Abstract

About one-third of the Earth's land surface is used for agricultural production. Due to rapid population growth and increasing prosperity, the demand for food will continue to rise significantly in the future. At the same time, climate change is constantly altering the regions where food is grown. The increasing frequency and intensity of droughts and extreme weather events also lead to an increased risk of crop failures. To monitor these effects on agriculture and to ensure future food security, there is an increasing need for improved agricultural monitoring.

Remote sensing allows large-scale and consistent monitoring of the Earth's land surface. Microwave remote sensing is a particularly valuable data basis as it ensures continuous data availability and is sensitive to key vegetation characteristics. Synthetic Aperture Radar (SAR) satellites such as the Copernicus C-band mission Sentinel-1 allow retrieving this information at a high temporal and spatial resolution and to persistently assess plant health, agricultural productivity, and water management. Artificial Intelligence (AI) and in particular, deep learning (DL) allow exploiting this data efficiently. Numerous studies in the context of microwave remote sensing and DL for agricultural monitoring have already been published in recent years, underlining their potential. Despite the high number of existing publications, there is further research required in this field.

The aim of this dissertation is to improve agricultural monitoring based on microwave remote sensing and DL by better understanding the potential and limitations of the data and algorithms for different applications. In detail, it addresses the following questions: i) How do Long Short-Term Memory (LSTM) networks and Random Forest (RF) compare for microwave remote sensing-based crop classification? ii) What is the potential and what are the limitations of microwave remote sensing data and DL for grassland cut detection? iii) What is the value of meteorological data for these applications? iv) What is the value of satellite-derived and model-based Surface Soil Moisture (SSM) for spring barley yield prediction?

The results from these studies demonstrate a great potential of microwave remote sensing and deep learning for agricultural monitoring. They further suggest that i) LSTM networks outperform decision tree algorithms like RF with increasing spatiotemporal scale, ii) C-band backscatter and DL models can be used to reliably detect first cuts in grassland. Limitations occur with decreasing grass height and precipitation can cause false positives. iii) Meteorological data shows limited value to improve DL based crop classification. iv) Both satellite-derived and modeled SSM have great value for predicting spring barley yield. In areas where the landcover hinders reliable satellite-based SSM retrievals, the modeled SSM product can be advantageous. These findings contribute to a better understanding of the potential and limitations of microwave remote sensing and DL for agricultural monitoring, allowing the development of more robust and scalable monitoring applications.