MACHINE LEARNING ALGORITHMS OF SOIL DRYING

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Construction, environmental management, and agricultural activities often require the use of heavy equipment and vehicles on unpaved lands. When soil conditions are wet, equipment can cause substantial damage, leaving deep ruts. In extreme cases, implements can sink and become mired, causing considerable delays and expense to extricate the equipment. Land managers, who are often located remotely, cannot assess sites before allocating equipment, causing considerable difficulty in reliably assessing conditions of countless sites with any reliability and frequency. For example, farmers often trace serpentine paths of over one hundred miles each day to assess the overall status of various tracts of land spanning thirty, forty, or fifty miles in each direction. One means of assessing the moisture content lies in the strategic positioning of remotely-monitored in situ sensors. Unfortunately, land owners are often reluctant to place sensors across their properties due to the significant monetary cost and complexity. This work aspires to overcome these limitations by modeling the process of wetting and drying statistically by location - remotely assessing field readiness using only information that is publically accessible. Such data include Nexrad radar and state climate network sensors, as well as Twitter-based reports and/or soil moisture sensor readings of field conditions for validation. Three algorithms, classification trees, k-nearest-neighbors, and boosted perceptrons, are deployed to deliver statistical field readiness assessments of an agricultural site located in Urbana, IL. Two of the three algorithms agreed with onsite validation assessments in 91-94% of cases, with the majority of misclassifications falling within the calculated margins of error. This demonstrates the feasibility of using a machine learning framework with only public data, knowledge of system memory from previous conditions, and statistical tools to assess “readiness” without the need for real-time, on-site physical observation. Continuing efforts will integrate this work with a national climate-based classification system, allowing for forecasting algorithms tailored to specific areas, which can then be further customized based on local soil moisture sensors or reports of field readiness. Additionally, subsequent work will produce a workflow assimilating Nexrad, climate network, and Twitter data to generate a real-time Web map of estimated readiness conditions.