Land degradation risk mapping using novel machine learning algorithms

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INTRODUCTION

Land degradation, defined as declining capability of the biological or economic productivity of land to provide ecosystem services, is closely connected to energy security. It is caused by a combination of direct factors (land use/land cover changes, climate change) and indirect factors (population pressure, socioeconomic and social-ecological conditions, interactions between humans and nature, land management policy), and can vary in severity over time and with location. As a result of human activities such as land use change, LD can alter hydrological conditions that are crucial for water resources and sustainable river basin management. To assess LD, it is necessary to consider both natural and human-induced factors, e.g., climate change, urbanization, and rising demand for food and fuel. Due to the many interacting factors causing LD, machine learning techniques could be useful in LD impact assessment. The aim of the present study was thus to develop a new quantitative LD mapping approach using new machine learning techniques, benchmark models, and selected socio-environmental conditioning variables.

METHOD

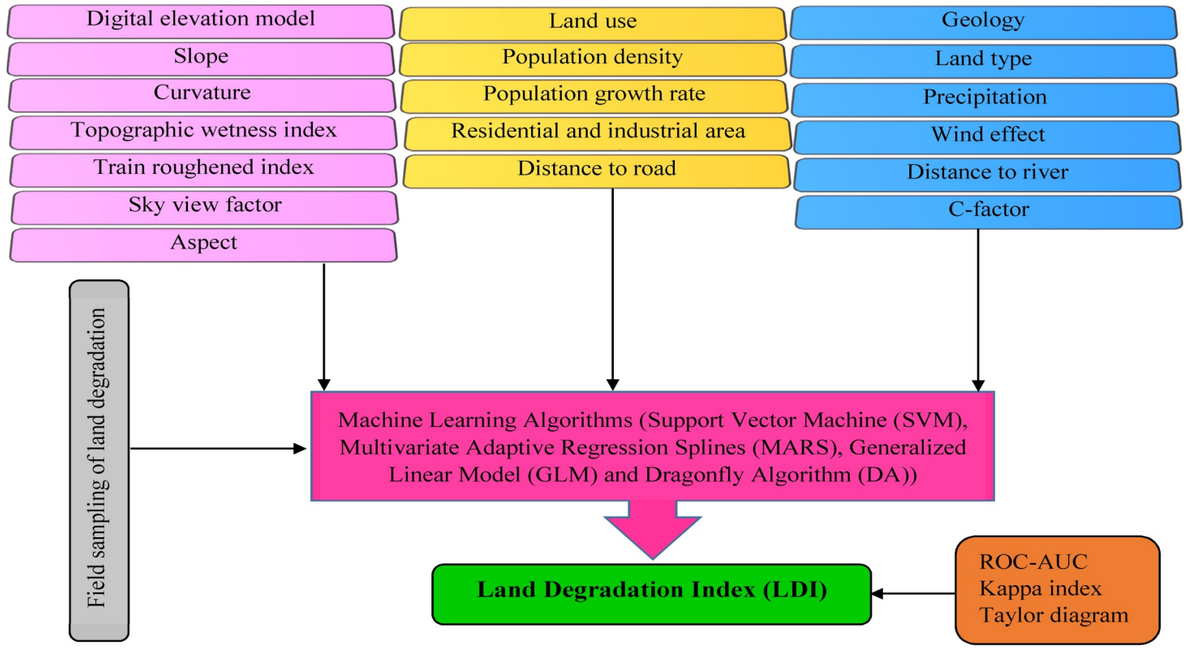

Fig. 1. Flowchart of the research process

RESULTS

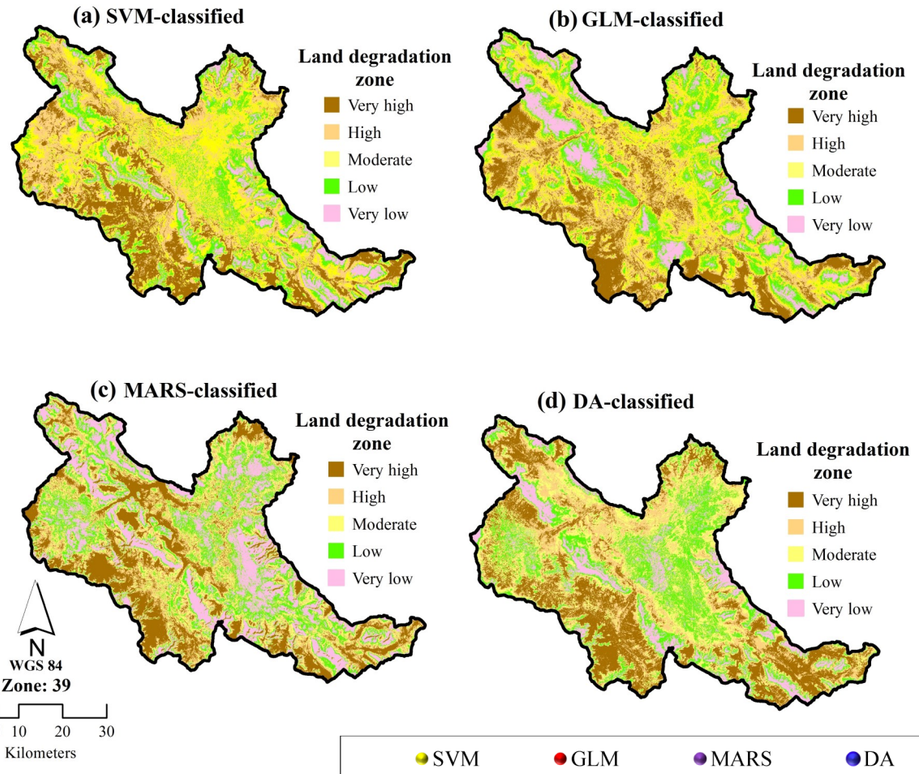

Fig. 2. Land degradation maps based on the benchmark algorithms: a) Support Vector Machine (SVM), b) Generalized Linear Model (GLM), c) Multivariate Adaptive Regression

Table 1. Performance of the model used

Models	ROC-AUC	Kappa index
SVM	0.864	0.866
GLM	0.829	0.823
MARS	0.825	0.812
DA	0.880	0.892

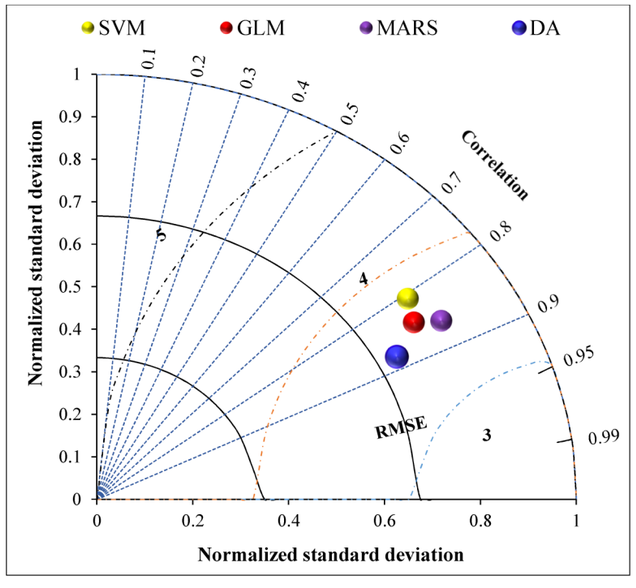

Fig. 3. Taylor diagram comparing the performance of the Support Vector Machine (SVM), Generalized Linear Model (GLM), Multivariate Adaptive Regression Splines