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Odnos okolišnih čimbenika i razine pogodnosti poljoprivrednoga zemljišta za uzgoj soje određene strojnim učenjem

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THE RELATIONSHIP OF ENVIRONMENTAL FACTORS AND THE CROPLAND SUITABILITY LEVELS FOR SOYBEAN CULTIVATION DETERMINED BY MACHINE LEARNING

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SUMMARY

The relationship between cropland suitability and the surrounding environmental factors has an important role in understanding and adjusting agricultural land management systems to natural cropland suitability. In this study, the relationship between soybean cropland suitability, determined by a novel machine learning-based approach, and three major environmental factors in continental Croatia was evaluated. These constituted of two major land cover classes (forests and urban areas), utilized soybean growth seasons per agricultural parcels during a 2017–2020 study period and soil types. The sensitivity analysis in geographic information system (GIS) using a raster overlay method, along with auxiliary spatial processing, was performed. The proximity of soybean agricultural parcels to forests showed a high correlation with suitability values, indicating a potential benefit of implementing agroforestry in land management plans. A notable amount of suitable agricultural parcels for soybean cultivation, which were previously not utilized for soybean cultivation was observed. A disregard of crop rotations was also noted, with the same soybean parcels within the study period in three and four years. This analysis showed considerable potential in understanding the effects of environmental factors on cropland suitability values, leading to more efficient land management policies and future suitability studies.

Keywords: land cover, crop rotation, soil types, land management, machine learning

INTRODUCTION

Present agricultural land management plans are based on the obsolete observations of cropland suitability, being unable to meet the growing need of crop yield production due to population increase. Additionally, the recent climate change seriously threatens to reduce the yield of major crop types, indicating an urge to reassess the current agricultural land management plan (Food and Agriculture Organization of the United Nations, 2017). Previous studies indicated that cropland suitability determination is necessary for sustainable agricultural production, leading to stable yields with minimal application of fertilizer and pesticides (Mesgaran et al., 2017). In addition to cropland suitability determination, it is necessary to understand its interaction with the surrounding environment, such as land cover types and soil properties (Stoebner and Lant, 2014). This approach enables voluntary impact on suitability levels by adjusting the agrotechnical operations or agricultural land management plans (Jiang et al., 2021). Among the crops which are essential for human and animal diet in the future, soybean was positioned as one of the primary oil and protein sources. The flexibility of soybean varieties per maturing group imposes itself as one of the principal advantages of soybean in the re-evaluation of new crop rotations as a part of climate change adaption. According to Vratarić and Sudarić (2008), soybean is being cultivated in the entire climatologically heteroge-

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neous area of the United States by using eleven different varieties. The importance of both cropland suitability studies, and the improvement of soybean cultivation is indicated by a growing number of scientific articles indexed in the Web of Science Core Collection (WoSCC) in the past two decades (Figure 1). With the emergence of machine learning classification methods in the geographic information system (GIS) environment, a significant increase in the accuracy and efficiency of predicting environmental variables was noted. Hengl et al. (2017) introduced this approach to predict various soil physical and chemical properties, noting its superiority to the conventional geostatistical interpolation methods. Although still in the very early development phase in a cropland suitability determination, these methods offer a strong alternative in prediction objectivity and computational efficiency to the conventional GIS-based multicriteria analysis. Taghizadeh-Mehrjardi et al. (2020) noted a superior prediction accuracy of machine learning for cropland suitability prediction, compared to the traditional parametric methods. Møller et al. (2021) acknowledged the applicability of machine learning for cropland suitability assessment but currently only in the limited representation of its socio-economic and ecological components. One of the main drawbacks of machine learning application in cropland suitability determination in terms of training data shortage could be resolved by adopting biophysical variables derived from satellite remote sensing missions (Radočaj et al., 2021). Purnamasari et al. (2019) applied the biophysical properties and vegetation indices from the Sentinel-2 to supplement the GIS-based multicriteria analysis to improve crop yield prediction. Individual LAI observations produced the highest coefficient of determination of 0.70 with the in-situ yield data, which was further increased in combination with biophysical variables and vegetation indices. Besides the application in crop yield assessment, biophysical variables were successfully used in harvestable crop biomass evaluation (Marshall and Thenkabail, 2015).

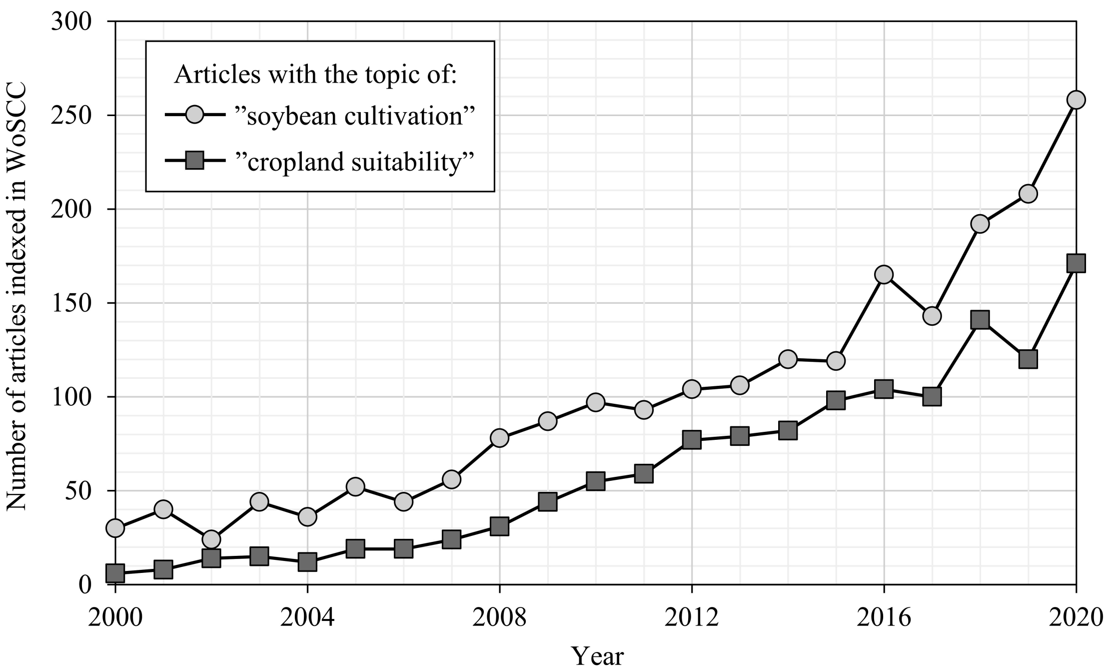

Figure 1. The number of scientific articles indexed in WoSCC with the topics of "soybean cultivation" and "cropland suitability" during 2000–2020.

Grafikon 1. Broj znanstvenih radova indeksiranih u WoSCC bazi s temom "uzgoj soje" i "pogodnost poljoprivrednog zemljišta" tijekom 2000.–2020.

The objective of this study was to assess the relationship of cropland suitability for soybean cultivation determined by machine learning approach according to administrative, land cover and soil type neighboring data. The observations of this study were aimed at the detection of patterns in the relationship of environmental components and cropland suitability for the adjustment of agricultural land management plans.

MATERIALS AND METHODS

The relationship between the cropland suitability levels for soybean cultivation and surrounding environmental factors was performed by sensitivity analysis in three components (Figure 2). These constituted the suitability analysis per soil type, high suitability agricultural parcels that were not utilized for soybean cultivation during the study period, and proximity zones to two major land cover classes other than agricultural areas.

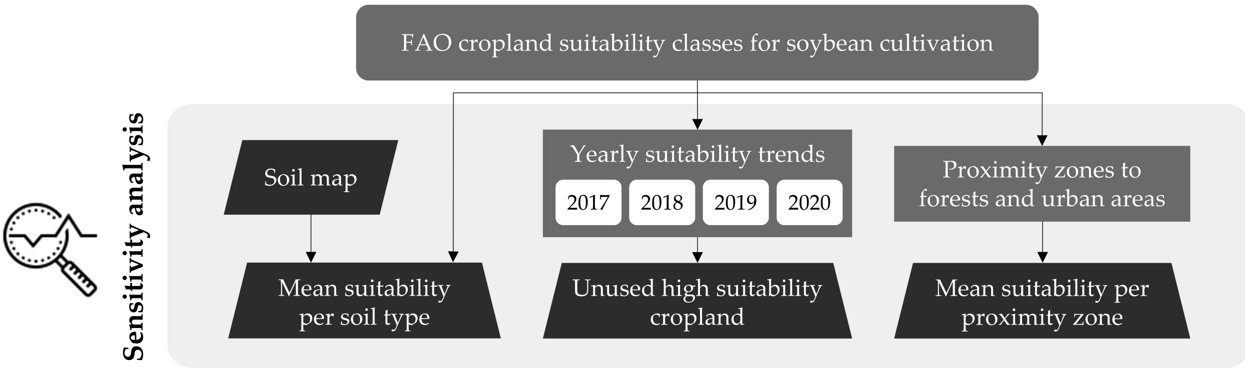

Figure 2. Workflow of the study.

Grafikon 2. Tijek rada u istraživanju.

Study area and cropland suitability data

The study area includes two 50 x 50 km subsets covering areas with the highest density of soybean parcels in Croatia during the study period between 2017 and 2020. Previous studies highlighted the heterogeneity of cropland suitability in the study area according to relevant environmental criteria (Đurđević et al., 2019; Jurišić et al., 2021). Reference soybean parcels were collected from the official database of the Agency for Payments in Agriculture, Fisheries and Rural Development (APPRRR). The cropland suitability values were obtained from the study by Radočaj et al. (2021), based on the novel machine learning prediction approach using the biophysical variables derived from the PROBA-V multispectral satellite mission. The yield data are considered crucial for validating cropland suitability results (Dedeoğlu and Dengiz, 2019) but previous studies dominantly neglected them due to lack of official and reliable yield database for individual agricultural parcels, as is the case in Croatia. To provide the most reliable representation of yield as possible using global open data remote sensing missions, leaf area index (LAI) and fraction of absorbed photosynthetically active radiation (FAPAR) were used to assess yield potential due to their high correlation of actual yield (Frampton et al., 2013; Purnamasari et al., 2019). Training and test samples representing yield potential were created by aggregating LAI and FAPAR data using K-means unsupervised classification. Abiotic factors, divided into climate, soil and topographic groups, were used as covariates for the prediction. Suitability was classified according to the specifications of the Food and Agriculture Organization of the United Nations (FAO) in five classes, ranging from highly suitable (S1) to permanently non-suitable (N2). The display of study area subsets and cropland suitability values is presented in Figure 3.

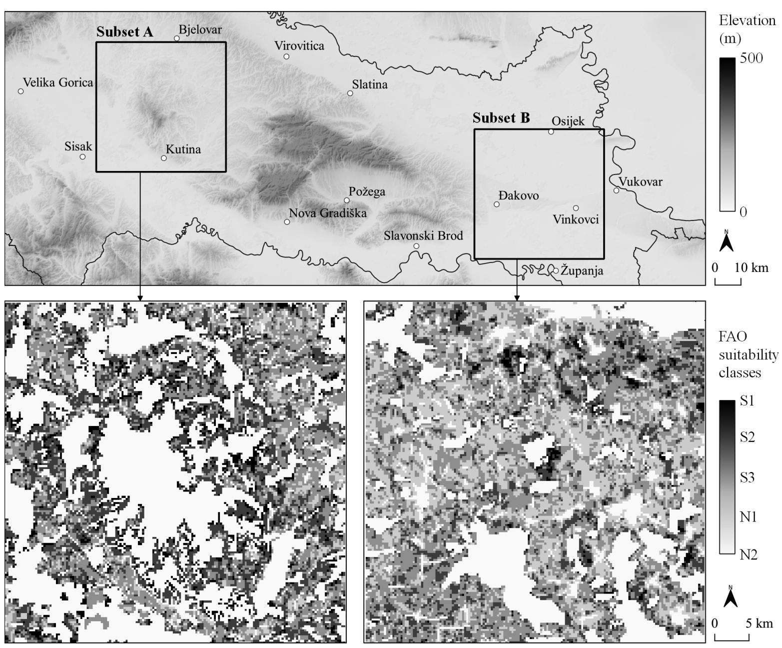

Figure 3. Study area and cropland suitability values for soybean cultivation according to Radočaj et al. (2021).

Slika 3. Područje istraživanja i vrijednosti pogodnosti poljoprivrednoga zemljišta za uzgoj soje, prema Radočaju i sur. (2021).

Input data for the sensitivity analysis consisted of the freely available global spatial datasets. These were CORINE 2018 Land cover for the proximity calculation to forests and urban areas and SoilDB soil type classification from the European Soil Data Centre. The evaluation of unused cropland with high suitability for soybean cultivation was performed according to all agricultural parcels from the APPRRR database.

Sensitivity analysis

The sensitivity analysis of determined soybean cropland suitability was performed in three components, referring to major environmental impacts on cropland management planning.

The first component focused on determining soybean cropland suitability according to its proximity to major land cover classes in the study area. Forests and urban areas, which comprise most of the study area besides agricultural areas, were used in the analysis. Previous studies noted the benefit of soybean cultivation suitability according to its proximity to forests due to the increased number of natural enemies of soybean pests (Gonzalez et al., 2017). Similarly, areas proportionally more distant from settlements and other artificial areas are at times associated with the higher cropland suitability for soybean cultivation due to present contamination caused by heavy metals and other pollutants (Radočaj et al., 2020). Proximity zones from both forests and urban areas were created by buffers from their CORINE 2018 extents. Five proximity zones with a gradual 500 m distance increment from a particular land cover class were created. These include areas below 500 m, 500–1000 m, 1000–1500 m, 1500–2000 m and 2000 m or above distance to forests and urban areas.

The second component analyzed yearly suitability trends, indirectly representing annual impacts of the abiotic environmental conditions, primarily represented by weather variations. This approach enabled the evaluation of present crop rotation systems, including soybean, in the study area. Mean aggregated cropland suitability for soybean cultivation was assessed according to the number of soybean growth seasons within four years between 2017 and 2020. Agricultural parcels with zero growing seasons were not utilized for soybean cultivation and represent possible areas for extending its production. One and two soybean growing seasons implied the application of recommended conventional crop rotation systems. Three and four growing seasons were indicators of the intensive soybean cultivation against crop rotation systems, which can seriously affect important soil biochemical processes (Kelley et al., 2003).

According to the soil types from the European Soil Database v2.0 (European Commission and the European Soil Bureau Network, 2021), Soybean cropland suitability was assessed in the third component of the sensitivity analysis. This approach enabled establishing the connection of soybean cropland suitability results from the proposed approach with the present agricultural land management systems in Croatia. Present procedures implement soil type as a primary component of cropland suitability determination, which can be used to link the transition to cropland suitability determination method proposed in this study.

RESULTS AND DISCUSSION

Mean aggregated suitability values from the proximity zones to major land cover classes supported the visual observation of the aggregated suitability classes (Table 1). The suitability in Subset A grew proportionally to the proximity of the agricultural land to forests. The proximity zone of <500 m to forests showed considerably higher suitability values than the next proximity zone of 500 – 1,000 m, with a 17.5% higher mean aggregated suitability value. This proximity zone covers the majority of the agricultural land in Subset A, reducing a possible bias due to potential outliers caused by spectral mixing with forest areas. A clear trend of mean suitability increase with the proximity to forests was observed in Subset B as well, with the 9.8% higher mean suitability of <500 m zone to the next proximity zone. The only difference to suitability trends from Subset A was a slight anomaly in the mean suitability of the most distant proximity zone to forest areas and its heterogeneity. This effect indicates another major influence on cropland suitability values, which was not quantified in the sensitivity analysis. A possible cause was the interference to the proximity zones of the water bodies, as the fourth-largest land cover class in Subset B.

The mean suitability values of the proximity zones to urban areas showed the opposite trend to the proximity to forests. A near-regular increase of the mean suitability with the distance from the urban areas was observed in both subsets. The additional regularity was the proportionally higher heterogeneity of suitability values with the proximity to urban areas in Subset A, with the reversed effect in the case of more densely populated Subset B.

The agricultural parcels that were not utilized for soybean cultivation during the 2017–2020 period showed higher mean suitability than the majority of presently utilized parcels in Subset A (Table 2). The same agricultural parcels on Subset B generally produced lower mean suitability than those utilized for soybean cultivation two or more times. However, these suitability values produced a high standard deviation, indicating multiple agricultural parcels that had the top aggregated suitability values. The total area of intensively cultivated agricultural parcels with three of four soybean growth seasons within the four years during 2017–2020 was 1.2% in Subset A and 2.7% in Subset B. Agricultural parcels with all four soybean growing seasons during this period produced the highest mean suitability values in both subsets.

The distribution of aggregated suitability values per soil type is represented in Table 3. Soil type was not a major factor in cropland suitability for soybean cultivation, producing only up to 9.3% and 16.9% higher mean aggregated suitability than the entire Subsets A and B, respectively. Gleysol soils were the major soil types considering both subsets, while Stagno-Gleyic Podzoluvisol achieved stable above average suitability values in both subsets. Haplic Phaeozem produced the highest mean aggregated suitability value, but its effect on soybean suitability levels is unclear due to relatively low subset area coverage.

Table 1. Aggregated suitability values per proximity zones to forests and urban areas.

Tablica 1. Zbirne vrijednosti pogodnosti prema zonama udaljenosti do šuma i izgrađenih područja.

Land cover class / *Klasa pokrova zemljišta*	Proximity zones / *Zone udaljenosti*	Subset A / *Podskup A*		Subset B / *Podskup B*	
		Area (%) / *Površina (%)*	Mean aggregated suitability value / *Srednja vrijednost pogodnosti*	Area (%) / *Površina (%)*	Mean aggregated suitability value / *Srednja vrijednost pogodnosti*
Forests / *Šume*	<500 m	53.0	3.573 ± 1.054	20.0	2.987 ± 0.936
	500 – 1,000 m	26.8	3.042 ± 0.955	17.8	2.721 ± 0.836
	1,000 – 1,500 m	12.7	2.942 ± 0.965	15.6	2.632 ± 0.856
	1,500 – 2,000 m	4.5	2.900 ± 1.011	12.6	2.531 ± 0.868
	>2,000 m	2.9	2.745 ± 0.798	34.0	2.652 ± 0.929
Urban areas / *Naseljena područja*	<500 m	26.2	2.001 ± 1.427	22.7	2.130 ± 1.186
	500 – 1,000 m	22.8	2.327 ± 1.450	23.8	2.559 ± 1.093
	1,000 – 1,500 m	16.4	2.491 ± 1.378	21.2	2.659 ± 0.974
	1,500 – 2,000 m	11.0	2.783 ± 1.263	14.5	2.690 ± 0.878
	2,000 m >	23.5	2.961 ± 1.038	17.7	2.542 ± 0.761

Table 2. Aggregated suitability values per utilized soybean growth seasons.

Tablica 2. Zbirne vrijednosti pogodnosti prema sezonama sjetve soje.

Soybean growing seasons (2017–2020) per agricultural parcel / *Sezone uzgoja soje (2017.–2020.) po poljoprivrednoj čestici*	Subset A / *Podskup A*		Subset B / *Podskup B*	
	Area (%) / *Površina (%)*	Mean aggregated suitability value / *Srednja vrijednost pogodnosti*	Area (%) / *Površina (%)*	Mean aggregated suitability value / *Srednja vrijednost pogodnosti*
0	88.1	3.504 ± 0.851	95.0	2.857 ± 0.786
1	10.2	3.300 ± 0.857	1.1	2.781 ± 0.705
2	0.5	3.253 ± 0.803	1.2	2.925 ± 0.717
3	1.1	3.324 ± 0.772	2.6	3.018 ± 0.769
4	0.1	3.818 ± 0.936	0.1	3.375 ± 1.053

Table 3. Aggregated suitability values per soil type.

Tablica 3. Zbirne vrijednosti pogodnosti prema tipu tla.

Subset A / *Podskup A*			Subset B / *Podskup B*		
Soil type according to FAO85 / *Tip tla prema FAO85*	Area (%) / *Površina (%)*	Mean aggregated suitability value / *Srednja vrijednost pogodnosti*	Soil type according to FAO85 / *Tip tla prema FAO85*	Area (%) / *Površina (%)*	Mean aggregated suitability value / *Srednja vrijednost pogodnosti*
Dgs	11.2	2.597 ± 1.331	Dgs	0.6	2.532 ± 0.865
Gd	44.1	2.260 ± 1.385	Ge	30.0	2.362 ± 1.103
Jc	0.3	2.429 ± 1.191	Gm	29.2	2.511 ± 1.013
Lgs	44.3	2.591 ± 1.330	Hh	4.7	2.813 ± 0.957
Lo 32.6			Jc	2.9	1.436 ± 0.918
			2.385 ± 1.003		

Soil type descriptions according to FAO85 classification: Dgs – Stagno-Gleyic Podzoluvisol, Gd – Dystric Gleysol, Ge – Eutric Gleysol, Gm – Mollic Gleysol, Hh – Haplic Phaeozem, Jc – Calcaric Fluvisol, Lgs – Stagno-Gleyic Luvisol, Lo – Orthic Luvisol.

While applied biophysical variables, LAI and FAPAR, did not allow complete representation of actual yield data for the assessment and validation of cropland suitability models, their application ensures much more objective and straightforward determination than conventional methods (Radočaj et al., 2021). Also, their global and costless availability for all users allows an important step towards sustainable agricultural land management plans and regionalization, which is largely neglected in Croatia. The variability of soybean cropland suitability values during the four-year period indicated a likely benefit of a longer study time period for the more robust cropland suitability assessment. However, unfavorable weather events in 2018 and 2020 were largely contained in suitability values determined using K-means, which retained the relative relationship of suitability within the subsets. A strong relationship between the increased cropland suitability for soybean cultivation and the proximity to forests is in agreement with previous studies on that topic (Gonzalez et al., 2017). This might encourage present agricultural land management towards the concept of agroforestry, which could especially be a solution for achieving stable yield under limited water conditions (Nasielski et al., 2015). The proximity to urban areas is also associated with elevated carbon dioxide levels, negatively affecting mineral and protein concentrations in crops, which is especially relevant for soybean (Food and Agriculture Organization of the United Nations, 2017). However, strong conclusions about the proximity effect to urban areas cannot be drawn without additional analyses due to the large presence of small and semi-abandoned settlements in both subsets. Low sensitivity of aggregated suitability values with soil type might indicate that the individual soil properties are more impactful than its general classification, most notably soil drainage and water retention abilities (Kumar et al., 2013). The presence of parcels with three or more soybean growth seasons within a four-year period indicated the local farmers' intensive exploitation of naturally highly suitable cropland for soybean cultivation. These parcels covered a very small percentage of the study area, so the connection between elevated soybean cropland suitability values and disregarding the crop rotation systems should be additionally explored in future studies. While this may result in short-term financial profits, this approach could also produce detrimental long-term consequences to the soil chemical and biological structure (Kelley et al., 2003). These implications of the crop rotation systems and cropland suitability classes should be considered in agricultural land management plans to ensure stable conservation of the environment and present natural resources.

CONCLUSIONS

The study of the relationship between environmental factors and cropland suitability for soybean cultivation determined by machine learning showed considerable potential in observing their dependence. The increasing cropland suitability values for soybean cultivation with the proximity to forests indicated a possible benefit of shifting towards the concept of agroforestry, which could ensure stable yield and sustainable soybean cultivation. While a strong pattern between suitability values and proximity to urban areas was not detected, there were indications that it might have an impact on soybean suitability as well. The most notable observation of this study were cases of disregarding the crop rotation, having up to three and four years of consecutive soybean cultivation. This urges for the implementation of a widespread agricultural subsidy control system, possibly based on the open-access satellite multispectral missions. A relatively high number of agricultural parcels that were not utilized for soybean cultivation in the study period was also observed, indicating a likely benefit of suitability studies in agricultural land management planning. The relationship between suitability values and soil types was not established in any subset. Mean suitability values of particular soil types were very similar, regularly having high heterogeneity. These observations have the potential to improve the adaptability to existing cropland suitability in land management and provide a basis for their improvement by adjusting agrotechnical operations.

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REFERENCES

1. Dedeoğlu, M., & Dengiz, O. (2019). Generating of land suitability index for wheat with hybrid system approach using AHP and GIS. *Computers and Electronics in Agriculture*, *167*, 105062. https://doi.org/10.1016/j.compag.2019.105062
2. Đurdević, B., Jug, I., Jug, D., Bogunović, I., Vukadinović, V., Stipesević, B., & Brozović, B. (2019). Spatial variability of soil organic matter content in Eastern Croatia assessed using different interpolation methods. *International Agrophysics*, *33*(1). https://doi.org/10.31545/intagr/104372
3. European Commission and the European Soil Bureau Network (2021). The European Soil Database Distribution Version 2.0. Retrieved from https://esdac.jrc.ec.europa.eu/ESDB_Archive/ESDBv2/fr_intro.htm.
4. Food and Agriculture Organization of the United Nations (2017). *The future of food and agriculture: Trends and challenges*. http://www.fao.org/3/i6583e/i6583e.pdf
5. Frampton, W. J., Dash, J., Watmough, G., & Milton, E. J. (2013). Evaluating the capabilities of Sentinel-2 for quantitative estimation of biophysical variables in vegetation. *ISPRS journal of photogrammetry and remote sensing*, *82*, 83-92. https://doi.org/10.1016/j.isprsjprs.2013.04.007
6. Gonzalez, E., Salvo, A., & Valladares, G. (2017). Arthropod communities and biological control in soybean fields: Forest cover at landscape scale is more influential than forest proximity. *Agriculture, ecosystems & environment*, *239*, 359-367. https://doi.org/10.1016/j.agee.2017.02.002.
7. Hengl, T., Mendes de Jesus, J., Heuvelink, G. B., Ruiperez Gonzalez, M., Kilibarda, M., Blagotić, A., ... & Kempen, B. (2017). SoilGrids250m: Global gridded soil information based on machine learning. *PLoS one*, *12*(2), e0169748. https://doi.org/10.1371/journal.pone.0169748
8. Jiang, H., Xu, X., Wang, L., & Zhang, T. (2021). Integrating Ecosystem Service Values and Economic Benefits for Sustainable Land Use Management in Semi-

Arid Regions in Northern China. *Sustainability*, *13*(18), 10431. https://doi.org/10.3390/su131810431

9. Jurišić, M., Radočaj, D., Plaščak, I., & Rapčan, I. (2021). A comparison of precise fertilization prescription rates to a conventional approach based on the open-source GIS software. *Poljoprivreda*, *27*(1), 52-59. https://doi.org/10.18047/poljo.27.1.7
10. Kelley, K. W., Long Jr, J. H., & Todd, T. C. (2003). Long-term crop rotations affect soybean yield, seed weight, and soil chemical properties. *Field Crops Research*, *83*(1), 41-50. https://doi.org/10.1016/S0378-4290(03)00055-8.
11. Kumar, S., Patel, N. R., Sarkar, A., & Dadhwal, V. K. (2013). Geospatial approach in assessing agro-climatic suitability of soybean in rainfed agro-ecosystem. *Journal of the Indian Society of Remote Sensing*, *41*(3), 609-618. https://doi.org/10.1007/s12524-012-0249-9.
12. Marshall, M., & Thenkabail, P. (2015). Developing in situ non-destructive estimates of crop biomass to address issues of scale in remote sensing. *Remote Sensing*, *7*(1), 808-835. https://doi.org/10.3390/rs70100808.
13. Mesgaran, M. B., Madani, K., Hashemi, H., & Azadi, P. (2017). Iran's land suitability for agriculture. *Scientific reports*, *7*(1), 1-12. https://doi.org/10.1038/s41598-017-08066-y
14. Møller, A. B., Mulder, V. L., Heuvelink, G., Jacobsen, N. M., & Greve, M. H. (2021). Can We Use Machine Learning for Agricultural Land Suitability Assessment? *Agronomy*, *11*(4), 703. https://doi.org/10.3390/agronomy11040703.
15. Nasielski, J., Furze, J. R., Tan, J., Bargaz, A., Thevathasan, N. V., & Isaac, M. E. (2015). Agroforestry promotes soybean yield stability and N 2-fixation under water stress. *Agronomy for Sustainable Development*, *35*(4), 1541-1549. https://doi.org/10.1007/s13593-015-0330-1.
16. Purnamasari, R. A., Noguchi, R., & Ahamed, T. (2019). Land suitability assessments for yield prediction of cassava using geospatial fuzzy expert systems and remote sensing. *Computers and Electronics in Agriculture*, *166*, 105018. https://doi.org/10.1016/j.compag.2019.105018.
17. Radočaj, D., Velić, N., Jurišić, M., & Merdić, E. (2020). The remediation of agricultural land contaminated by heavy metals. *Poljoprivreda*, *26*(2), 30-42. https://doi.org/10.18047/poljo.26.2.4.
18. Radočaj, D., Jurišić, M., Gašparović, M., Plaščak, I., & Antonić, O. (2021). Cropland Suitability Assessment Using Satellite-Based Biophysical Vegetation Properties and Machine Learning. *Agronomy*, *11*(8), 1620. https://doi.org/10.3390/agronomy11081620.
19. Stoebner, T. J., & Lant, C. L. (2014). Geographic determinants of rural land covers and the agricultural margin in the Central United States. *Applied Geography*, *55*, 138-154. https://doi.org/10.1016/j.apgeog.2014.09.008
20. Taghizadeh-Mehrjardi, R., Nabiollahi, K., Rasoli, L., Kerry, R., & Scholten, T. (2020). Land suitability assessment and agricultural production sustainability using machine learning models. *Agronomy*, *10*(4), 573. https://doi.org/10.3390/agronomy10040573.
21. Vratarić, M., & Sudarić, A. (2008). *Soja: Glycine max* (L.) Merr. Agricultural Institute Osijek, Osijek.

ODNOS OKOLIŠNIH ČIMBENIKA I RAZINE POGODNOSTI POLJOPRIVREDNOGA ZEMLJIŠTA ZA UZGOJ SOJE ODREĐENE STROJNIM UČENJEM

SAŽETAK

Odnos između pogodnosti poljoprivrednoga zemljišta i okolnih čimbenika okoliša ima važnu ulogu u razumijevanju i prilagodbi sustava upravljanja poljoprivrednim zemljištem prirodnoj razini pogodnosti. U ovoj studiji procijenjen je odnos između pogodnosti poljoprivrednoga zemljišta za uzgoj soje, utvrđene suvremenim pristupom temeljenom na strojnome učenju, i triju čimbenika okoliša u kontinentalnoj Hrvatskoj. Njih su činile dvije najzastupljenije klase zemljišnoga pokrova (šume i urbana područja), broj sezone uzgoja soje po poljoprivrednim česticama tijekom razdoblja istraživanja od 2017. do 2020. te vrste tla. Provedena je analiza osjetljivosti u geografskome informacijskom sustavu (GIS) metodom rasterskoga preklapanja, uz dopunske prostorne analize. Blizina poljoprivrednih čestica soje šumama pokazala je visoku korelaciju s vrijednostima pogodnosti, što ukazuje na potencijalnu korist od implementacije agrošumarstva u planove upravljanja zemljištem. Detektirana je značajna količina visoko pogodnih poljoprivrednih čestica za uzgoj soje, koje se tijekom razdoblja istraživanja nisu koristile za njezin uzgoj. Uočeno je i zanemarivanje plodoreda, na kojima je soja uzgajana uzastopno tijekom triju ili četiriju godina. Ova analiza pokazala je značajan potencijal u razumijevanju učinaka čimbenika okoliša na pogodnost poljoprivrednoga zemljišta, što dovodi do učinkovitijih politika upravljanja zemljištem i budućih studija prikladnosti.

Ključne riječi: zemljišni pokrov, plodored, vrste tla, upravljanje zemljištem, strojno učenje.

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