WATER STRESS ASSESSMENT IN AUSTRIA BASED ON DEEP LEARNING AND CROP GROWTH MODELLING

Silke Migdall[1], Sandra Dotzler[1], Christian Miesgang[1], Florian Appel[1], Markus Muerth[1], Heike Bach[1], Giulio Weikmann[2], Claudia Paris[2], Daniele Marinelli[2], Lorenzo Bruzzone[2]

[1]VISTA GmbH, Gabelsbergerstr, 51, 80333 Munich, Germany, email: migdall@vista-geo.de
[2]Dept. of Information Engineering and Computer Science, University of Trento, Povo, Trento, Italy

ABSTRACT

Water is one of the most precious resources on this planet. With climate change, weather conditions, water availability and food security show ever higher variability. In this paper, the reaction of the different crop types in the Austrian part of the Danube basin to the extreme drought during 2018 in terms of water stress and water use efficiency are shown. For this, crop types were classified using deep learning methods and Sentinel-2 data were analyzed and combined with crop growth modelling to derive the water stress levels of the different crops.

Index Terms— Food Security, Thematic Exploitation Platform, cloud processing, crop type classification, biophysical parameter retrieval, water stress, water use efficiency, sustainable food production.

1. INTRODUCTION

Austria – and really much of Central Europe – was hit with a spring drought in 2018 that was following an already too dry 2017. Not unexpectedly, cereal harvests were disappointing, bringing in an average of 7% less than in the 5 years before [1]. Climate conditions that we are likely bound to see more often in Europe as climate change makes weather extremes more likely and temperature records in late winter and early spring keep being set.

These changes in environmental conditions are one of the most challenging issues of this century as they directly affect agriculture and with it our food security. Measures to stabilize and sustainably heighten the efficiency of agricultural production need a new level of information quality. This is where this study has its target: Set within the Horizon 2020 project ExtremeEarth, the issues of water availability and water demand for agricultural production are addressed. The goal is to support irrigation management decisions by combining big data EO analysis with water balance and crop growth modelling within European pilot catchments.

In this paper, a system architecture for the automatic water availability mapping is proposed. Experiments have been carried out in Austria for the year 2018, however, the proposed processing chain can be used to produce multi-year results for larger study areas. Austria, with its location in the center of Europe and the Upper part of the Danube Basin and its different geographic regions from the cold and humid Alps to the warm and more arid regions in the East, is a perfect example of the challenges faced by agriculture. Big data Earth Observation (EO) analysis can offer a unique insight into large scale processes and challenges. Within the study, we used Cloud Computing and European platform infrastructures to pre-process dense time series of optical multispectral Sentinel-2 (S2) data. Fig. 1 shows the block-scheme of the proposed method which takes in the S2 big data and a publicly available thematic product and produces as output the water demand and water availability maps to derive the water stress levels of the different crops. First, the S2 are pre-processed to generate the plant parameter maps and the harmonized TS of 12 monthly composites. Then, crop type and crop boundary maps are produced using a

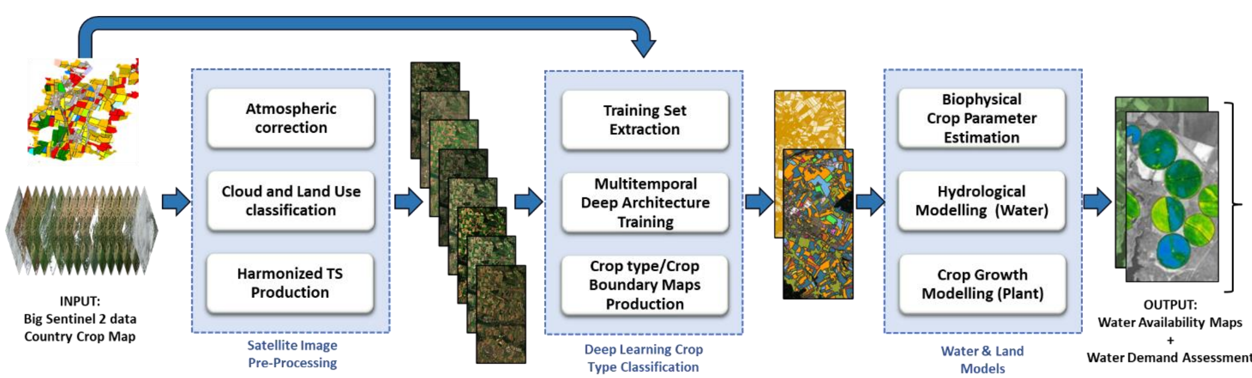

Fig 1: Proposed System Architecture for the Automatic Water Availability Mapping

multitemporal deep learning model trained using the harmonized TS of S2 images and the publicly available thematic product. Finally, the water-stress the different crops suffered is modelled and the Water-Use-Efficiency (WUE) is calculated using physically-based models for crop parameter retrieval and crop growth modelling. This step is fundamental towards understanding the needs and demands of water management in the Danube Basin in the future.

2. METHODS

2.1. Satellite Data Pre-Processing

Pre-processing of the S2 imagery used in this study has been done on the Food Security TEP, the ESA-supported Thematic Exploitation Platform for agriculture and aquaculture [2]. Its infrastructure allows, among many other data sets, also direct access to all S2 satellite imagery. This also includes older scenes, which are not available anymore through the Copernicus Rolling Archive but stored within the Copernicus Long-Term-Archive and therefore have a long access time. Scalable resources for processing, data handling and storage help to overcome the challenges of Big Data for large-area EO applications.

Within the ExtremeEarth project, a federation with the deep learning platform Hopsworks [3] is being established to allow machine and deep learning approaches for agriculture on the Food Security TEP in the future.

Dense time series of multi-spectral S2 data are the input needed for both the crop type classification and water stress and water-use-efficiency calculations. Especially for the deep learning model, highest quality atmospheric corrections, including high accuracy cloud and cloud shadow masking as well as cirrus correction are necessary. This is offered by VISTA's image processing chains (VIAs), which are implemented as processors on the Food Security TEP. Starting from S2 Level 1b data, they comprise sophisticated methods on all necessary pre-processing steps (atmospheric correction incl. cirrus correction, cloud and cloud shadow masking, land cover classification for snow, water, vegetation, open soils) as well as a crop-type independent derivation of plant physiological parameters [4], so that time series of high-quality atmospherically corrected multispectral S2 data can be delivered for the deep learning from the Food Security TEP.

Finally, the atmospherically corrected images are preprocessed to generate a Time Series (TS) of 12 monthly composites per tile. Hence, TS acquired over different tiles are made up of images acquired on different dates and have different lengths (different temporal sampling). Moreover, they are noisy due to the presence of clouds at irregular intervals. To achieve accurate and consistent crop type mapping at large-scale, we consider a pixel composite approach that collapses the optical images acquired within each month down to a single image. This is done by a statistic-based approach that computes the median value for each pixel [5], thus providing a harmonized TS from the temporal and radiometric view point across tiles.

2.2. Deep Learning Crop Type Classification

To successfully train a deep learning model, very large training datasets are required. From the operational viewpoint this goal is not trivial, since the collection of field data or manually annotated samples is demanding at large scale. To solve this problem, we consider the publicly available 2018 Austrian crop type map, which is based on farmer's declarations collected by surveys within the subsidy application process in the context of the Common Agricultural Policy. An automatic Machine Learning (ML)-based procedure has been defined to identify pure spectral pixels having the highest probability to be correctly associated to their labels in an automatic and unsupervised way [6]. The obtained dataset is made up of more than 1 million of labeled units and presents a detailed classification scheme of 16 crop categories. A stratified random sampling strategy is applied to select labeled units per crop type proportional to the number of fields present in the study area. Please note that while the 2018 Austrian crop type map can be used to perform experiments at country scale for one specific year, the deep learning model trained with the extracted training set can be used to classify a study area larger than the Austrian country and for multiple years.

To accurately model the phenological characteristics of the different crop types, we train a recurrent deep learning architecture from scratch using the large training dataset. The model used is a Long-Short Term Memory (LSTM) made up of three layers, a fully connected layer and a softmax layer, having 200, 125 and 100 hidden units for the first, second and third layer, respectively. The hyper-parameters of the LSTM are selected according to the standard grid-search approach by testing all combinations of the number of network layers {2,3,4} and the number of cells per layer {100, 125, 200, 225, 300}. The cross-entropy loss is evaluated at each training step by comparing the predicted and the real class probabilities. The fine-tuning of the model weights is carried out by back propagating the loss through the network layers as gradient. The RMSProp optimizer is considered [7]. The initial learning rate and the weight decay are set equal to 10^{-3} to 0.4, respectively. The deep learning architecture is implemented in the Hops data platform, the Big Data and Artificial Intelligent (AI) platform for the development of scalable Deep Learning models [8].

2.3. Water Demand Modelling with PROMET

Based on the crop type classification a representative sample of pixels (355000) is distributed over the study area of 83.879 km^2. Samples are located with distance from field boundaries or roads to guarantee pure crop information. For each crop, the development of the leaf area, represented by the LAI, is retrieved by inversion of the pre-processed S2 time series (bottom of atmosphere reflectance values), for 15 tiles covering 100 x 100 km each, using the radiative transfer model SLC [9]. The LAI is then assimilated into the crop growth model PROMET [10]. The physically-based agro-hydrological model allows to simulate e.g. photosynthesis, evapotranspiration, soil moisture, biomass increase, phenological development, and crop water stress in an hourly temporal resolution. Yield in t/ha and water use efficiency (WUE) in kg yield/m³ evapotranspiration are then derived for a crop season. The model is forced by meteorological parameters (precipitation, air temperature, humidity, radiation and wind speed). Those datasets are extracted from ERA5 reanalysis data (e.g. available from C3S [11]) and made available for the model.

Crop water stress is indicated as soon as photosynthesis is limited by water shortage and is displayed as a normalized index ranging between 0 (max. stress) and 1 (no stress). WUE links yield with water loss through the plant (total evapotranspiration) during the vegetation period [12].

Regional differences can be seen both in soil moisture development and crop water stress over time. Severe crop water stress is visible in Upper Austria in May and June as precipitation was not able to reach deeper soil layers resulting in constantly decreasing soil moisture (Fig. 2).

3. RESULTS

3.1. Crop Classification Accuracy

To assess the quality of the crop type maps, we validate the results obtained considering: (1) the Austrian crop type map, and (2) the 2018 Land Use and Cover Area frame Statistical survey (LUCAS) database [13]. To check the results obtained on the Austrian crop type map, we considered the samples extracted from tile T33UVP, not included in the training set. This condition allows us to have statistically independent validation. For the LUCAS validation, only the crop types present in the database were considered.

The results are evaluated considering the Fscore (F1%) and the Overall Accuracy (OA%) (Tab. 1). While on the LUCAS database the proposed LSTM achieves an average F1% of 77.57% with an OA% of 88.99%. Similarly, on the Austrian crop type map the proposed LSTM obtains an average F1% of 86.03% with an OA% of 91.26%.

3.2. Water demand simulation results

The spatially and temporally distributed PROMET results allow an explicit analysis of different growing conditions for the crops in the extreme year of 2018. While the northern part of Upper Austria suffers from drought in the spring months March - May, Styria shows a strong precipitation surplus. In the summer months June - August, the regions received almost normal precipitation again.

The WUE results for Winter Wheat are given in Fig. 3. The limited water availability in Upper Austria in spring also results in a lower WUE. In contrast, in Styria, the slightly increased amount of precipitation in spring results in a good efficiency to build up biomass. Higher water availability during the early season leads to increased biomass production during the entire season. Findings for Vorarlberg and Tyrol have limited relevance due to their limited acreage.

Based on the detailed crop type mapping not only regional differences can be analyzed, but also crop specific reactions on water availability. In Tab. 2 the number of days with crop water stress is shown for various crops in Austria.

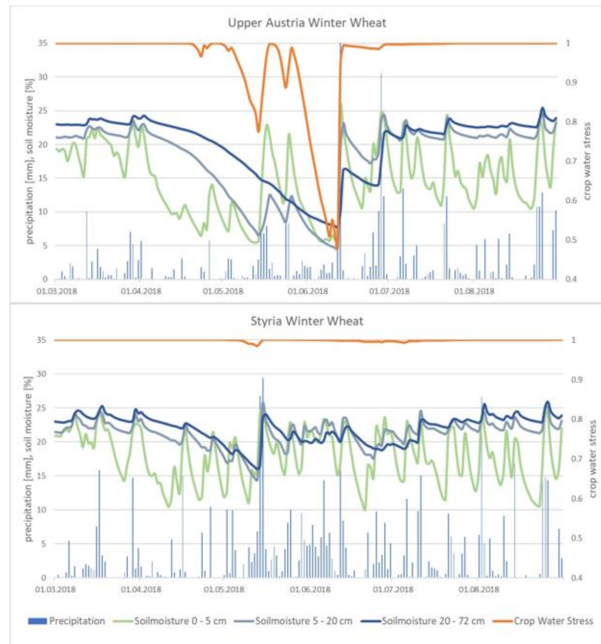

Fig 2: Modelled soil moisture in three soil depths and crop water stress from March to August 2018 for example regions Upper Austria (top) and Styria (bottom).

Table 1: Crop type classification results obtained on tile T33UVP and the LUCAS database. The overall accuracy (OA%) and the Fscore (F1%) are reported.

	T33UVP		LUCAS	
	#Samples	**F1%**	**#Samples**	**F1%**
Legumes	2031	88.33	-	-
Grassland	15080	95.66	2756	95.07
Maize	15001	99.34	467	94.64
Potato	4015	87.98	44	88.89
Sunflower	240	78.65	31	88.52
Soy	10712	96.22	104	93.09
Barley	15001	90.29	219	78.22
Winter Caraway	577	59.45	-	-
Rye	9701	79.75	70	52.83
Rapeseed	5086	96.98	59	90.60
Beet	4212	97.20	40	93.98
Spring Cereals	11987	93.13	-	-
Winter Wheat	15001	95.85	372	81.54
Triticale	14363	75.77	61	31.15
Perm. Plantations	411	55.98	22	18.26
OA%		91.26		88.99

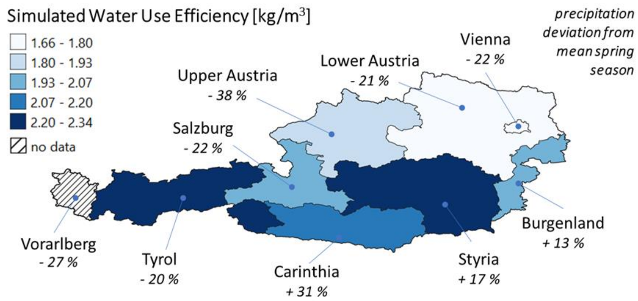

Fig 3: Regional overview of simulated WUE [kg/m³] and deviation from mean spring precipitation (Mar-May) 2001-2020 [%] for the main crop winter wheat.

Table 2: Number of days with crop water stress in 2018 and acreage for different crops in Austria, assuming that crops are not irrigated.

Crop	Days with crop water stress	total area in Austria [1000 ha]	% of farmland in Austria
Corn	46	293	22
Winterwheat	17	269	20
Spring Cereals	24	115	9
Soy	35	68	5
Winterbarley	24	93	7
Triticale	17	57	4
Sugarbeet	30	31	2
Sunflower	43	22	2
Legumes	12	21	2
Potato	6	24	2

Giving also the total area of the different crops in Austria, it can be reported that for most of the arable land water shortage and negative effects of plant growth had occurred. Especially for the main crop corn, a sum (mean over all monitored parcels) of 46 days was calculated. But also other relevant crops suffered from water stress if not irrigated. Assuming a daily water requirement per crop and area, the total amount of needed water can be derived in a next step for all classified crop types. With PROMET, it is also possible to simulate the yield and the effect of dry years and water stress on the harvest volume.

4. CONCLUSIONS & OUTLOOK

The presented work gives a small example of the capabilities of solution driven methods of water demand calculations making use of S2 and crop growth modelling. Using EO (Big) Data and DL to retrieve detailed crop type information and local phenological and biomass development, then feeding the information into the physical model, enabled us to qualify and quantify the water stress of a variety of crops on farm and regional level in Austria for the extreme year 2018. During Extreme Earth, the presented methods will be extended to more seasons and regions. In a next step, the study area will be extended to comprise the Danube catchment up to Komarno (SK) and the year 2019, using the already trained model to derive crop type in the adjacent area and years, where no training data are available. Using both short term and mid-season weather forecasts, also predictive analyses of water stress can be calculated. In combination with water availability calculations (integrating the hydrological cycle of the catchments) the water demand calculations will lead to being able to give irrigation policy advice, suitable on local to regional level. EO derived crop information has proven its potential to support and improve crop and water related challenges in future farming and food security management.

5. ACKNOWLEDGEMENTS

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