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Using GeoAI for Assessing Habitat Suitability of Vetiver Grass Planting to Support Soil and Water Conservation in Thailand

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Abstract

In Thailand, the utilization of vetiver grass or VG *(Chrysopogon zizanioides*) is not only encouraged for soil and water conservation 28 years and has proven to be an effective and low-cost technique. The objective focused on assessing habitat suitability-based GeoAI techniques for planting VG. The catchment area of Huai Pa Daeng Reservoir, Phetchabun province was selected as a study area. There were 6 studied environmental factors related to ecology of VG: Land use/Land cover (LU/LC), bioclimate, topography and modified soil and they were analyzed by their specific processes to be ecologically modelled in Ecological Niche Factor Analysis (ENFA) of Biomapper. This ENFA produced various Ecological Niche Models (ENM) including explicated niche factors before they were used for generating Habitat Suitability (HS) based on Build Virtual Raster and Deepness technique in QGIS with two aspects: 1) extremely high data and 2) extremely low data. As results, there were 3 produced ENMs in ENFA and ENM2 was selected for generating HS of VG planting because it had the highest percent of explanation and accuracy assessment with 0.819 of AVI and 0.042 of CVI. In ENM2, there were 4 respectively important factors: (1) mean annual temperature (°C), (2) mean monthly maximum temperature (°C), (3) mean monthly minimum temperature (°C) and (4) elevation, respectively. These 4 factors relate to the mentioned ecology of VG, can tolerate drought or high temperatures. Moreover, there were 9.04 km^2 (0.23%) of HS areas for VG planting in the first aspect and 18.52 km^2 (0.46%) of HS areas for VG planting in the second aspect. Consequently, the findings of this research can be the base foundation to deeper understanding to potential areas of VG.

Keywords: Vetiver grass; GeoAI; Habitat suitability; Spatial distribution modeling

1. Introduction

Currently, the northern region of Thailand faces a problem of large amounts of soil sediment or mud from flash floods flowing from high places to low areas. A destroyed upstream forest become one of critical cause. Therefore, restoring upstream areas to reduce soil erosion that flows with heavy rain is necessary to solve the problem. One interested natural method is the utilization of vetiver grass (VG), it has not only been introduced and by encouraged in Thailand by King Rama IX since 1991 (The Vetiver Network International, 2023), but it also was identified by the World Bank (Greenfield, 1988; Grimshaw and Helfer, 1995) as the most effective at preventing soil erosion. Thus, VG was seriously promoted for soil and water conservation from various concerned Thai and private sectors (such as Royal Forest Department (FRD) Department of Highways (DOH), Land development Department (LDD), PTT Public Company Limited and educational institutions) because it is a suitable way for Thai society to address these problems with a simple technology that was easy to implement and cost-effective compared to other methods (Leknoi and Likitlersuang, 2020). For 30 years, VG has been empirically proven to be an effective and low-cost technique which readily be practiced by farmers and researchers for slowing water-runoff, reducing erosion, and increasing the soil moisture for crop and plant growth (The Vetiver Network International, 2023), especially trapping soil sediment or decreasing soil erosion, for example, using VG for stabilization of structures by Grimshaw and Faiz (1995), the vetiver system for slope stabilization by Truong et al. (2008), the hedge against soil erosion by Greenfield (2012) and studying a living trap of VG in a variety of areas by Chomchalow (2015).

VG is formerly known scientific name by *Vetiveria Zizanioides* L. Nash, has been shown to survive for up to 100 years in tropical environments (The Vetiver Network International, 2021). This plant has a wide range of adaption and will tolerate soil pH from 3 to 11, temperatures from -15 to +55 degrees C and is extremely drought proof, and yet can survive complete submergence in water for at least 3 months (Grimshaw and Faiz, 1995; Greenfield, 2002; The Vetiver Network International, 2021). It is saline tolerant, tolerant to most heavy metals, and to all herbicides except for glyphosate (Truong *et al.,* 2008; The Vetiver Network International, 2021).

Based on the importance of VG for preventing soil erosion, this study emphasizes on using VG as an environmental innovation to support communities in handling extremely climate changes, as well as achieving Sustainable Development Goals (SDGs). However, this study must consider is firstly important before using VG to reduce soil erosion, it is a matter of finding suitable areas to use VG or finding habitat suitability (HS) of VG. In GIScience, there are various HS proposed approaches from academic papers, include landscape VVF: integrating modelling and GIS in a software tool for habitat suitability assessment (Ortiggosa and Gatto, 2000), HIS models software (Dijak *et al.,* 2007), the ArcGIS extension tool CorridorDesigner (Beier *et al.,* 2007; Stricker *et al.,* 2019), Habby (Coarer *et al.,* 2018), Maxent (Jayakody *et al.,* 2024), Biomapper (Rosas *et al.,* 2023) etc. Now, Geospatial (or Geographical) Artificial Intelligence (shortly named, 'GeoAI'), has very quickly become a critical role of spatial analysis, has been developed to analyze more deeply spatial data. More fundamentally, GeoAI reflects a radical shift in our approach to understanding the geographic domain (Gao *et al.,* 2024). GeoAI is the integration of AI with spatial data, science, and geospatial technology to increase understanding and solve spatial problems (ESRI (2024). The attractive feature of AI is its ability to identify relevant patterns within complex, nonlinear data without the need for any a priori mechanistic understanding of the geomatics processes (Pierdicca and Paolanti, 2022). Today, DL and AI algorithms have been successfully developed and applied in many geomatics applications (MartínJiménez *et al.,* 2018; Zhang *et al.,* 2020; Pierdicca and Paolanti, 2022), for example, Tuan *et al.* (2024) studied land susceptibility with a deep learning approach in Phuoc Son, Quang

Nam; Gianquintieri *et al.* (2024) studied implementation of a GeoAI model to assess the impact of agricultural land on the spatial distribution of $PM_{2.5}$ concentration in city.

Therefore, the objective of this study aimed to apply GeoAI techniques for assessing habitat suitability (HS) of VG planting to trap soil sediment or to reduce soil erosion. The catchment area of Huai Pa Daeng Reservoir at Phetchabun province, Thailand was selected as study area because this area has been obviously seen by the problem of soil sediment in water bodies, are caused by the movement of flash floods from the mountains into the study area during the heavy rain season (Figure 1). This obtained HS of VG will be planned for planting VG to trap or reduce soil sediment in such study area further.

Study area

The study area is the catchment area of Huai Pa Daeng Reservoir, Phetchabun province is in Royal initiative projects to promote the utilization of VG for soil and water conservation under FRD responsibility. This area has approximately 40.14 km², located in watershed area 1b, watershed levels 2, 3, and 4, respectively. Moreover, the studied site is under the Pa Sak River basin in a part of no. 2 with geographic coordinates is between latitude 16.42° - 16.51°N and longitude 101.01° - 101.11°E as Figure 2.

2. Methodology

This paper highlights the use of GeoAI techniques in QGIS for studying the environmental factors of VG and analyzing HS of VG planting to trap soil sediment, designed framework of this methodology as shown Figure 3 and more details as below.

Figure 1. Comparison of water source condition between two temporal data

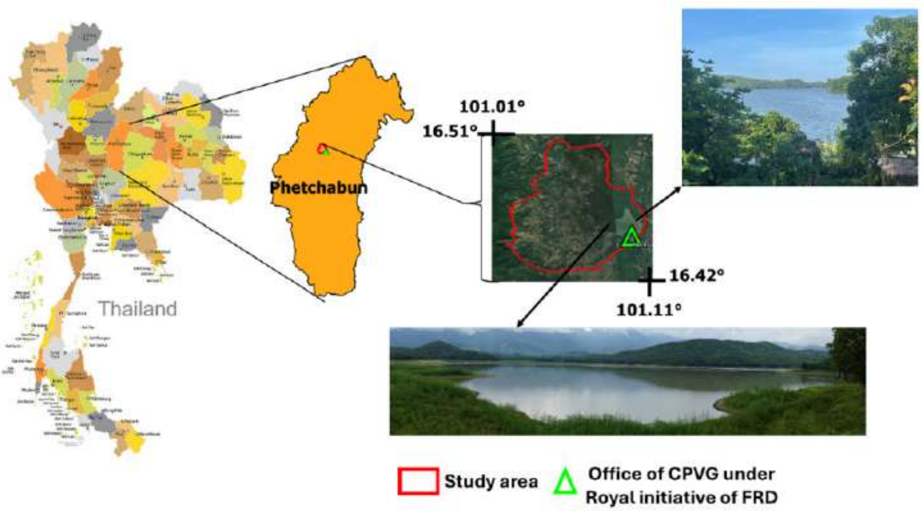

Figure 2. Location of study area

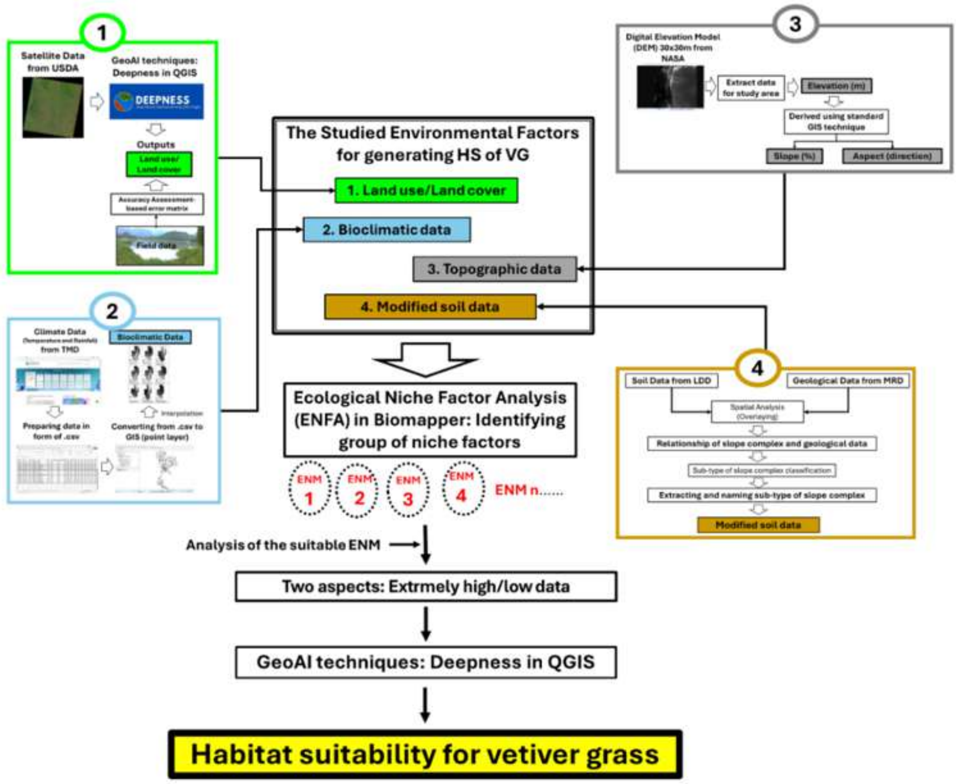

Figure 3. Methodology of this study included two main processes: (1) Analysis of the studied environmental factors for generating HS of VG (LU/LC, bioclimatic data, topographic data and the modified soil data) and (2) Analysis of HS for VG

2.1 Analysis of the studied environmental factors for generating HS of VG

2.1.1 Analysis of LU/LC

From no. 1 in Figure 3, satellite data (from February1 to May 31, 2024) of study area was downloaded from web of U.S. Geological Survey or USGS EarthExplorer at https://earthexplorer.usgs.gov/. They were classified by Deepness technique in QGIS to analyze LU/LC and then was assessed accuracy with error matric between the analyzed data and the field data.

2.1.2 Analysis of bioclimatic data

From no. 2 in Figure 3, the rainfall and temperature data were used to generate bioclimate with spatial interpolation. Bioclimatic data was calculated by approach of USGS (2012). Moreover, this study determined the characteristic of two climatic data as the monthly mean data of 30 years (May 1993 - May 2024) from of Thai Meteorological Department (TMD). Then they were prepared in the form of spreadsheet and saved as table (.cvs) before were converted into shapefile (.shp) to be interpolated by Inverse distance weighted (IDW) in QGIS.

2.1.3 Analysis of topographic data

From no. 3 in Figure 3, topographic data is one important input for this study that comprises of elevation (m), slope (degree) and aspect (direction). Elevation data had directly extracted from Digital Elevation Model (DEM) 30x30m while slope and aspect were derived using standard GIS technique from DEM.

2.1.4 Analysis of modified soil data

From no. 4 in Figure 3, soil data from Land Development Department (LDD) was analyzed with geological data from Department of Mineral Resources (DMR). This analysis was overlaying under vector analysis in QGIS to extract the relationship of slope complex with geological formations.

2.2 Analysis of HS for VG

The environmental factors were obtained by -3.1, were modeled by Ecological Niche Factor Analysis (ENFA) in Biomapper to produce Ecological Models (ENM). And then the ENMs were selected by percent of statistical explanation including the group of best niche factors for generating HS of VG. In this HS analysis, we set two aspects (as Figure 4): 1) extremely high data and 2) extremely low data. Then HS was evaluated by Absolute Validation Index (AVI) and Contrast Validation Index (CVI) based on the field data.

3. Results and Discussion

3.1 The studied environmental factors

3.1.1 LU/LC

This is output of LU/LC, was checked by accuracy assessment with error matrix between the studied output and field data about 82% as Figure 5. LU/LC included forest areas 18.69 km2 (46.55%), Agriculture area 19.04 km2 (47.43%), Building up area 0.06 km2 (0.15%), Water area 2.13 km^2 (5.31%) and miscellaneous area 0.23 km^2 (0.57%).

3.1.2 Bioclimatic data

This is output of bioclimate variables as Figure 6, were spatially interpolated by the 30 year-climatic data of TMD.

3.1.3 Topographic data

This is topographical data (as Figure 7) that consisted of DEM 30 x 30m slope (%) and aspect (direction). Slope and aspect were derived by DEM.

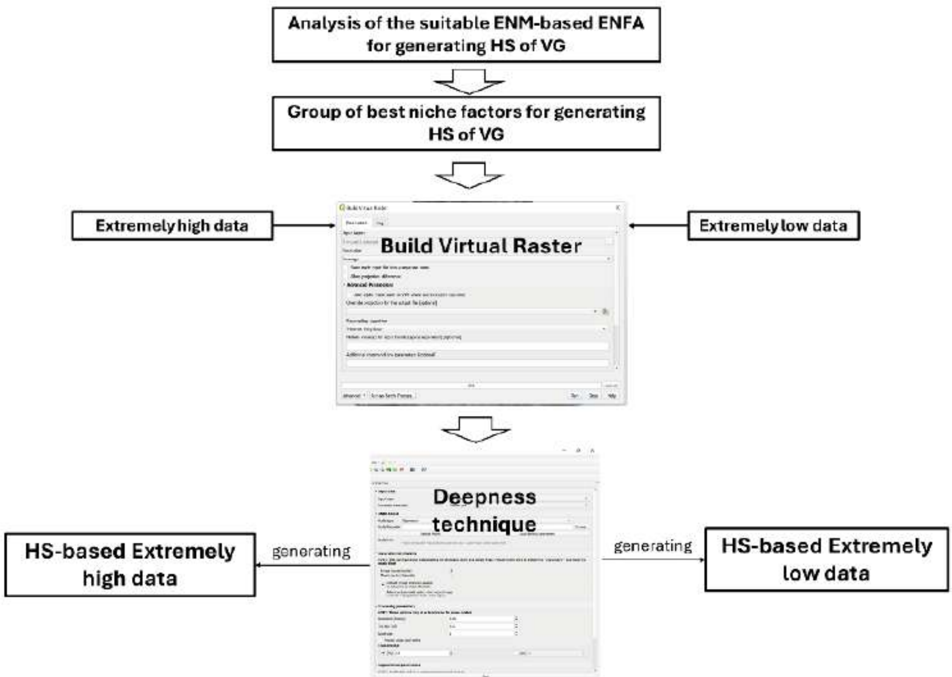

Figure 4. Generating HS of VG -based Build Virtual Raster and Deepness technique in QGIS with two aspects: 1) extremely high data and 2) extremely low data.

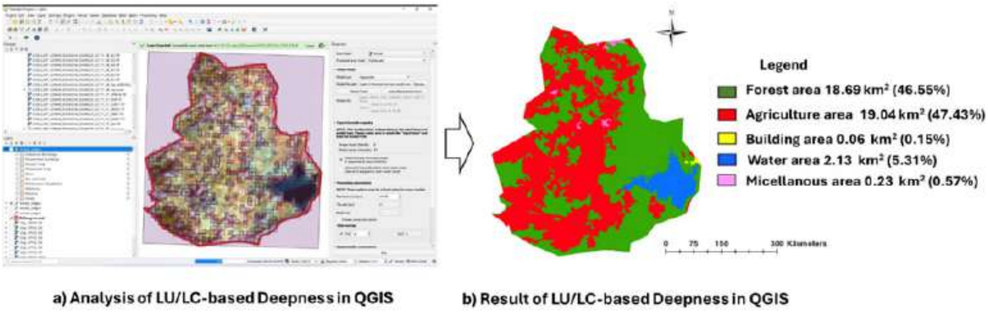

Figure 5. Output of LU/LC-based Deepness (using virtual band 5,4 and 3)

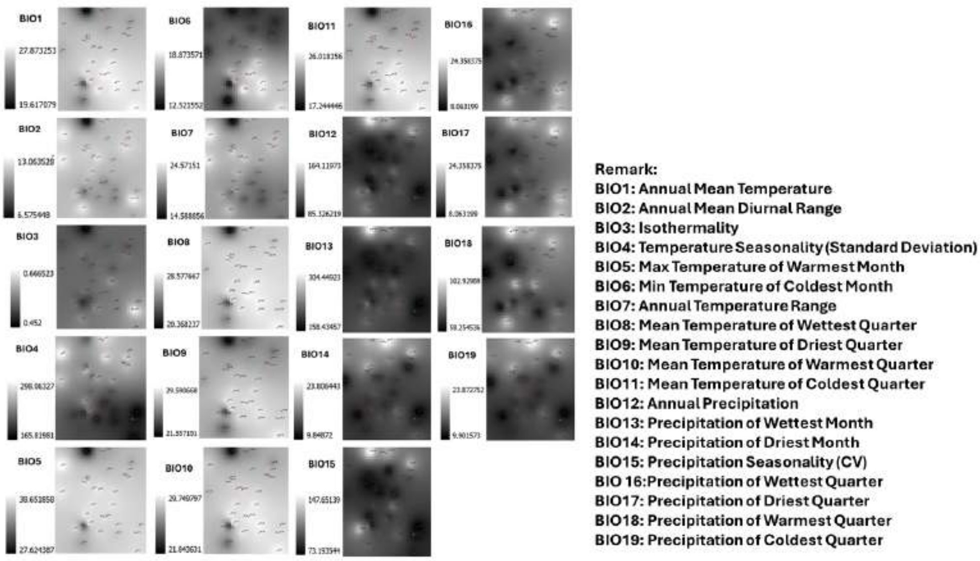

Figure 6. Output of 19 bioclimate data-based spatial interpolation

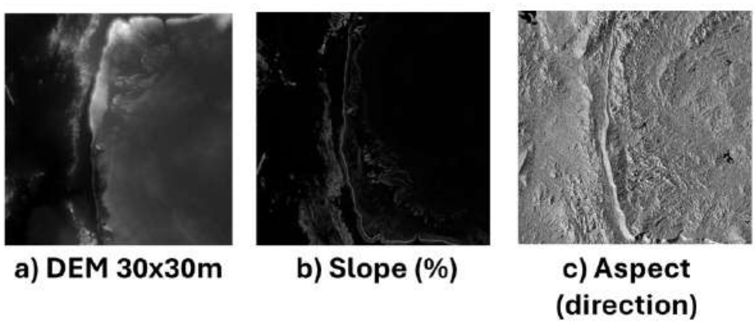

Figure 7. Output of three topographic data: a) DEM 30 x 30m, b) Slope (%) and c) Aspect (direction)

3.1.4 Modified soil data

This is output of the modified soil data (as Figure 8) that was generated by soil data of LDD and geological data of DMR in QGIS-based overlay tool.

3.2 Analysis of the suitable ENM and HS for VG

The studied environmental factors in 3.1, were ecologically modelled by ENFA in Biomapper to identify groups of niche factors for VG. As results, there were three ENFA groups as

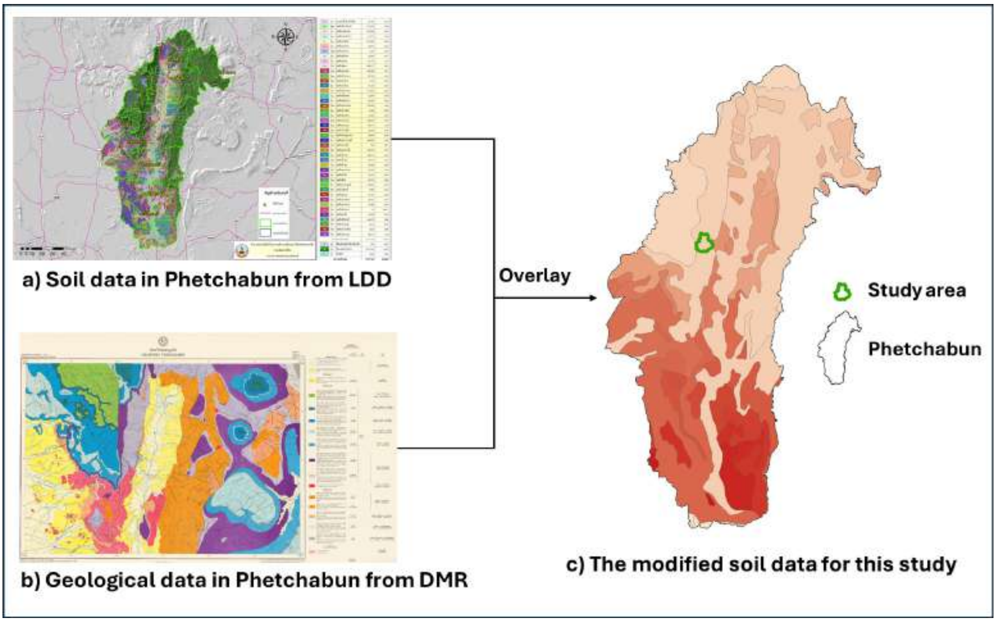

Figure 8. Output of the modified soil data for this study

Table 1. Identification of niche environmental factors based on ENFA

Variables	Marginality (M)	Specialization (S)
Group no.1 (ENM1)		
BIO14: Precipitation of Driest Month	0.718	0.282
BIO15: Precipitation Seasonality (CV)	0.620	-0.380
BIO2: Annual Mean Diurnal Range	0.243	0.757
BIO7: Annual Temperature Range	-0.204	0.796
Overall	1.785	2.215
% of Explanation	92%	8%
Group no.2 (ENM2)		
BIO1: Annual Mean Temperature	-0.667	0.333
BIO5: Max Temperature of Warmest Month	0.561	0.439
BIO6: Min Temperature of Coldest Month	0.327	-0.673
DEM	0.364	0.636
Overall	1.919	2.081
% of Explanation	97%	3%
Group no.3 (ENM3)		
BIO4: Temperature Seasonality (Standard Deviation)	0.950	0.05
BIO12: Annual Precipitation	0.010	-0.990
BIO13: Precipitation of Wettest Month	0.09	-0.100
Overall	1.050	1.140
% of Explanation	79%	21%

Remark: Positive and negative signs of marginality and specialization coefficient indicate each ecological model prefer higher or lower than the global distribution in each particular variable of environment.

From Table 1, ENM2 had the highest percent of explanation so it was selected for generating HS with 0.819 of AVI and 0.042 of CVI. The ENM2 included 97% of marginality and 3% of specialization that showed the existing vetiver grasses have more highly spatial distribution than durability. Moreover, there were 4 respectively important factors: (1) mean annual temperature (°C), (2) mean monthly maximum temperature (°C), (3) mean monthly minimum temperature (°C) and (4) elevation, respectively. These 4 factors relate to the mentioned ecology of vetiver grass above, can tolerate drought or high temperatures.

In this HS analysis based on the 4 best niche factors above, this study had generated HS with two aspects (as Figure 9): 1) extremely high data and 2) extremely low data.

From Figure 9, this study found that there were 9.04 km² (0.23%) of HS areas for VG planting in the first aspect and 18.52 km² (0.46%) of HS areas for VG planting in the second aspect.

4. Conclusion

This study used GeoAI techniques for assessing HS of VG planting to support trapping soil sediment in the catchment area of Huai Pa Daeng Reservoir, Phetchabun province, Thailand. There were 6 studied environmental factors related to ecology of VG: LU/LC, bioclimate, topography and modified soil. These environmental factors were analyzed by their specific processes to be ecologically modelled in ENFA of Biomapper. In ENFA, there were 3 produced ENMs and ENM2 was selected for generating HS of VG planting because it had the highest percent of explanation and accuracy assessment with 0.819 of AVI and 0.042 of CVI. In ENM2, there were 4 respectively important factors: (1) mean annual temperature (°C), (2) mean monthly maximum temperature (°C), (3) mean monthly minimum temperature (°C) and (4) elevation, respectively. These 4 factors relate to the mentioned ecology of vetiver grass, can tolerate drought or high temperatures. Therefore, this HS analysis was based on the 4 best niche factors above and was generated by Build Virtual Raster and Deepness technique in QGIS with two aspects: 1) extremely high data and 2) extremely low data. This study found that there were 9.04 km² (0.23%) of HS areas for VG planting in the first aspect and 18.52 km² (0.46%) of HS areas for VG planting in the second aspect. Consequently, the findings of this research can be the base foundation to deeper understanding to potential areas of vetiver grass.

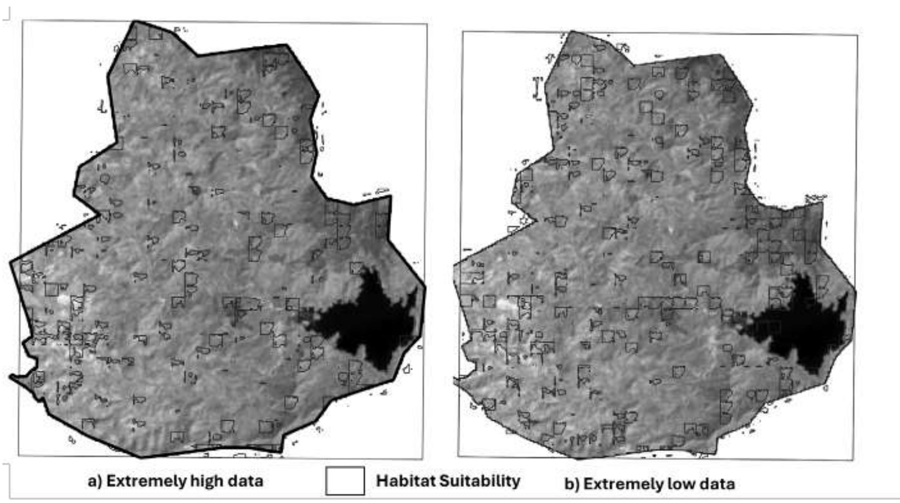

Figure 9. HS Distribution of VG-based two aspects

Acknowledgement

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