Analysis of methods and tools of artificial intelligence for analysis and interpretation of active remote sensing data

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Abstract. Remote sensing data, like most types of spatial data, are complex, dynamic, semi-structured, which makes it difficult to create an unambiguous and universal process for their processing and use. At the same time, the development of hardware, methods and algorithms of artificial intelligence and machine learning has led to the fact that the areas of information technology are used in almost all areas of science and technology, including the processing of spatial data. The article formulates the main difficulties and tasks of processing remote sensing data, presents the most common methods and tools for their processing at present, using artificial intelligence technologies to automate processes. The possibilities of using specific algorithms and methods of artificial intelligence for all stages of processing data from active remote sensing are considered.

Keywords: artificial intelligence, active remote sensing, data processing, machine learning, point clouds

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Received 14.03.2022