

## TRADITIONAL AND MODERN METHODS OF SATELLITE IMAGES PROCESSING FOR OPERATIONAL MAPPING OF FOREST COVER DISTURBANCES

*Andrey V. Tarasov*

Perm State University, 15, Bukireva St., Perm, 614990, Russia, Ph. D. Student, Department of Cartography and Geoinformatics, e-mail: andrew.tarasov1993.study@gmail.com

Real-time mapping of forest disturbances is important for forest management. Detection of forest stands damaged by natural or human-induced factors allows making immediate necessary management decisions. To implement such a management strategy, it is necessary to use the methods of operational mapping. With the advent of the Earth remote sensing data (RSD), which have high spatial and temporal resolution (Planet Scope and Sentinel-2), it becomes possible to implement modern operational mapping methods for forest management operations (particularly, forest disturbance detection). Since the monitoring area and the number of images sharply increases, the need for automated image processing methods also rises. This paper provides an overview of “traditional methods” for identifying forest cover disturbances (vegetation indexes, Tasseled Cap, multiband and single band change detection etc), their basis, limitations, and experience of their application in Russia and in the world. Instead, algorithm based on machine learning methods and their classification are presented. Benefits and limitations of both groups of forest disturbances detection algorithms are noted. In addition, it was found out that there is limited experience of application of machine learning algorithms for RSD processing and such kind of research is relevant.

**Key words:** real-time mapping, processing methods of remote sensing data, Planet Scope, Sentinel-2, machine learning.

### REFERENCES

1. Berlyant, A. M. (2006). *Teoriya geoizobrazheniy [Geoimages theory]*. Moscow: GEOS Publ. [in Russian].
2. Salishev, K. A. (1990). *Kartovedenie [Cartography]*. Moscow: MSU Publ. [in Russian].
3. Krylov, A., McCarty, J. L., Potapov, P., Loboda, T., Tyukavina, A., Turubanova, S. & Hansen, M. C. (2014). Remote sensing estimates of stand-replacement fires in Russia 2002–2011. *Environmental Research Letters*, 9(10), Art. No. 105007.
4. Loupian, E. A., Balashov, I. V., Bartalev, S. A., Byrtsev, M. A., Dmitriev, V. V., Senko, K. S. & Krasheninnikova Y. S. (2019). Forest fires in Russia: features of the 2019 fire season. *Sovremennye problemy distantsionnogo zondirovaniya Zemli iz kosmosa [Modern Problems of Remote Sensing of the Earth from Space]*, 16(5), 356–363 [in Russian].
5. Seidl, R., Fernandes, P. M., Fonseca, T. F., Gillet, F., Jönsson, A. M., Merganičová, K., Netherer, S., Arpacı, A., Bontemps, J.-D., Bugmann, H., González-Olabarria, J. R., Lasch, P., Meredieu, C., Moreira, F., Schelhaas, M.-J. & Mohren, F. (2011). Modelling natural disturbances in forest ecosystems: A review. *Ecological Modelling*, 222(4), 903–924.
6. Krylov, A. M., Sobolev, A. A., & Vladimirova, N. A. (2011). Identification seat of a bark beetle typograph in the Moscow region using Landsat images. *Lesnoy vestnik [Forest Bulletin]*, 4, 54–60 [in Russian].
7. Potapov, P. V., Turubanova, S. A., Tyukavina, A., Krylov, A. M., McCarty, J. L., Radeloff, V. C., & Hansen, M. C. (2015). Eastern Europe's forest cover dynamics from 1985 to 2012 quantified from the full Landsat archive. *Remote Sensing of Environment*, 159, 28–43.
8. Williams, D. L., & Stauffer, M. L. (1978) Monitoring gypsy moth defoliation by applying change detection techniques to Landsat imagery. In *Proceedings of symposium on Remote Sensing for Vegetation Damage Assessment* (pp. 221–229). Seattle, United States.
9. Sayn-Wittgenstein, L., & Wightman, J. M. (1975). Landsat application in Canadian forestry. In *Proceeding of the 10th International Symposium on Remote Sensing of Environment* (pp. 1209–1218). Michigan, United States.
10. Hardisky, M. A., Klemas, V., & Smart R. M. (1983). The influence of soil salinity, growth form and leaf moisture on the spectral radiance of *Spartina alterniflora* canopies. *Photogrammetric Engineering and Remote Sensing*, 49(1), 77–83.
11. Krylov, A. M., & Vladimirova, N. A. (2011). Space based monitoring of forest health. *Geomatika [Geomatics]*, 3, 53–58.
12. Wang, W., Qu, J. J., Hao, X., Liu, Y., & Stanturf, J. A. (2010) Post-hurricane forest damage assessment using satellite remote sensing. *Agricultural and Forest Meteorology*, 150, 122–132.
13. Cocke, A. E., Fulé, P. Z., & Crouse, J. E. (2005). Comparison of burn severity assessments using Differenced Normalized Burn Ratio and ground data. *International Journal of Wildland Fire*, 14(2), 189–198.

14. Crist, E. P., Laurin, R., & Cicone, R. C. (1986). Vegetation and soils information contained in transformed Thematic Mapper data. In *Proceedings of International Geosciences and Remote Sensing Symposium (IGARSS)* (pp. 1465–1470). Paris, France.
15. Wang, F., & Xu, Y. J. (2010). Comparison of remote sensing change detection techniques for assessing hurricane damage to forests. *Environmental Monitoring and Assessment*, 162, 311–326.
16. Nielsen, A. A., Conradsen, K., & Simpson, J. J. (1998). Multivariate alteration detection (MAD) and MAF postprocessing in multispectral, bitemporal image data: New approaches to change detection studies. *Remote Sensing of Environment*, 64(1), 1–9.
17. ScanEx Image Processor v.5.1. (2018). Software for remote sensing data processing. Manual. Moscow, 379 p.
18. Coppin, P. R., & Bauer, M. E. (1994). Processing of multi-temporal Landsat TM imagery to optimize extraction of forest cover change features. *IEEE Transactions on Geoscience and Remote Sensing*, 32, 918–927.
19. Allen, T. R., & Kupfer, J. A. (2001). Spectral response and spatial pattern of Fraser fir mortality and regeneration, Great Smoky Mountains, USA. *Plant Ecology*, 156, 59–74.
20. Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., & Townshend, J. R. G. (2013). High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science*, 342, 850–853.
21. Bartalev, S. A., Egorov, V. A., Krylov, A. M., Stycenko, F. V., & Chovratovich T. S. (2010). Research of possibility to estimate post-fired forest condition according to multispectral satellite images. *Sovremennye problemy distantsionnogo zondirovaniya Zemli iz kosmosa [Modern Problems of Remote Sensing of the Earth from Space]*, 7(3), 215–225 [in Russian]
22. Krylov, A. M., Malahova, E. G., & Vladimirova, N. A. (2012). Detection and estimation of areas of catastrophic windthrows 2009–2010 according to space imagery data. *Izvestiya Sankt-Peterburgskoi lesotehnicheskoi akademii [Bulletin of the St. Petersburg Forestry Academy]*, 200, 197–207 [in Russian].
23. Koroleva, N. V., & Ershov, D. V. (2012). Estimation of error of windthrow area detection according to space images with high spatial resolution LANDSAT-TM. *Sovremennye problemy distantsionnogo zondirovaniya Zemli iz kosmosa [Modern Problems of Remote Sensing of the Earth from Space]*, 9(1), 80–86 [in Russian].
24. Baumann, M., Ozdogan, M., Wolter, P. T., Krylov, A. M., Vladimirova, N. A., & Radeloff, V. C. (2014). Landsat remote sensing of forest windfall disturbance. *Remote Sensing of Environment*, 143, 171–179.
25. Huo, L.-Z., Boschetti, L. & Sparks, A. M. (2019). Object-based classification of forest disturbance types in the conterminous United States. *Remote Sensing*, 11(5), Art. No. 477.
26. Rosenblatt, F. (1958). The perceptron: A probabilistic model for information storage and organization in the brain. *Psychol. Rev.*, 65, 386–408.
27. Goodfellow I., Bengio Y., & Courville A. (2016). Deep learning. MIT Press.
28. Samuel, A. L. (1959). Some Studies in Machine Learning Using the Game of Checkers. *IBM JOURNAL*, 3(3), 210–229.
29. Mitchell, T. M. (1997). Machine learning. New York: McGraw–Hill.
30. Krizhevsky, A., Sutskever, I. & Hinton, E. G. (2012). ImageNet Classification with Deep Convolutional Neural Networks. In *Proceedings of the 25th International Conference on Neural Information Processing Systems* (pp. 1097–1105). New York, United States.
31. Li, Z., Shen, H., Cheng, Q., Liu, Y., You, S., & He, Z. (2019). Deep learning based cloud detection for medium and high resolution remote sensing images of different sensors. *ISPRS Journal of Photogrammetry and Remote Sensing*, 150, 197–212.
32. Syrris, V., Hasenohr, P., Delipetrev, B., Kotsev, A., Kempeneers, P., & Soille, P. (2019). Evaluation of the potential of convolutional neural networks and random forests for multi-class segmentation of Sentinel-2 imagery. *Remote Sensing*, 11(8), Art. No. 907.
33. Hethcoat, M. G., Edwards, D. P., Carreiras, J. M. B., Bryant, R. G., França, F. M., & Quegan, S. (2019). A machine learning approach to map tropical selective logging. *Remote Sensing of Environment*, 221, 569–582.
34. Aas, C., Jochemsen, A., Mantas, V., Lewyckyj, N., Jozefiak, M., & Buchhorn, M. (2018). Maximizing forest value through using Sentinel-2 in combination with hyperspectral UAVs. In *Proceedings of the 69th International Astronautical Congress* (pp. 4492–4498). Bremen, Germany.
35. Silvisense. (n. d.). Retrieved from <https://silvisense.com/>.
36. Sub weekly detection of deforestation with planet data. Retrieved from <https://medium.com/planet-stories/sub-weekly-detection-of-deforestation-with-planet-data-7699553b3926>.
37. Ronneberger, O., Fischer, P., & Brox, T. (2015) U-Net: Convolutional Networks for Biomedical Image Segmentation. In *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. MICCAI 2015. Lecture Notes in Computer*

*Science: Vol 9351*. N. Navab, J. Hornegger, W. Wells, & A. Frangi (Eds.). Springer, Cham.

38. Banko, M., & Brill, E. (2001). Scaling to Very Very Large Corpora for Natural Language Disambiguation. In *Proceedings of the 39th Annual Meeting of the Association for Computational Linguistics* (pp. 26–33). Toulouse, France.

39. Khryashchev, V., Ivanovisky, L., Pavlov, V., Rubtsov, A., & Ostrovskay, A. (2018). Comparison

of different convolutional neural network architectures for satellite image segmentation. In *Proceeding of the 23rd Conference of Fruct Association* (pp. 172–180). Jyvaskyla, Finland.

40. Russakovsky, O., Deng J., & Su, H. (2015). ImageNet large-scale visual recognition challenge, 2010–2015.

Received 11.03.2020

© A. V. Tarasov, 2020