Using Support Vector Machine to Predict Eco-environment Burden: A Case Study of Wuhan, Hubei Province, China[1]

XIANG-MEI LI[#], JING-XUAN ZHOU[#,2], SONG-HU YUAN[#],
XIN-PING ZHOU[#], AND QIANG FU[+]

[#]School of Environmental Science and Engineering, Huazhong University of Science and Technology, Wuhan 430074, Hubei, China; [+]China Environmental Monitoring Center, Beijing 100029, China

Objective The human socio-economic development depends on the planet's natural capital. Humans have had a considerable impact on the earth, such as resources depression and environment deterioration. The objective of this study was to assess the impact of socio-economic development on the ecological environment of Wuhan, Hubei Province, China, during the general planning period 2006-2020. **Methods** Support vector machine (SVM) model was constructed to simulate the process of eco-economic system of Wuhan. Socio-economic factors of urban total ecological footprint (TEF) were selected by partial least squares (PLS) and leave-one-out cross validation (LOOCV). Historical data of socio-economic factors as inputs, and corresponding historical data of TEF as target outputs, were presented to identify and validate the SVM model. When predicted input data after 2005 were presented to trained model as generalization sets, TEFs of 2005, 2006, …, till 2020 were simulated as output in succession. **Results** Up to 2020, the district would have suffered an accumulative TEF of 28.374 million gha, which was over 1.5 times that of 2004 and nearly 3 times that of 1988. The per capita EF would be up to 3.019 gha in 2020. **Conclusions** The simulation indicated that although the increase rate of GDP would be restricted in a lower level during the general planning period, urban ecological environment burden could not respond to the socio-economic circumstances promptly. SVM provides tools for dynamic assessment of regional eco-environment. However, there still exist limitations and disadvantages in the model. We believe that the next logical step in deriving better dynamic models of ecosystem is to integrate SVM and other algorithms or technologies.

Key words: Urban eco-environment; Total ecological footprint; Support vector machine; Partial least square

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[2]Correspondence should be addressed to Jing-Xuan ZHOU. Tel: 86-27-87792240. E-mail: gougou_2004@126.com

Biographical note of the first author: Xiang-Mei LI, female, born in 1975, Ph. D. candidate, majoring in environmental planning and management. Tel: 13971383234. E-mail: xmli2001@tom.com

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