African Crop Science Journal, Vol. 30, No. 4, pp. 539 - 545
ISSN 1021-9730/2022 $4.00

DOI: https://dx.doi.org/10.4314/acsj.v30i4.11

PREDICTING SPATIAL VARIATION IN SOIL NITROGEN FOR SUSTAINABLE AGRICULTURAL MANAGEMENT IN BENIN

E.E. GONGNET[1, 2], C.E. AGBANGBA[1,3], S.A.T. AFFOSSOGBE[1] and R. GLÈLÈ KAKAÏ [1]

[1]Laboratoire de Biomathématiques et d'Estimations Forestières, Faculty of Agronomic Sciences, University of Abomey-Calavi Campus (LABEF/FSA/UAC), Building CBIG (2nd floor), Abomey-Calavi, O4 BP 1525 Cotonou, Bénin
[2]Institut Tchadien de Recherche Agronomique pour le Développement (ITRAD), BP 5400, N'Djaména, Tchad
[3]Laboratoire de Recherche en Biologie Appliquée (LaRBA), Département de Génie de l'Environnement, Université d'Abomey-Calavi, Calavi, 01 BP 2009 Cotonou, Benin
Corresponding author: ehnon.gongnet@gmail.com

(*Received 28 May 2022; accepted 20 September 2022*)

ABSTRACT

Nitrogen plays an important role in plant nutrition and sustainable agriculture. The objective of this study was to assess the distribution pattern of nitrogen in arable land of Benin. A Bayesian Maximum Entropy (BME) method was used for spatial mapping. Hard data consisted of a total of 305 sampled locations of nitrogen collected at 20 cm depth across the country. Soft data were generated from environmental variables using geographical weight regression (GWR) technique. The study revealed very low (<0.03%) N concentrations across the country. The N concentrations ranged from 0 to $0.8.10^{-6}$ %, with higher concentrations in the north and low concentrations beginning from the centre toward the south. In general, low prediction errors (around 0.005) were observed across the country (0.005 to 0.04). The maximum values around 0.035 were due to low sampling density observed at the boundary. These results are important for rational management of nitrogen in fertilisation programmes in Benin.

Key Words: Bayesian Maximum Entropy, Geographical Weight Regression

RÉSUMÉ

L'azote (N) joue un rôle important dans le sol et la vie humaine et sa connaissance est essentielle dans la gestion de la fertilité des sols. L'étude a permis d'analyser la structure spatiale de la teneur en azote au Bénin en utilisant l'approche du Bayesian Maximum Entropy (BME). BME est une méthode de cartographie spatio-temporelle de plus en plus utilisée en science du sol. Au total, 305 emplacements sont échantillonnés et les valeurs de concentration d'azote (N) collectée à une profondeur de 20 cm à travers tout le pays et considéré comme hard data. Les données secondaires (soft data) ont été générées à partir des variables bioclimatiques en utilisant la technique de régression par poids géographique (GWR). Les données de grandes précisions (hard data) et les données de faibles précisions (soft data) ont été utilisées. Cette étude a révélé des teneurs très faibles en azote (<0,03%) dans tout le pays. La carte de distribution de N a révélé des concentrations allant de 0 à $0,8.10^{-6}$ % avec des concentrations plus élevées dans la partie nord du pays et des concentrations faibles commençant du centre vers la partie sud du pays. En général, de faibles erreurs de prédiction (0.005) ont été observées dans l'ensemble du pays (0,005 à 0,04). Les valeurs maximales observées (0.035) à l'extrême nord du pays étaient dues à la faible densité d'échantillonnage observée dans cette zone. Les résultats obtenus sont importants pour une gestion rationnelle de la fertilisation azotée au Bénin.

Mots Clés: Bayesian Maximum Entropy, Geographical Weight Regression

INTRODUCTION

Nitrogen is a major nutrient affecting crop production in sub-Saharan Africa (Sadej and Przekwas, 2008). Together with phosphorus and potassium, they have the power to profoundly influence terrestrial processes by changing the physicochemical makeup of the soil and the behavior of soil microbes, and performance of crops (Hati *et al.,* 2008; Quilchano *et al*., 2008; Guan *et al*., 2017). In sub-Saharan Africa, arable soils are invariably extensively depleted of mineral N to the extent of leveraging from spatial nutrient distribution maps. In Africa, several countries possess soil property map (Hounkpatin *et al*., 2018; Silatsa *et al*., 2020), generated mostly using classical interpolation approaches such as ordinary Kriging (OK) and machine learning method (Hounkpatin *et al*., 2018); inverse distance weighting, natural neighbour, spline, radial basis functions, local polynomial, Kriging and bayesian maximum entropy (Liu *et al.,* 2011; Hamzehpour and Mola, 2020; Shan *et al.*, 2021).

Bayesian maximum entropy (BME), a spatiotemporal method of prediction (Christakos, 1990), is the most reliable approach for spatial prediction. It is a knowledge-based approach, with a strong mathematical background and inferences scheme (He and Kolovos, 2018). BME computation process gives room to researchers to include several types of data, referred to as general knowledge, into prediction (Gengler and Bogaert, 2016). Its performance compared to other methods of interpolation leads to wide applications in many fields, including environmental sciences, soil sciences, ecology, remote sensing and public health (Yang *et al.*, 2016). This approach can be used to assess the spatial variability in nitrogen as understanding soil nutrient distributions is crucial for fertiliser management and environmental protection in vulnerable ecological regions (Gao *et al*., 2019). The determination of soil mineral N patterns and variability is extremely important for agricultural management and planning (Pawlak, 2008; Staszewski, 2011). Therefore, this study aimed at assessing the pattern of nitrogen distribution in arable soils of Benin.

MATERIALS AND METHODS

Study area. This study was carried out in the Dahomey gap, located between 6-10°N and 0.40-3°E in Benin Republic, West Africa. The climatic zones are mainly; The Guinean zone (6°252 N to 7°302 N), with an average yearly rainfall of 1200 mm, and with temperature and relative humidity between 25 -29 °C and 69-97%, respectively. The Sudano-Guinean zone (7°302 N to 9°452 N), has an annual rainfall around 900 mm; temperature between 25 and 29 °C, and the relative humidity between 31 to 98%. On the other hand, the Sudanian zone (9°452 N to 12°502 N), has a mean annual rainfall below 1000 mm, the relative humidity (18 to 99%), and the temperature varying between 24 to 31 °C (Hounkpèvi *et al.*, 2020).

Data collection. Hard data for the BME were made up of a total of 306 samples collected randomly at 30 cm depth using an auger across Benin in crop lands (Fig. 1). The soil samples were first dried, grounded, sieved and then, the nitrogen content for each sample determined in the soil laboratory. Environmental data (http://www.worldclim.org/bioclim, De Santana *et al.*, 2019) and nitrogen attributes were used to generate soft data based on the Geographical weight regression techniques (Leung *et al.*, 2000; Fotheringham *et al.*, 2002; 2003; Zhang and Yang, 2019).

Data analysis. Bayesian Maximum Entropy (BME) was applied to predict N concentration at the unsampled locations, and generate a continuous map (Xu *et al.*, 2016). The computational process involved three major steps: prior, meta-prior and the posterior stage (Douaik *et al.*, 2004). Data on the general knowledge (previous experiences, beliefs, etc.) were collected during the prior stage. On the other hand, data collected on site (hard and soft data) were used to build up the site-specific knowledge base at the Meta prior stage. For the posterior stage, data from prior and meta prior were combined to build the posterior pdf, which was used to derive the conditional mean, mode and median (He and Kolovos, 2018). The analysis was carried out in Matlab, using *BMElib* packages (Christakos *et al.,* 2001). During the soft data computation process, 305 sampling points were split into calibration and validation (70 and 30%).

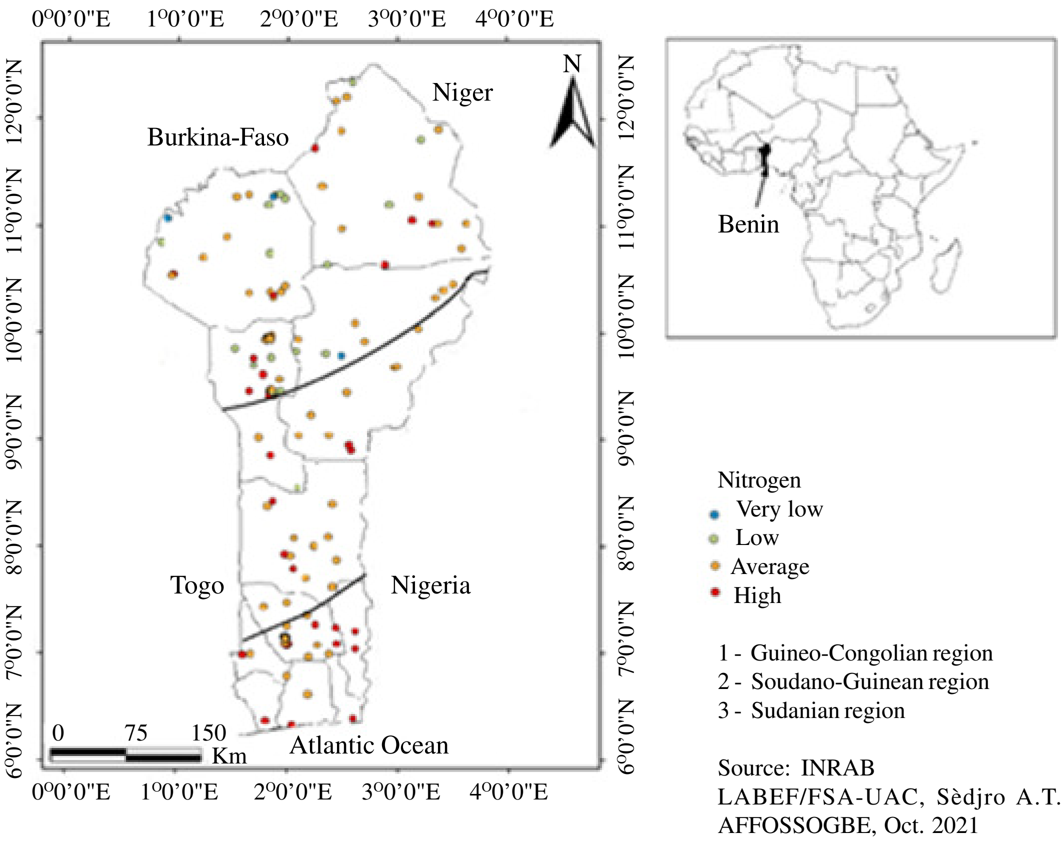

Figure 1. Location of the study area and sampled locations in Benin.

Nitrogen level was classified using Sys (1993), as high (>0.08%), moderate (0.045%-0.08%), low (0.03%-0.045%) and very low (<0.03%).

RESULTS AND DISCUSSION

Descriptive statistics. The coefficient of variation was 73%, suggesting the existence of high variability of N across areas. The coefficient of Kurtosis and skewness were low, with a value of 2.23 and 0.56, respectively; indicating that nitrogen distribution was close to a normal distribution.

Variogram modeling. The experimental variogram representing the measure of spatial variability of N between pairs of points at various distances presented in Figure 2, shows that East-West and North-South Empirical variograms were not influenced directionally, indicating an isotropy.

BME prediction. The map generated from 205 hard and 1000 soft data shows nitrogen concentrations between 0 to $0.8.10^{-6}$ % (Fig. 3). Higher concentrations of nitrogen were observed toward the north; while lower concentrations began from the center toward the south. In general, low prediction errors were observed across the country (0.005 to 0.04). The maximum values of prediction errors were due to low sampling density observed at the boundary.

The spatial map revealed very low N concentration (<0.03%) across Benin (Fig. 3). Nitrogen is often the most limiting nutrient crop to production in smallholder farms in Africa (Kiboi *et al*., 2019). Many soils of Africa are low in N due to low inherent nutrient reserves, N mining, low buffering capacity, as well as rapid decomposition of soil organic matter triggered by high tropical temperatures and changes in land use (Tully *et al.,* 2015).

Lower concentrations were observed from the centre toward the south. Low prediction error was observed across the study area, indicating the accuracy of the map. This also shows that BME produces maps with minimum variance (Christakos, 2000).

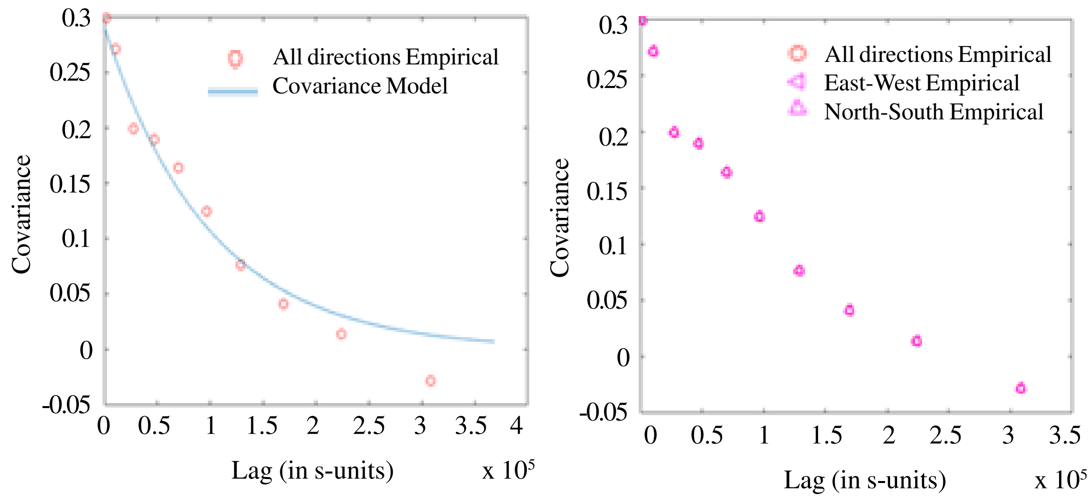

Figure 2. Experimental variogram of mineral nitrogen concentration in Benin.

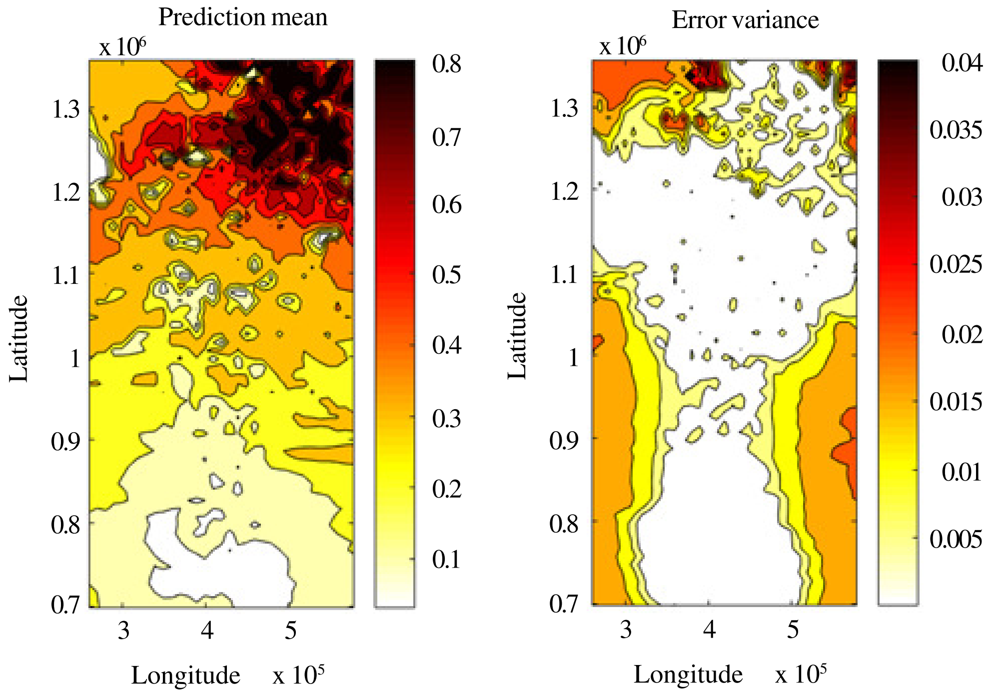

Figure 3. Maps of estimated mineral nitrogen for the arable soils of Benin Bayesian Maximum Entropy (BME) and geographical weight regression (GWR).

CONCLUSION

A N distribution map has been generated from hard and soft data, showing N concentrations range of 0 to $0.8.10^{-6}$ % in the arable soils of Benin. Higher concentrations were observed in the northern part of the country; while lower concentrations began from the centre toward the south. In general, low prediction errors were observed across the country (0.005 to 0.04); with maximum values attributed to low sampling density observed at the boundary. This study revealed very low N concentrations across the country; however, these results are important for a rational management of N fertilisation programmes in Benin.

REFERENCES

Christakos, G. 1990. A Bayesian/maximum-entropy view to the spatial estimation problem. *Mathematical Geology* 22(7): 763-777. https://doi.org/10.1007/BF00890661

Christakos, G. 2000. Modern spatiotemporal geostatistics (Vol. 6). Oxford University Press. Oxford, UK. pp. 71-123.

Christakos, G., Bogaert, P. and Serre, M.L. 2001. The BME Computer Library. In: Temporal GIS. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-56540-3_7 .

De Santana, M.R.M., Bavia, M.E., Fonseca, E.O.L., Cova, B.O., Silva, M.M.N., Carneiro, D.D.M.T. and Malone, J.B. 2019. Ecological niche models for sand fly species and predicted distribution of Lutzomyia longipalpis (Diptera: Psychodidae) and visceral leishmaniasis in Bahia state, Brazil. *Environmental Monitoring and Assessment* 191(S2):1-12. https://doi:10.1007/s10661-019-7431-2 .

Douaik, A., Van Meirvenne, M., Tóth, T. and Serre, M. 2004. Space-time mapping of soil salinity using probabilistic bayesian maximum entropy. *Stochastic Environmental Research and Risk Assessment* 18(4): 219-227. https://doi.org/10.1007/s00477-004-0177-5

Fotheringham, A.S., Brunsdon, C. and Charlton, M. 2002. Geographically weighted regression: The analysis of spatially varying relationships (John Wiley, Chichester, Sussex). pp. 103-124.

Fotheringham, A.S., Brunsdon, C. and Charlton, M. 2003. Geographically weighted regression: the analysis of spatially varying relationships. John Wiley & Sons, New York, US. pp. 2-35.

Gao, X., Xiao, Y., Deng, L., Li, Q., Wang, C., Li B., Deng, O. and Zeng, M. 2019. Spatial variability of soil total nitrogen, phosphorus and potassium in Renshou County of Sichuan Basin, China. *Journal of Integrative Agriculture* 18(2):279-289.

Gengler, S. and Bogaert, P. 2016. Bayesian data fusion applied to soil drainage classes' spatial mapping. *Mathematical Geosciences* 48(1):79-88.

Guan, F., Xia, M., Tang, X. and Fan, S. 2017. Spatial variability of soil nitrogen, phosphorus and potassium contents in Moso bamboo forests in Yong'an City, China. *CATENA* 150:161-172.

Hati, K.M., Swarup, A., Mishra, B., Manna, M.C., Waniari, R.H., Mandal, K.G. and Misra, A.K. 2008. Impact of long-term application of fertilizer, manure and lime under intensive cropping on physical properties and organic carbon content of an Alfisol. *Geoderma* 148:173-179.

Hamzehpour, N. and Mola, A.A.S. 2020. Spatial prediction of soil organic matter with soft and axillary data using Bayesian Maximum Entropy method. *Applied Soil Research* 7(4):18-34.

He, J. and Kolovos, A. 2018. Bayesian maximum entropy approach and its applications: A review. *Stochastic Environmental Research and Risk Assessment* 32(4): 859-877.

Hounkpatin, K.O., Schmidt, K., Stumpf, F., Forkuor, G., Behrens, T., Scholten, T., Amelung, W. and Welp, G. 2018. Predicting reference soil groups using legacy data: A data pruning and random Forest approach for tropical environment (Dano catchment, Burkina Faso). *Scientific Reports* 8(1):1-16.

Hounkpèvi, A., Salako, V.K., Donhouédé, J.C.F., Houévo Daï, E., Tovissodé, F., Glèlè Kakaï, R. and Assogbadjol, A.E. 2020. Natural intraspecific trait variation patterns of the wild soursop *Annona senegalensis* (Annonaceae) along a climatic gradient in Benin, West Africa. *Plant Ecology and Evolution* 153(3):455-465. https://doi.org/10.5091/plecevo.2020.1576

Kiboi M.N., Ngetich, F.K. and Mugendi, D.N. 2019. Nitrogen budgets and flows in African smallholder farming systems. *AIMS Agriculture and Food* 4(2):429-446. doi: 10.3934/agrfood.2019.2.429.

Leung, Y., Mei, C.L. and Zhang, W.X. 2000. Testing for spatial autocorrelation among the residuals of the geographically weighted regression. *Environment and Planning A* 32(5):871-890.

Liu, X., Hu, J. and Ma, J. 2011. Quantitative evaluation of spatial interpolation models based on a data-independent method. Advances in data, methods, models and their applications in geoscience. Rijeka, Croatia: Innovative Technologies. pp. 53-70.

Pawlak, J. 2008. Precision farming, its role and economic efûciency. *Advanced Journal of Agricultural Sciences* 1:3-14.

Quilchano, C., Maranon, T., Perez-Ramos, I.M., Noejovich, L., Valladares, F. and Zavala, M.A. 2008. Patterns and ecological consequences of abiotic heterogeneity in managed cork oak forests of Southern Spain. *Ecological Research* 23:127-139.

Sadej, W. and Przekwas, K. 2008. Fluctuations of nitrogen levels in soil profile under conditions of a long-term fertilization experiment. *Plant Soil Environment* 54(5):197-203.

Shan, M., Liang, S., Fu, H., Li, X., Teng, Y., Zhao, J. and Ma, Z. 2021. Spatial prediction of soil calcium carbonate content based on Bayesian maximum entropy using environmental variables. *Nutrient Cycling in Agroecosystems* 120(1):17-30.

Silatsa, F.B., Yemefack, M., Tabi, F.O., Heuvelink, G.B. and Leenaars, J.G. 2020. Assessing countrywide soil organic carbon stock using hybrid machine learning modelling and legacy soil data in Cameroon. *Geoderma* 367. Article 114260. https://doi.org/10.1016/j.geoderma.2020.114260

Staszewski, Z. 2011. Nitrogen in soil and its impact on the environment. *Scientific Notebooks of Civil Engineering Environmental Improvement* 4:50-58.

Tully, K., Sullivan, C.C., Weil, R. and Sanchez, P.A. 2015. The state of soil degradation in Sub-saharan Africa: Baselines, trajectories, and solutions. *Sustainability* 7:6523-6552. https://doi.org/10.3390/su7066523.

Xu, J., Yin W., Ai L., Xin, X. and Shi, Z. 2016. Spatiotemporal patterns of non-point source nitrogen loss in an agricultural catchment, *Water Science and Engineering* 9(2):125-133. https://doi.org/10.1016/j.wse.2016.03.003.

Yang, Y., Zhang, C. and Zhang, R. 2016. BME prediction of continuous geographical properties using auxiliary variables. *Stochastic Environmental Research and Risk Assessment* 30:9-26. https://doi.org/10.1007/s00477-014-1005-1

Zhang, C. and Yang, Y. 2019. Can the spatial prediction of soil organic matter be improved by incorporating multiple regression confidence intervals as soft data into BME method? *Catena* 178:322-334. doi:10.1016/j.catena.2019.03.027.