APPLICATION OF IMAGE RECOGNITION METHODS TO DETERMINE LAND USE CLASSES

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ABSTRACT

- Researchers have investigated a range of methodologies at various stages of data processing, including data acquisition, pre-processing, classification, and post-processing. Each of these stages is crucial to the overall accuracy of the classification system.
- The question thus arises as to *whether it is possible to purposefully classify land-use classes within the territory of Lithuania*?
- This research introduces an Integrated Satellite Data Analysis Model (ISDAM) that systematically enhances land use classification for Lithuania by incorporating machine learning with Sentinel-2 satellite data.
- ISDAM bridges multiple processing layers with advanced algorithms, enhancing the accuracy and reliability of land use maps essential for sustainable environmental governance and policy-making.

SENTINEL-2 SATELLITE DATA

- Table 1 presents data derived from the Sentinel-2 satellite. The highlighted bands are specifically selected for utilization within the ISDAM system.

Table 1. Sentinel-2 bands.

Sentinel-2 band	Resolution
Band 1 (B1) – Coastal aerosol	60 m.
Band 2 (B2) – Blue	**10 m.**
Band 3 (B3) – Green	**10 m.**
Band 4 (B4) – Red	**10 m.**
Band 5 (B5) – Vegetation Red Edge	**20 m.**
Band 6 (B6) – Vegetation Red Edge	**20 m.**
Band 7 (B7) – Vegetation Red Edge	**20 m.**
Band 8 (B8) – NIR	**10 m.**
Band 8A (B8A) – Vegetation Red Edge	**20 m.**
Band 9 (B9) – Water vapour	60 m.
Band 10 (B10) – SWIR - Cirrus	60 m.
Band 11(B11) – SWIR	**20 m.**
Band 12 (B12) – SWIR	**20 m.**

VEGETATION INDICES

- Satellite vegetation indices, i.e., NDTI and NDVI, employ spectral data to facilitate enhanced land use classification by discerning between diverse vegetative and terrestrial surface types. Equations 1, 2, and 3 illustrate selected indices to improve classification accuracy [1-2].

$$NDTI = \frac{Band11 - Band12}{Band11 + Band\ 12} \quad (1)$$

$$NDVIre = \frac{Band5 - Band4}{Band5 + Band4} \quad (2)$$

$$MNDWI = \frac{Band3 - Band11}{Band3 + Band11} \quad (3)$$

CLOUD REMOVAL AND INTERPOLATION

- The process of cloud removal is based on the utilisation of a classification layer, which is obtained in conjunction with satellite data and mask generation [3-5].
- Figure 1 displays the image before cloud removal.
- Figure 2 represents the image after cloud removal.

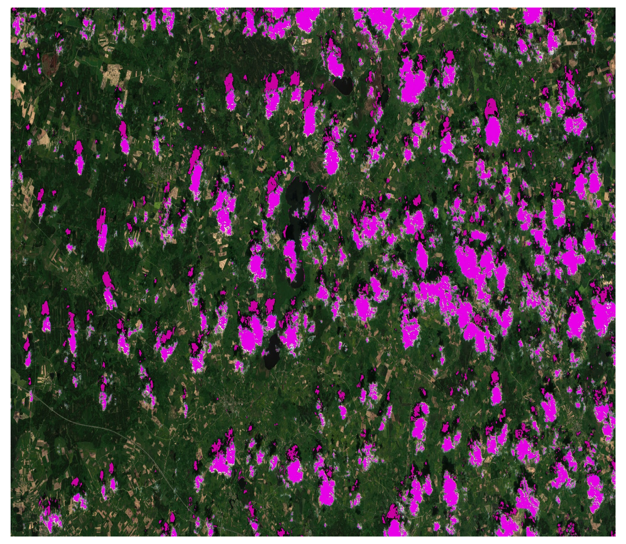

Figure 1. Satellite image before cloud removal with highlighted clouds

Figure 2. Satellite image after cloud removal

- The fundamental premise of the cloud interpolation algorithm is the transformation of available satellite imagery of a given territory into the most optimal representation thereof. Figures 3, 4 and 5 represent the cloud interpolation process.

Figure 3. Input satellite image for cloud interpolation algorithm

Figure 4. Input satellite image for cloud interpolation algorithm

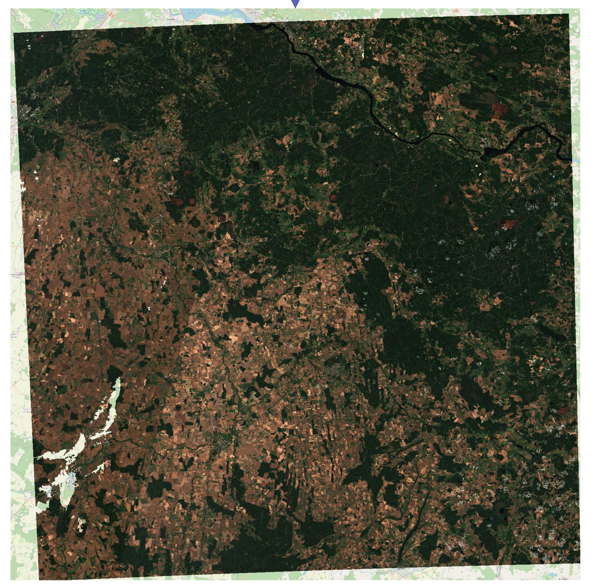

Figure 5. Output satellite image of cloud interpolation algorithm

SATELLITE IMAGES CLASSIFICATION

- To ensure the highest possible degree of accuracy, the learning dataset is based on crop data from the National Paying Agency (liet. Nacionalinė Mokėjimų Agentūra, https://nma.lrv.lt/lt/).
- Based on the rapid systematic literature review, the most accurate algorithm is Random Forest (RF) [6-8].

Figure 6. Input satellite image for classification algorithm

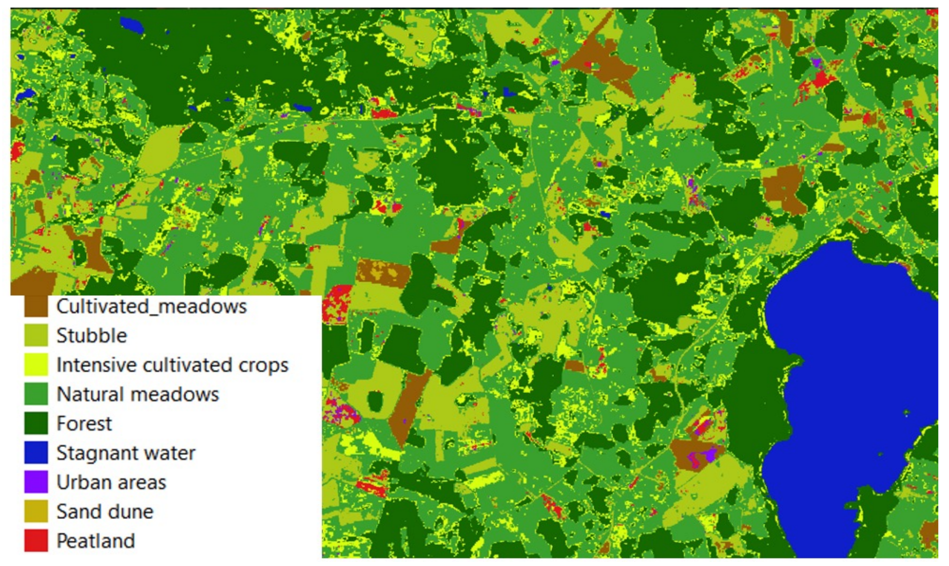

Figure 7. Example of classification algorithm result

- An illustrative example of the classification result is provided in Figures 6-7.
- The mean value of the results obtained for the testing period is presented in Table 2.

Table 2. Mean value of accuracy through the months

Accuracy Metric	Result
Cohen's Kappa	86,34 %
Overall Accuracy	88,02 %
Precision	83,93 %
Recall	87,34 %
F1	85,61 %

CONCLUSIONS

- The Random Forest algorithm with a pre-applied cloud interpolation has proven most effective for classifying cloudy regions.
- The proposed approach (ISDAM), consisting of multiple layers (i.e., raster merging, background cleaning, indices calculation, and cloud removal), prepares satellite data for accurate classification of satellite images during Lithuania's spring, summer and autumn.
- ISDAM facilitates comprehensive land-use classification across Lithuania with an accuracy of ±90%.

REFERENCES

[1] Capolupo, A., Monterisi, C., & Tarantino, E. (2020). Landsat Images Classification Algorithm (LICA) to automatically extract land cover information in Google Earth Engine environment. *Remote Sensing*, *12*(7). https://doi.org/10.3390/rs12071201.

[2] Casamitjana, M., Torres-Madroñero, M. C., Bernal-Riobo, J., & Varga, D. (2020). Soil moisture analysis by means of multispectral images according to land use and spatial resolution on andosols in the colombian andes. *Applied Sciences (Switzerland)*, *10*(16). https://doi.org/10.3390/app10165540.

[3] Shao, M., & Zou, Y. (2021). Multi-spectral cloud detection based on a multi-dimensional and multi-grained dense cascade forest. *Journal of Applied Remote Sensing*, *15*(02). https://doi.org/10.1117/1.jrs.15.028507.

[4] Zou, X., Li, K., Xing, J., Zhang, Y., Wang, S., Jin, L., & Tao, P. (2023). *DiffCR: A Fast Conditional Diffusion Framework for Cloud Removal from Optical Satellite Images*. http://arxiv.org/abs/2308.04417.

[5] Shepherd, J. D., Schindler, J., & Dymond, J. R. (2020). Automated mosaicking of sentinel-2 satellite imagery. *Remote Sensing*, *12*(22), 1–14. https://doi.org/10.3390/rs12223680.

[6] Layton, J. C., Wecker, L., Runions, A., & Samavati, F. F. (2023). Cloud Shadow Detection via Ray Casting with Probability Analysis Refinement Using Sentinel-2 Satellite Data. *Remote Sensing*, *15*(16). https://doi.org/10.3390/rs15163955.

[7] Xue, H., Xu, X., Zhu, Q., Yang, G., Long, H., Li, H., Yang, X., Zhang, J., Yang, Y., Xu, S., Yang, M., & Li, Y. (2023). Object-Oriented Crop Classification Using Time Series Sentinel Images from Google Earth Engine. *Remote Sensing*, *15*(5). https://doi.org/10.3390/rs15051353

[8] Cuypers, S., Nascetti, A., & Vergauwen, M. (2023). Land Use and Land Cover Mapping with VHR and Multi-Temporal Sentinel-2 Imagery. *Remote Sensing*, *15*(10). https://doi.org/10.3390/rs15102501