific objectives were as follows: (1) identify the most suitable environmental parameters (criteria) for the optimal production of SL; (2) develop an automated geospatial model in the ArcGIS Pro ModelBuilder platform using the SL production parameters; (3) create a webGIS site in the ArcGIS Online dashboard format to enable livestock producers in the southeastern U.S., comprising Alabama, Florida, Georgia, Mississippi, and South Carolina, that are interested in transitioning from cattle to small ruminant farming to obtain decision support on the suitability of SL production for their land.

2. Materials and Methods

2.1. Study Area

Twenty on-farm sites where SL is currently growing in the southeastern U.S. are depicted in Figure 1, and the SL growing plot size polygons are illustrated on the tri-state map of Alabama, Georgia, and South Carolina. The topography, soil composition, precipitation, and other climatic conditions of the study areas are diverse (heterogeneous among and within areas). High-resolution environmental data from each site were collected, processed, and rasterized to develop the SL production suitability model. These data included the land cover map of 2019, maps of slope, soil bulk density, soil texture, average minimum temperature (1990–2020), average maximum temperature (1990–2020), and average annual rainfall (1990–2020). It is to be noted that 15 farms out of the 20 are in Georgia, and the ultra-high resolution spatial data essential for SL production suitability analysis were available for these farms for each of the modeling parameters discussed in Section 2.2. Thus, Georgia was used as a case study in our SL crop suitability modeling. Also, we followed a similar modeling process, with low-resolution spatial data for other southeastern states (Alabama, Florida, Georgia, Mississippi, and South Carolina), to develop an SL production suitability map and present it on the ArcGIS Online Dashboard.

2.2. Environmental Data Collection and Processing

Sericea lespedeza can be cultivated effectively in any region where specific production conditions are present [4], as outlined in Table 1. It thrives in open areas, so we chose urban open spaces, pastures, agricultural fields, and bare soil land for its cultivation, as these land cover types facilitate better production with low environmental degradation without the need for clearing forests [4]. While pure clay soil is unsuitable for optimal SL growth, all other soil textures are conducive to its cultivation. Therefore, a soil bulk density lower than 1.6 was considered to optimize SL production modeling. Sericea lespedeza can grow on any topography except on steep slopes over 45° [20]. A minimum temperature of lower than 5 °C impedes its growth and may cause it to become dormant, while a maximum temperature of over 45 °C may reduce its growth. Fortunately, SL is drought resistant, so precipitation was not a significant concern in Georgia, where the average annual precipitation ranges from 1143 to 1905 mm, distributed relatively evenly throughout the year. Occasional snowfall in the Appalachian Mountains of north Georgia possesses no issues for SL production.

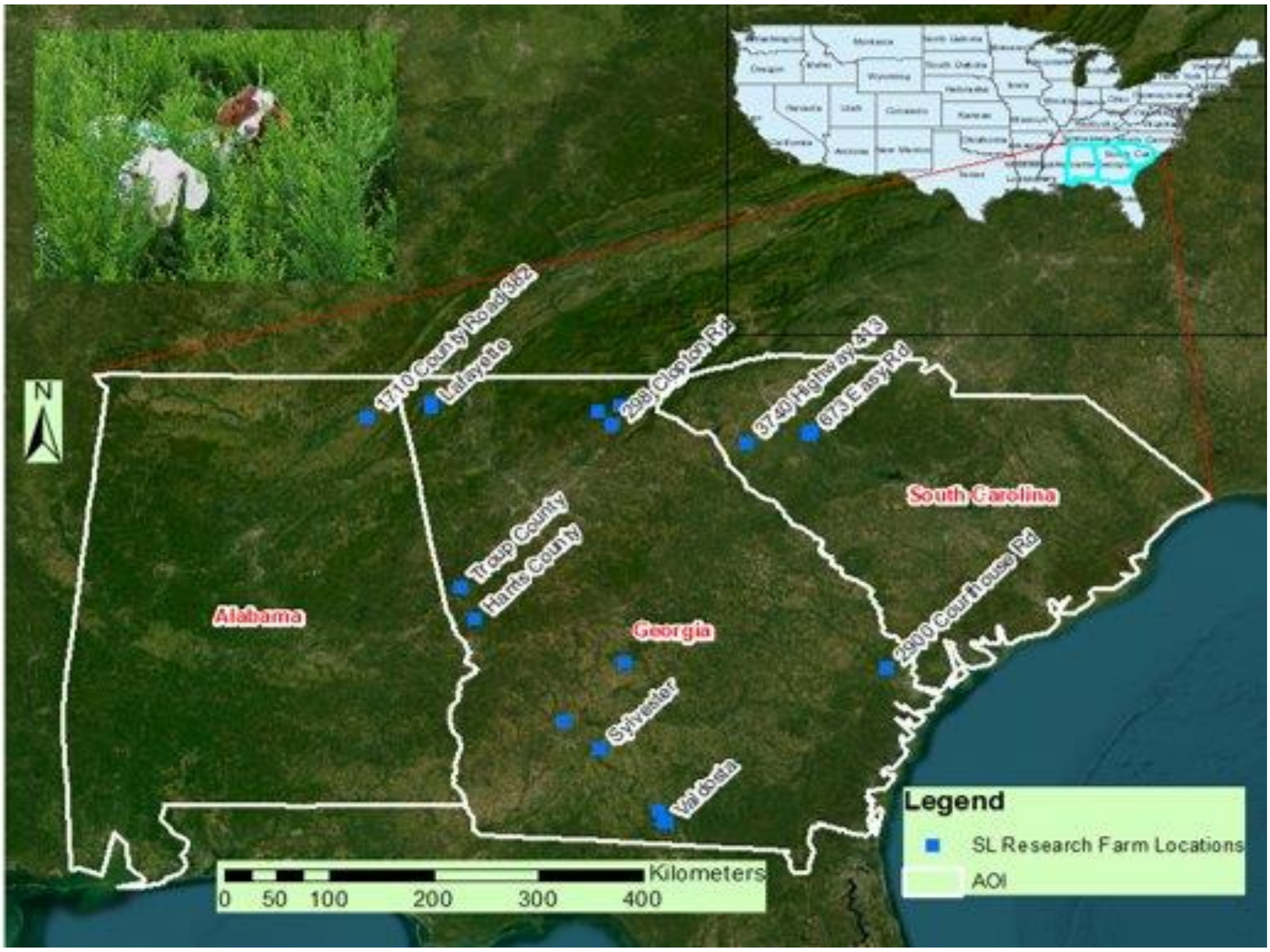


Figure 1. Twenty on-farm research locations (small polygons inside the three-state boundary; blue-squares represents the experimental location sites in three states) where sericea lespedeza is currently growing in the southeastern United States (Alabama, Georgia, and South Carolina from Left to Right), including Fort Valley State University, GA.

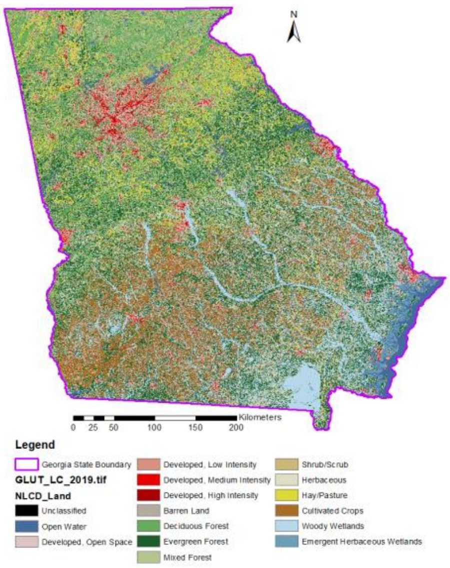
Table 1. Weight factors assigned to sericea lespedeza production suitability rasters.

SSFM DSS Model Factors	Suitability Criteria	Assigned Weights per Delphi Method
Land use/land cover (LULC)	Open land (any land cover)	0.20 (20%)
Slope	>45-degree slope	0.15 (15%)
Soil characteristics	Non-Clay Soil (Texture)	0.15 (15%)
	<1.6 BDL (Bulk Density)	0.15 (15%)
Temperature	>15° Min. Temp.	0.15 (15%)
	<45 °C Max. Temp.	0.15 (15%)
Precipitation		0.05 (5%)

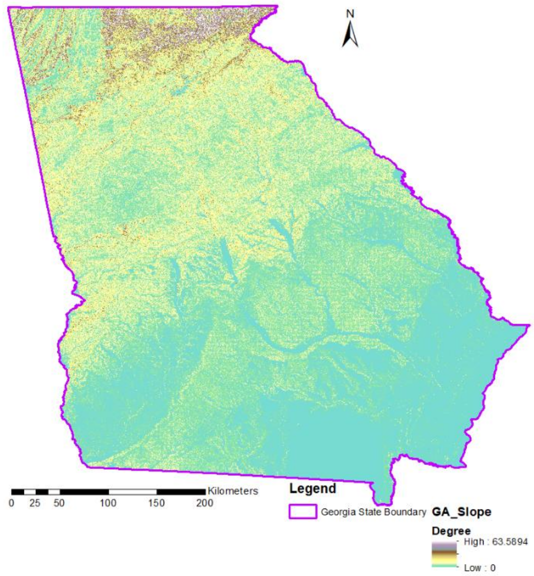
Table 1 provides detailed criteria for the suitability of each environmental parameter, along with a Delphi-based weight for each. The Delphi Process is an expert-opinion-gathering approach that determines the contribution percentage of each parameter for modeling decision support. We took the services of pasture specialists, agronomists, animal husbandry personnel, agriculture engineers, soil and water experts, biotechnologists, farmers, county agents, geospatial scientists, and students with varied backgrounds to determine the contributing weights for each parameter, as shown in Table 1. Each expert, based on their understanding of SL production, provided their analytic weights, and then all experts' weight values for each of the seven parameters (Table 1) were combined, and a relative weight (out of 100%) of each were determined (Table 1, Column # 3). With expert opinion and score tallying, we assigned a 20% weight to land cover, and 15% weight to each slope, minimum and maximum temperatures, soil texture, and bulk density, as these factors significantly affect SL production. Precipitation was not deemed critical, and hence, a low weighting of only 5% was assigned to it. Findings highlight the broad potential for SL cultivation and offer an environmentally conscious solution for forage production that does not require the clearing of forests. With its Delphi-based weighting system, the proposed model provides decision support to optimize SL production in regions with suitable environmental conditions, contributing to sustainable and resilient agriculture practices.

A foundational map delineating the boundaries of Georgia was acquired from the Georgia GIS Clearinghouse (http://www.gis.state.ga.us/ (accessed on 15 March 2023)). The gridded Soil Survey Geographic Database (gSSURGO) layer, featuring high spatial resolution (10 m) and recent development, was used to extract two soil attributes: texture and bulk density. Other attributes, such as pH, organic matter percentage, and salinity of soil, agronomically responsible for SL growth were also considered in our SSFM modeling approach. This layer was sourced from the USDA NRCS Geospatial Data Gateway (https://datagateway.nrcs.usda.gov/ (accessed on 15 March 2023)). Data from the Georgia Land Use Trend Program (GLUT) 2019, a Landsat-derived classification, was procured from the Multi-resolution Land Characteristics Consortium (https://www.mrlc.gov/data (accessed on 15 March 2023)). The GLUT 2019 constituted a 30 m resolution Landsat satellite imagery LULC classified map, which offered a spatial depiction of land use and land cover in the state for 2019, as extrapolated from the 2011 National Land Cover Dataset (NLCD). The resample tool of ArcGIS, which changes the spatial resolution of a raster dataset based on a set rule by aggregating or interpolating the surrounding pixels, was used with Cubic resampling technique to convert the GLUT 2019 spatial resolution to 10 m from the original 30 m. Cubic convolution calculates the value of each pixel by fitting a smooth curve based on the surrounding 16 pixels and is suitable for continuous data, as available with the LULC map. It was necessary to have a common spatial resolution of 10 m for each of the rasters developed from gSSURGO, DEM, and Climate spatial data. Land topography (slope) being a factor in SL production optimization, we obtained Digital Elevation Model (DEM) raster (10 m) from the USDA NRCS Geospatial Data Gateway (https://datagateway.nrcs.usda.gov/ (accessed on 15 March 2023)). Precipitation and minimum and maximum temperature data were obtained from the PRISM Climate Group data portal (https://prism.oregonstate.edu/normals/ (accessed on 15 March 2023)). The dataset incorporated in this study spans from 1990 to 2020, implying that the analysis considers climate variability under evolving global warming conditions. The PRISM data featured an 800 m spatial resolution. A similar Cubic convolution algorithm (technique)-based resampling process was followed to change the PRISM temperature and precipitation raster spatial resolution to 10 m.

The acquired data were processed and individually arranged into raster data layers, with Figure 2a–g illustrating the spatial variability of each layer. The gSSURGO soil rasters (Texture, Bulk Density, pH, Organic Matter (%), and salinity) were developed using the Reclassify tool, as the gSSURGO Map Unit Raster was a raster file that was modified to include other soil characteristics (available as table data upon download from USDA NRCS Geospatial Data Gateway) with the use of Join Field tool of ArcGIS. These datasets were subsequently used to develop the SSFM model-based decision support system.



(**a**)



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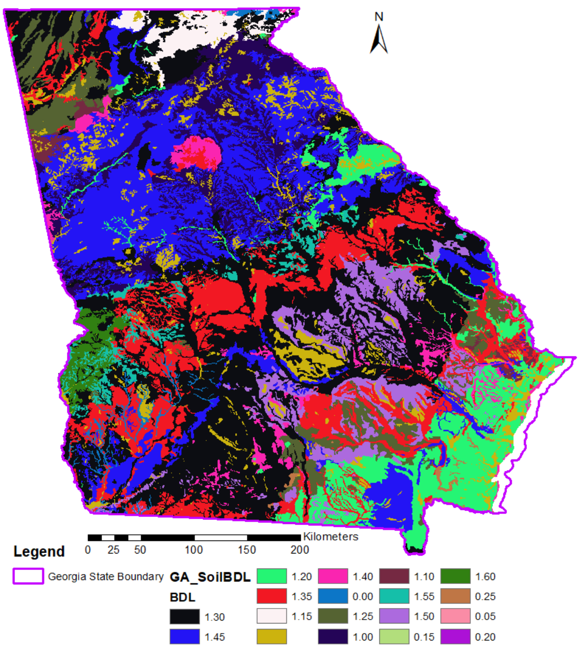

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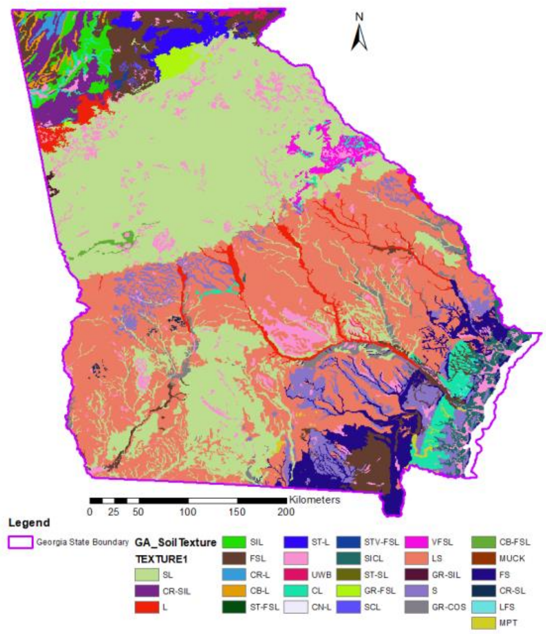
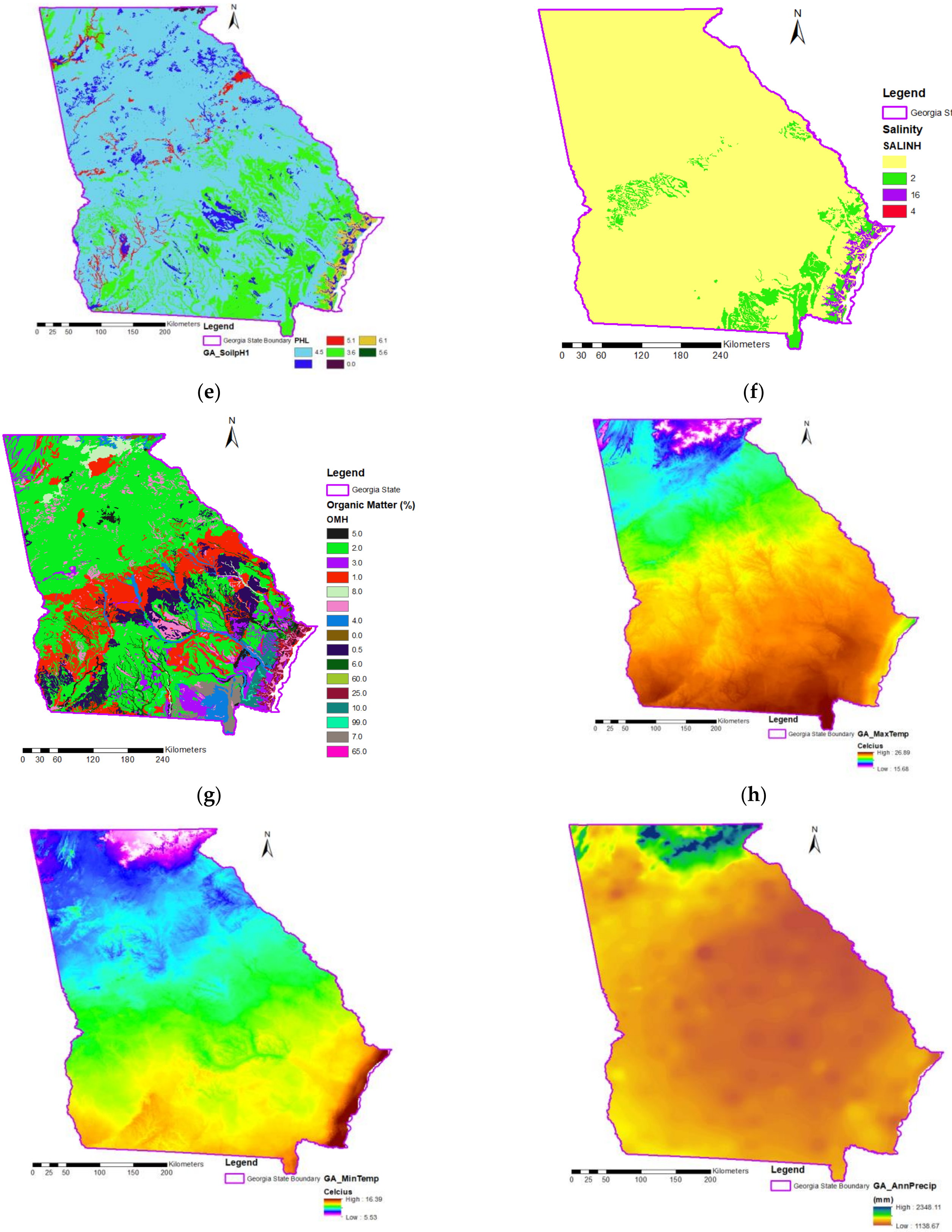


(**d**)

Figure 2. *Cont.*



(e) (f) (g) (h) (i) (j)

Figure 2. Georgia spatial environmental features map—(**a**) land cover map of 2019, (**b**) slope map, (**c**) soil bulk density map, (**d**) soil texture map, (**e**) soil pH map, (**f**) soil salinity map, (**g**) soil organic matter (%) map, (**h**) average maximum temperature (1990–2020) map, (**i**) average minimum temperature (1990–2020) map, and (**j**) average annual rainfall (1990–2020) map.

2.3. Precision Agriculture Model Development to Find Most Suitable Biomass Production Crop

Figure 3 illustrates the comprehensive methodology used in assessing the viability of SL cultivation in Georgia and for use in other global locations. The figure outlines a sequential approach to data processing within a modeling environment (specifically, the ArcGIS Pro ModelBuilder platform) to ultimately generate a spatial raster delineating SL production suitability for Georgia. Initial climate raster datasets were acquired from the PRISM Climate Group portal, covering the U.S. These datasets were subsequently confined to Georgia's borders using the Extract by Mask tool, as depicted in Figure 4. The ArcGIS Pro ModelBuilder platform has the Environment Setting option, which streamlines the process by configuring the workspace (input and output database), the data projection system (UTM NAD 83 Zone 17N), the spatial extent (limited to Georgia's boundary), and the spatial resolution (set at 30 m) for data used in the modeling. This optimization eliminated the need for numerous tools, as the layers automatically conformed to different spatial extents, spatial resolutions, and projection systems, resulting in significant time savings.

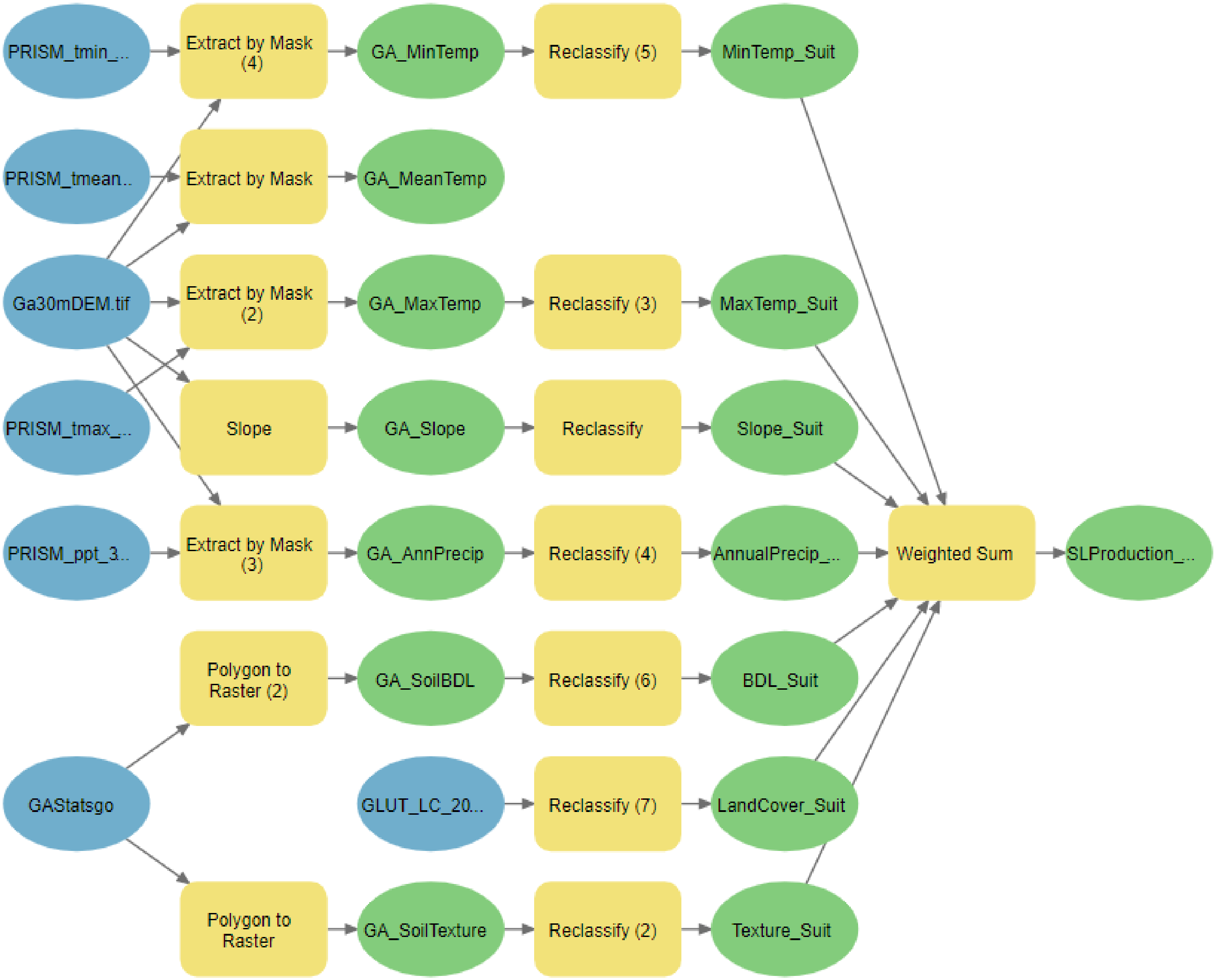
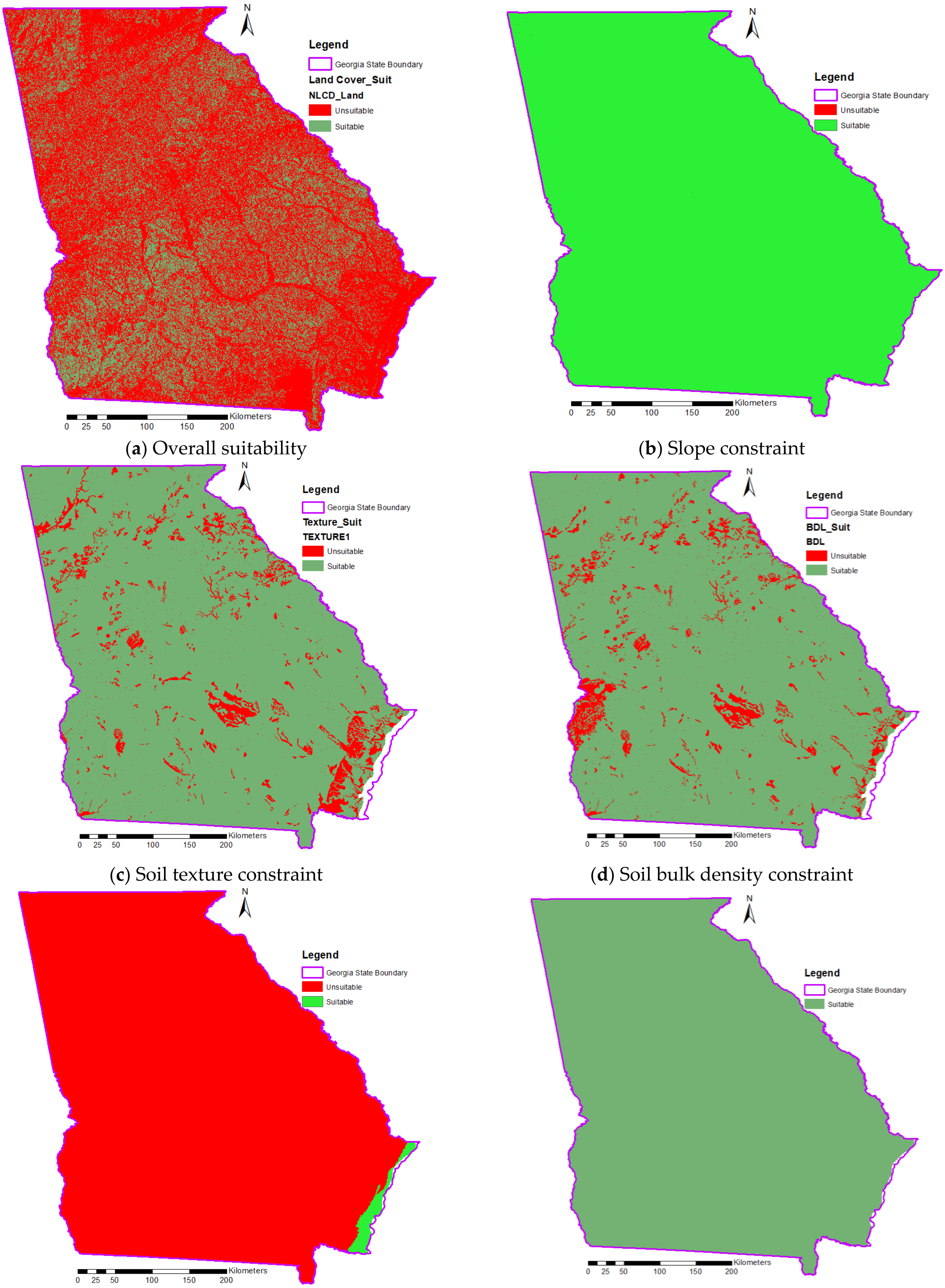
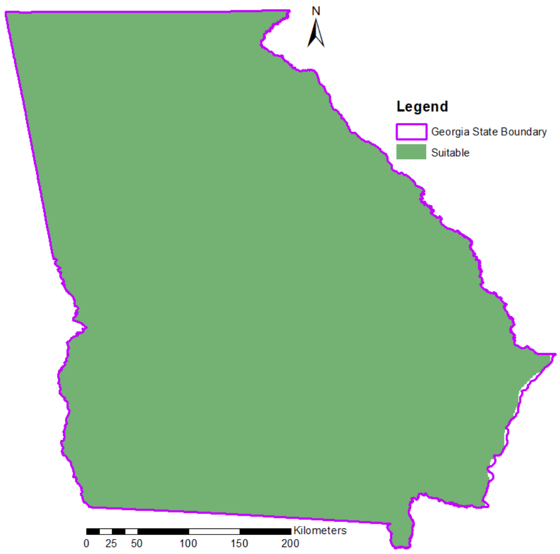


Figure 3. Working procedure (model architecture) for sericea lespedeza spatial production suitability analysis (in present condition and climate change-based future condition).



(**a**) Overall suitability
(**b**) Slope constraint
(**c**) Soil texture constraint
(**d**) Soil bulk density constraint
(**e**) Minimum annual temperature constraint
(**f**) Maximum annual temperature constraint

Figure 4. *Cont.*



(**g**) Average annual rainfall constraint

Figure 4. Georgia spatial environmental features map showing suitability and unsuitability for sericea lespedeza production—(**a**) land cover, (**b**) slope, (**c**) soil texture, (**d**) soil bulk density, (**e**) average minimum temperature, (**f**) average maximum temperature, and (**g**) average annual rainfall.

2.4. Raster Reclassification

Raster reclassification is commonly employed in geographical information systems (GIS). It involves manipulating or transforming input raster data, which may pertain to variables such as temperature, elevation, or soil type, by applying a predetermined set of criteria or rules. The procedure involves scrutinizing every cell, commonly called a pixel, within the input raster and allocating a new value in the output raster, considering the reclassification regulations. The study employs a raster reclassification technique to evaluate the aptness for SL production without explicitly mentioning the nature of the plant or crop by considering diverse environmental parameters (Table 2). The reclassification method employed is binary, whereby every raster cell is categorized exclusively as 0 or 1. The numerical value '1' denotes conducive circumstances to produce SL, while the numerical value '0' signifies adverse conditions. Cells that exhibit a temperature above 45 °C are deemed unfavorable and are consequently attributed a value of 0. Cells that exhibit a maximum temperature of 45 °C or less are deemed conducive and are attributed a numerical value of 1. Following the reclassification methodology, seven rasters have been produced through reclassification. Each of these rasters probably corresponds to a distinct environmental factor pertinent to the production of SL, such as temperature, precipitation, soil type, etc. The rasters consist of cells with binary values of either 0 or 1. These values signify the favorable or unfavorable conditions for SL production at the corresponding location based on the specific environmental factor. Although the soil organic matter spatial distribution in Georgia was studied (Figure 2g), it had a strong spatial correlation with soil bulk density (Figure 2c), so this soil characteristic was not used in the suitability model development to prevent duplication. Soil salinity (Figure 2f) was also studied but found to have similar values in most of the state. Our literature review showed that soil salinity has little relevance to SL production and hence was not considered in the suitability analysis. Similarly, as SL can grow well in acidic or basic soil, we observed from the soil pH map that the entire Georgia is suitable for SL production based on the pH level of soil. Thus, we also did not include this spatial layer in the SL production suitability analysis.

Table 2. Representation of on-farm sericea lespedeza site location and descriptions (precipitation in mm per year and temperatures in degrees Celsius; AL = Alabama; GA = Georgia; SC = South Carolina); Numbers in the states' name represents the experimental sites in each state.

Farm	NDVI Mean	NDVI Std	SAVI Mean	SAVI Std	Elevation Mean (m)	Elevation Std (m)	Avg. Precipitation (mm)	Min Temp (°C)	Max Temp (°C)	Band10 Mean (16-bit)	Band10 Std (16-bit)
AL1	0.29	0.03	0.53	0.05	248.20	2.13	1414.02	8.58	20.21	43,259.00	224.65
GA1	0.23	0.02	0.41	0.45	158.11	2.83	1142.61	9.61	23.26	43,141.69	565.14
GA2	0.37	0.03	0.67	0.06	48.20	1.00	1256.79	13.16	25.88	46,994.49	473.31
GA3	0.30	0.03	0.54	0.06	108.72	2.73	1168.40	11.74	24.70	47,909.33	364.40
GA4	0.33	0.02	0.59	0.04	115.71	0.45	1168.40	11.74	24.70	47,857.13	323.28
GA5	0.31	0.03	0.56	0.05	103.96	4.37	1219.20	12.79	25.28	47,032.92	249.50
GA6	0.48	0.03	0.86	0.07	539.48	2.38	1625.60	7.37	19.99	47,000.00	248.00
GA7	0.29	0.05	0.53	0.09	278.94	4.23	1320.80	9.03	21.32	43,364.72	261.60
GA8	0.29	0.03	0.53	0.05	248.20	2.13	1414.02	8.58	20.21	43,259.00	224.65
GA9	0.29	0.05	0.53	0.09	278.94	4.23	1320.80	9.03	21.32	43,364.72	261.60
SC1	0.38	0.03	0.69	0.06	174.73	7.01	1162.30	9.70	22.67	43,455.45	130.66
SC2	0.25	0.02	0.45	0.03	193.82	2.25	1143.00	9.29	22.85	44,964.82	343.21
SC3	0.29	0.03	0.53	0.05	411.52	0.79	1625.60	7.83	20.90	43,826.65	231.13

2.5. Spatial Overlay and Result Verification

The seven reclassified raster datasets were integrated using the map algebra functionality in ArcGIS Pro via the application of the 'Weighted Sum' tool, which permits the inclusion of individually assigned Delphi-based weighting factors (Table 1) for each raster, subsequently amalgamating them into a singular raster output. The next raster layer exhibited values between 0 and 1, signifying a suitability spectrum for individual cells, with 0 representing minimal suitability and 1 representing maximal suitability for SL production. Post-processing, any cell fulfilling all seven favorable conditions exhibited a value of 1, thereby indicating optimal suitability for SL production. Each raster cell has dimensions of 10 m $\times$ 10 m, implying a total area of 100 m^2 for a specific cell deemed entirely suitable for SL production. Existing SL farms in GA were superimposed onto the synthesized raster dataset to validate their positioning within spatially optimal locations conducive to SL production.

2.6. WebGIS-Based SL Production Interactive Suitability Dashboard Development

The emergence of the internet has revolutionized the process of data acquisition and distribution, encompassing GIS data as well. The WebGIS represents a paradigm or architectural framework that assists immediate online access to decision support systems (DSS) for end-users. This system permits the transfer and dissemination of spatial maps and/or analytical tools to users, devoid of temporal or spatial constraints, and empowers them to generate personalized decision support interactively. The ArcGIS Online server infrastructure created an SL production suitability map for the southeastern U.S., delivered to end-users via the custom-built WebGIS Dashboard. As mentioned earlier, we have used some low-resolution spatial layers in this analysis unlike all the 10 m spatial resolution data used in the Georgia case study. The result is not little crude, but we are in the process of obtaining ultra-high spatial data layers to have a smooth (100 m^2) pixel-based SL production suitability map for the entire southeastern U.S.

3. Results and Discussion

Figure 4a–g depict distinct suitability maps that illustrate spatial zones favorable or unfavorable for SL production. It is essential to highlight that these figures display two distinctive hues; red regions (pixels) represent unsuitability for SL production based on individual parameters, while green regions (pixels) indicate suitability concerning the parameter in question. Figure 4a demonstrates that a substantial portion of Georgia is suitable for SL production, with the exclusion of water bodies, wetlands, forests, and urban zones, which do not offer environmentally viable or optimal natural production sites. Nonetheless, much of south-central Georgia is suitable for SL production. Barring a few pixels, the entire state's slope is conducive to SL production, as depicted in Figure 4b.

Figure 4c,d reveal that most of the state of Georgia is suitable for SL production based on the evaluated soil characteristics. Predominantly, nonclayey soils and soils with bulk densities exceeding 1.6 are present, except for locations along the Georgian coast and the southwestern border. It is accurate to state that clay soils exhibit higher bulk densities. Incorporating distinct texture and bulk density of top soil (BDL) layers in the model is logical, as they do not provide identical suitability for SL production. The minimum average temperature suitability map (Figure 4e) suggests that Georgia's lower temperatures are unfavorable for year-round SL production. Nevertheless, SL can be cultivated during summer, late spring, and early fall in most parts of Georgia before entering dormancy in winter. A subsequent study is underway to examine monthly production suitability in Georgia and the southeastern U.S.

Figure 4f,g, representing maximum average temperature and precipitation, respectively, indicate that all of Georgia is suitable for SL production under these constraints, since maximum average temperatures do not surpass 45 °C, and all parts of the state receive sufficient rainfall to support the growth of this drought-tolerant crop.

Figure 5 presents a geospatial decision support tool as a cartographic representation designed to inform farmers or other stakeholders about the areas where SL production is most favorable and least favorable. Optimal growth locations for SL are depicted by green-colored pixels, while red-colored pixels indicate areas with minimal suitability.

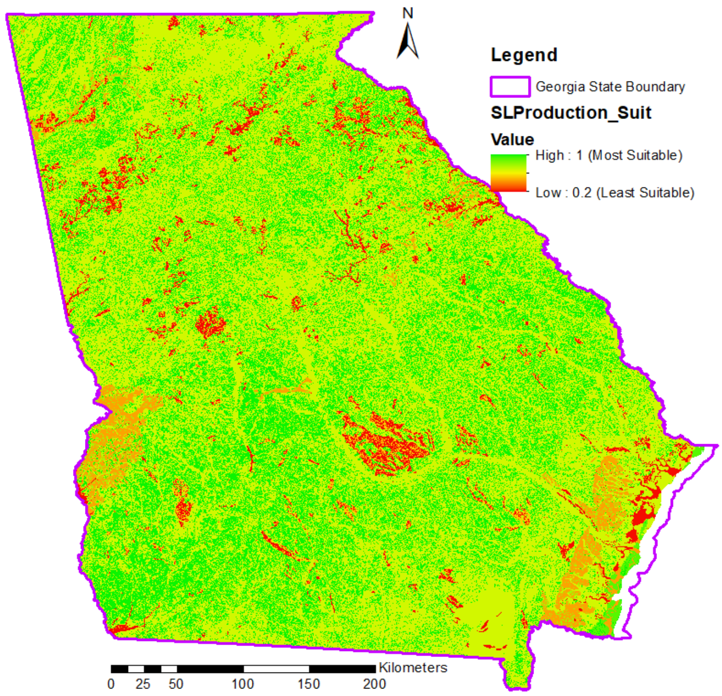


Figure 5. Map showing sericea lespedeza production suitability scale in Georgia.

Figure 6 illustrates the binary classification (suitable or unsuitable) of SL production viability in Georgia, using a two-level scale. The Jenks Classification algorithm was used to partition the SL production suitability values into two categories. Pixels with a score of 0.71 or higher were deemed statistically appropriate for successful SL cultivation, while the remaining areas (pixels) were considered unsuitable for optimal SL growth. The current operational SL farms in Georgia were overlaid on the map in collaboration with the research team, revealing a 100% presence within the green (suitable) pixels.

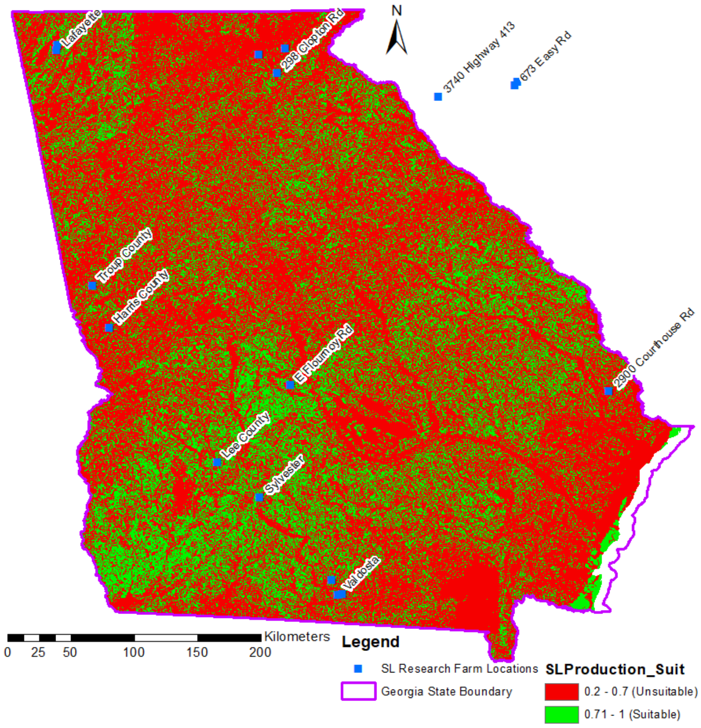


Figure 6. Sericea lespedeza (SL) production suitability map showing the present SL production on-farm sites in Georgia.

Figure 7 displays an interactive WebGIS map for the wider region, based on the algorithm developed for Georgia, that enables farmers to assess their land's suitability for SL production online. Should their land be deemed unsuitable, they can seek advice on necessary adjustments to enhance its suitability. The WebGIS platform can be accessed at https://iesa-ung.maps.arcgis.com/apps/mapviewer/index.html?webmap=15af0a782a8048cbb8f818828b4ac081 (accessed on 15 March 2023), which functions as a map viewer site. Users can search for their respective fields using an address-matching feature, zoom in on specific locations, and conduct fundamental GIS analysis within the map interface.

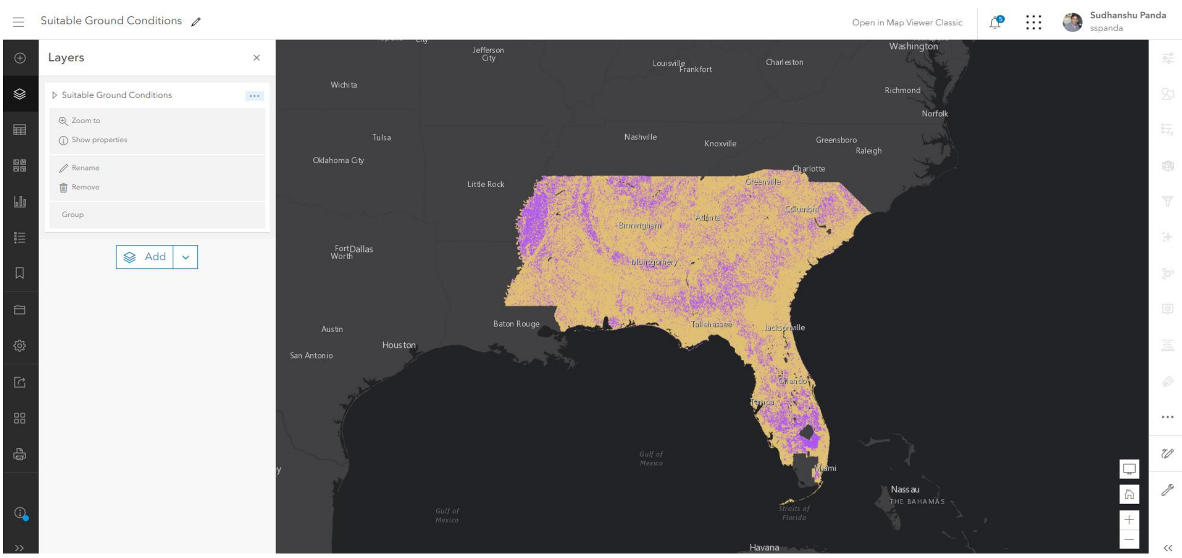


Figure 7. Screenshot of sericea lespedeza (SL) production suitability WebGIS map service for end-users to obtain online SL production management decision support interactively. (Purple shades on the image represents the sericea lespedeza (SL) production suitability areas).

4. Conclusions

This research employed Geographic Information System (GIS) technology and Bayesian Deep Learning models to evaluate the feasibility of cultivating SL in Georgia and other surrounding states, such as Alabama and South Carolina, due to similar weather conditions. The assessment considers topographical features, climatic conditions, and soil characteristics. Based on our developed model, most of Georgia possesses favorable conditions for SL production, including most soil types except pure clayey soils. Rainfall, pH, and temperature ranges in Georgia are generally favorable for SL production, although it will go dormant after a killing frost in winter.

Novel technological advancements have been devised, comprising an interactive decision support system, a binary classification scheme for assessing the feasibility of sustainable land production, and an interactive WebGIS cartographic interface. These technological instruments offer immediate support to farmers in evaluating the appropriateness of their soil for sustainable land cultivation. This research demonstrated that the use of geographic information systems (GIS) and machine learning techniques can be used in spatial examination that relies on empirical data to evaluate arable land.

The findings of this research underscore the promising prospects of utilizing spatial analytics to assess the appropriateness of land for SL production. The results of this study provide a foundation for further investigation into the temporal evaluation of SL production suitability and its adaptation to improve the usefulness of agricultural land. The replicability and adaptability of this research can be utilized to identify regions of similar environmental conditions worldwide that are conducive to SL production.

Author Contributions: S.S.P., as the first author of this original research, conceptualized the research methodology in consultations with the entire research team participating in this manuscript as coauthors. S.S.P. completed the data collection, processing, analyses, and geospatial model development, along with WebGIS dashboard development of this research. T.H.T. and A.K.M. provided technical help on geospatial data accuracy assessment and ground truthing, supported the Delphi-based study design and modeling, and reviewed the manuscript. J.A.v.W. and E.R.M. participated in the Delphi process of SL production input parameter weight development. They reviewed the manuscript and provided technical assistance that were necessary for the completion of the research as they were involved in an earlier study of Eswatini. A.S. and A.A.P.-C. provided the review and correction of manuscript. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author.

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