Land Suitability Assessment

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Land suitability assessment is a method of land evaluation, which identifies the major limiting factors for planting a particular crop. Land suitability assessment includes qualitative and quantitative evaluation. In the qualitative land suitability evaluations, information about climate, hydrology, topography, vegetation, and soil properties is considered and in quantitative assessment, the results are more detailed and yield is estimated. At present study we prepared land suitability assessment map for rain-fed wheat and barley crops based on FAO "land suitability assessment framework" using parametric method and machine learning algorithms in Kurdistan Province, located in west of Iran. This is a unique study that compared two machine learning-based and traditional-based approaches for mapping current and potential future land suitability classes. Moreover, potential yield of rain-fed wheat and barley crop were computed by FAO model.

Land suitability assessment Machine learning Crops

1. Introduction

Rapid population growth in developing countries means that more food will be required to meet the demands of growing populations. Rain-fed wheat and barley, as major grain crops worldwide, are planted under a wide range of environments and are a major staple source of food for humans and livestock [1][2][3][4]. The production of such staple crops influences local food security [5]. Rain-fed wheat and barley are cultivated on approximately 6 and 0.64 million ha in Iran, respectively [6]. They are well adapted to the rain conditions of western Iran, where mean precipitation is 350–500 mm. The production of rain-fed wheat and barley per unit area in Iran is low compared to developed countries worldwide [2]. One of the main causes for this low yield is that the suitability of land for their cultivation has not been determined. To overcome this problem, land suitability assessment is needed, which can help to increase crop yield by growing these crops in the locations that are most suited to their growth [7].

The first step in agricultural land use planning is land suitability assessment which is often conducted to determine which type of land use is suitable for a particular location [8]. Land suitability assessment is a method of land evaluation, which identifies the major limiting factors for planting a particular crop [9][10]. Land suitability assessment includes qualitative and quantitative evaluation. In the qualitative land suitability evaluations, information about climate, hydrology, topography, vegetation, and soil properties is considered [11] and in quantitative assessment, the results are more detailed and yield is estimated [12]. The FAO land evaluation framework [13][14] and physical land evaluation methods [15] have been widely used for land suitability assessment.

Land suitability maps provide the necessary information for agricultural planners and are vital for decreasing land degradation and for assessing sustainable land use. There is a lack of land suitability mapping and associated information in Iran because land suitability surveying and mapping in Iran have followed the traditional approach [16][17][18][19][20]. In the traditional approach, abbreviation of the soil variability through a soil map unit to a representative soil profile may cause the precision of the land suitability maps to be lacking and ignores the continuous nature of soil and landscape variation, resulting in the misclassification of sites and discrete and sharply defined boundaries [21][22]. Moreover, the traditional approach is time-consuming and costly [23].

Machine learning (ML) models are capable of learning from large datasets and integrate different types of data easily [24][25]. In digital soil mapping framework, these ML models have been applied to make links between soil observations and auxiliary variables to understand spatial and temporal variation in soil classes and other soil properties [24][26][27][28]. These ML models include artificial neural networks, partial least squares regressions, support vector machines, generalized additive models, genetic programming, regression tree models, k nearest neighbor regression, adaptive neuro-fuzzy inference system, and random forests [26][27][28]. It should be noted that random forests and support vector machines have been the most commonly used techniques in the digital soil mapping community in the last decade due to their relatively good accuracy, robustness, and ease of use. The auxiliary variables can be obtained from digital elevation models (DEM), remotely sensed data (RS), and other geo-spatial data sources [24][29][30][31][32][33][34][35].

2. Discussion

Although in recent years, ML models have been widely used to create digital soil maps [24], little attempt has been made for using ML models to digitally map land suitability classes [36][37]. For instance, Dang et al. [38] applied a hybrid neural-fuzzy model to map land suitability classes and predict rice yields in the Sapa district in northern Vietnam. Auxiliary variables included eight environmental variables (including elevation, slope, soil erosion, sediment retention, length of flow, ratio of evapotranspiration to precipitation, water yield, and wetness index), three socioeconomic variables, and land cover. Harms et al. [39] assessed land suitability for irrigated crops for 155,000 km^2 of northern Australia using digital mapping approaches and machine learning models. They concluded that the coupling of digitally derived soil and land attributes with a conventional land suitability framework facilitates the rapid evaluation of regional-scale agricultural potential in a remote area.

Although Kurdistan province is one of the main agriculturally productive regions of Iran and holds an important role in the country’s crop production rank, the mean yield of rain-fed wheat and barley in these regions is lower than 800 kg ha^{-1} [40]. Land suitability maps can classify the areas that are highly suitable for the cultivation of the two main crops and can help to increase their production. However, such information is commonly scarce in these semi-arid regions.

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