ExtremeEarth

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Deliverable

D2.4

Evaluation report on

Food Security use case output products

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Executive Summary

ExtremeEarth aims to advance the state of the art by developing ad-hoc distributed deep learning architectures tailored to the peculiar properties of Sentinel data. The information provided by the Copernicus Satellite Data will be used for deriving information by focusing the attention on the following use cases:

- **Food Security Use Case**: aims at the assessment of water availability for irrigation by combining a long time series of Sentinel 2 multispectral images with crop growth modelling to provide water availability. The deep learning architectures trained on Sentinel 2 data will generate crop type and crop boundaries maps;
- **Polar Use Case**: exploits a long time series of Sentinel 1 SAR images to develop processing architectures and algorithms to cope with the extreme analytics and big data challenges associated with sea ice monitoring.

In this document, we focus the attention on the Food Security Use Case and in particular on the WP2 whose main aim was the definition of a deep learning architecture for multi-year crop type classification. The document presents the final evaluation report of the activities.

The structure of the document is the following. Section 1 recalls the objectives and user requirements of the use case. In Section 2 we describe the main activities carried out during the project which are: i) the generation of the large training database; ii) the definition of the deep architecture. Section 3 describes the training of the architecture and its implementation of the cloud computing platforms. Finally, section 4 presents the validation results and analyzes the outcome of the project activities in terms of the objectives and user requirements.

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1. User Requirements and Objectives

The main objective of WP2 is the development of deep learning techniques for the computation of extreme analytics over big Copernicus data. In particular, the aim of the food security use case is to assess water availability and irrigation by combining crop type maps generated with big EO data and crop growth models. In this context, WP2 is aimed at providing a scalable deep learning architecture for the generation of crop type maps.

1.1. User Requirements

According to deliverable D4.1 [1], the user request can be summarized in these requirements: (1) the water availability, (2) the crop condition, and (3) irrigation recommendation. This is to be provided at a high spatial resolution (i.e., the Sentinel 2 based crop products are required at 10m resolution) and at high temporal resolution (i.e., weekly based). Such products are generated by the physically based agro-hydrological PROMET model which requires as input a crop-type map. According to the user and PROMET requirements, the implemented deep learning architecture deployed for the Food Security Use case must have these characteristics:

- The production of High Resolution (HR) yearly crop type and crop boundary maps (i.e., 10 m spatial resolution).
- The production of crop type maps having a detailed classification scheme tailored to the need of PROMET (i.e., the crop type information used in the simulations of the agro-hydrological model).
- Differentiation of crop types along the common farming practice in Europe, e.g. differentiation of winter- and summer wheat
- The production of multi-year crop type maps to study the impact of climate change / the season by season changes from farming practice on the considered crop parameters (e.g., photosynthesis, evapotranspiration, soil moisture, biomass increase, phenological development, and crop water stress).

1.2. Objectives

According to these requirements, the objectives of the Food Security part for WP2 are:

- the generation of a large training database with classes tailored to the PROMET requirements.
- The design and implementation of a Deep Learning architecture capable of exploiting Sentinel-2 dense time series to produce multi-year crop type maps.

In the context of the ExtremeEarth project, a key aspect is the impact that the products and architecture developed can have on the research community and potential final user. Here we recall the most relevant MIMP for the Food Security Use Case:

- **MIMP 1.3**: Full automation of workflows using processing chains and data sets from both TEPs for the Food Security use case.
- **MIMP 2.5**: The deep learning architectures running on Hopsworks are trained with millions of training data samples in a few hours compared with days of training with current approaches.
- **MIMP 3.1**: The ExtremeEarth software stack (EO processing and classification) deployed on the Food Security TEP and running on DIAS.

These focus on the availability and accessibility of the products and processing chain to the user and exploitation of cloud computing platforms for faster architecture training and processing.

2. Project Activities

2.1. Large Database Generation

To perform a reliable training, millions of annotated samples are required. While such large databases are typically available in different fields such as computer vision, this is not the case of remote sensing where the collection of in-situ data at such a scale is not feasible. Accordingly, in the context of the Food Security Use Case UNITN generated a large training database made up of crop type samples leveraging on existing Austrian crop type maps available at the country level, selected due to their rich classification scheme. Here we provide a brief description of the generation process although more details can be found in [2] and deliverable D2.1 [3].

The activity has been composed by two main steps:

1. map legend analysis and conversion.
2. database generation.

2.1.1. Map legend analysis and conversion

The first step was aimed at the selection of only classes that can be discriminated using the proposed multitemporal multispectral information provided by the time series of Sentinel 2 images. Indeed, since the used Austrian crop map (composed by 212 classes) is based on the farmer declarations, the legend may include classes that are undistinguishable using the available spectral and temporal information, leading to poor performances. Accordingly, the map has been analyzed searching for problematic cases such as:

- Double cultivations per crop (e. g. Summer fruit/Field Vegetables);
- Unclear Statement (e. g. Other surfaces protected cultivation);
- Strong semantic aggregation of natural classes (e. g., other agricultural crop land).

To address these cases, VISTA and UNITN revised the legend to:

- discard the ambiguous classes.
- detect the cultivations of interest.
- define a proper conversion between the map legend and the desired legend.
- dissolve linguistic overlaps, since original information was labeled in German

Table 1 contains the resulting legend with the 15 main cultivations required by VISTA.

	ID	Class Name	Austrian Map Legend
	1	Legumes	Beans; Lentils;
	2	Grassland	Alpine Meadow; Temporary Grassland; Permanent Pasture; Hay Land
	3	Maize	Maize Corn-Cob-Mix; Silage Maize; Green Maize; Grain Maize; Maize; Sugar Maize; Maize Cultivation
	4	Potato	Early Potato; Fodder Potato; Seed Potato; Ware industrial Potato; Ware Potato; Farina industrial Potato;
	5	Sunflower	Sunflower;
	6	Soy	Soybean;
	7	Winter barley	Winter Barley;
	8	Winter Caraway	Winter Caraway;
	9	Rye	Green Prunning Rye; Winter Rye;
	10	Rapeseed	Summer Rape; Winter Rape;
	11	Beet	Winter Sugar Beet; Sugar Beet; Fodderbeet;
	12	Spring Cereals	Spring Oat, Spring Barley, Spring Wheat
	13	Winter wheat	Winter Triticale; Winter Wheat;
	14	Winter Triticale	Winter Triticale

	15	Permanent plantations	Fruit Trees; Berries; Vineyards; Hop

Table 1 . The map legend conversion of the Austrian Crop Type Map in the 15 main cultivations required by VISTA.

2.1.2. **Database generation**

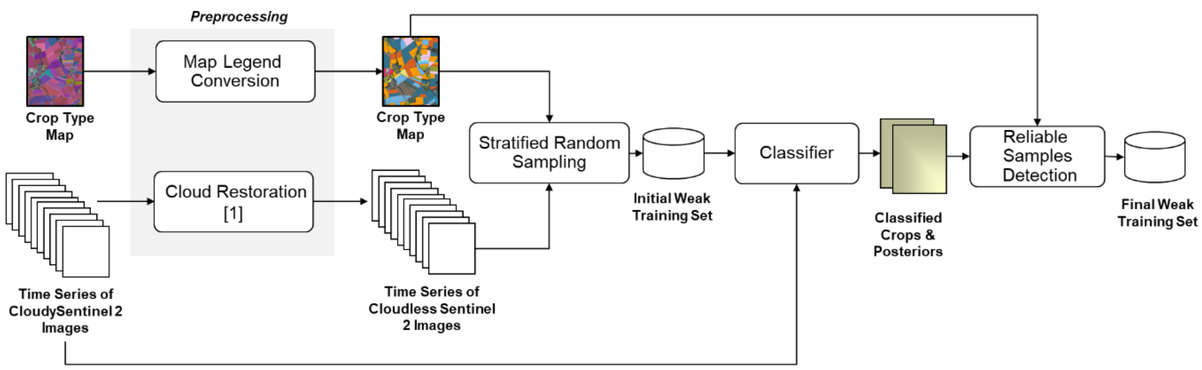

Figure 1 System architecture used to extract the weak training set from the Austrian crop type map.

The aim of this step was to exploit the publicly available crop type maps to generate the large training database. The used maps are the Integrated Administration and Control System (IACS) [1] maps published for selected countries of the EU)., i.e., the INVEKOS maps for Austria. While these maps are typically accurate, their use requires some careful considerations to select only reliable samples. We identified three main issues:

- samples may be mislabeled or be related to outdated information.
- Since the maps are generated yearly, the indicated crop type may not correspond to the real cultivation for the whole year due to the crop rotation practice.
- Samples associated with the wrong labels due to the polygon spatial aggregation.

According to this analysis, UNITN defined and developed an automatic system architecture based on recurrent deep neural networks which aims at selecting only the labelled samples having a high probability of being correctly labeled (i.e., reliable samples). Figure 1 shows the proposed system architecture. First, a time-series optical harmonization spatially and temporally harmonizes the irregular time-series obtaining a 12 monthly composites, covering a whole season, e.g. September to August. This simplifies the following step as it guarantees

[1] https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy/financing-cap/financial-assurance/managing-payments_en

time-series of equal length and strongly reduces the impact of cloud coverage. Then, the crop type map is used to generate an initial weak training set by means of a stratified random sampling. This is to select for each class a number of samples that is proportional to the presence of such class in the crop map. This is a critical step to obtain a balanced representation. The weak set is then used to train Long Short-Term Memory (LSTM) recurrent neural network which generates the crop label and its uncertainty (i.e., posterior probability) for each pixel. Finally, these products are used together with the original crop type map to generate the final reliable training set. Two criteria are considered for the selection of the final set:

- Intersection of the original thematic product with the generated map to select only samples belonging to areas of agreement.
- Selection of the samples having the highest confidence classification (i.e., high posterior).

The result of these steps is the million labeled sample TimeSen2Crop training database which is publicly available online [4].

2.2. Architecture Definition

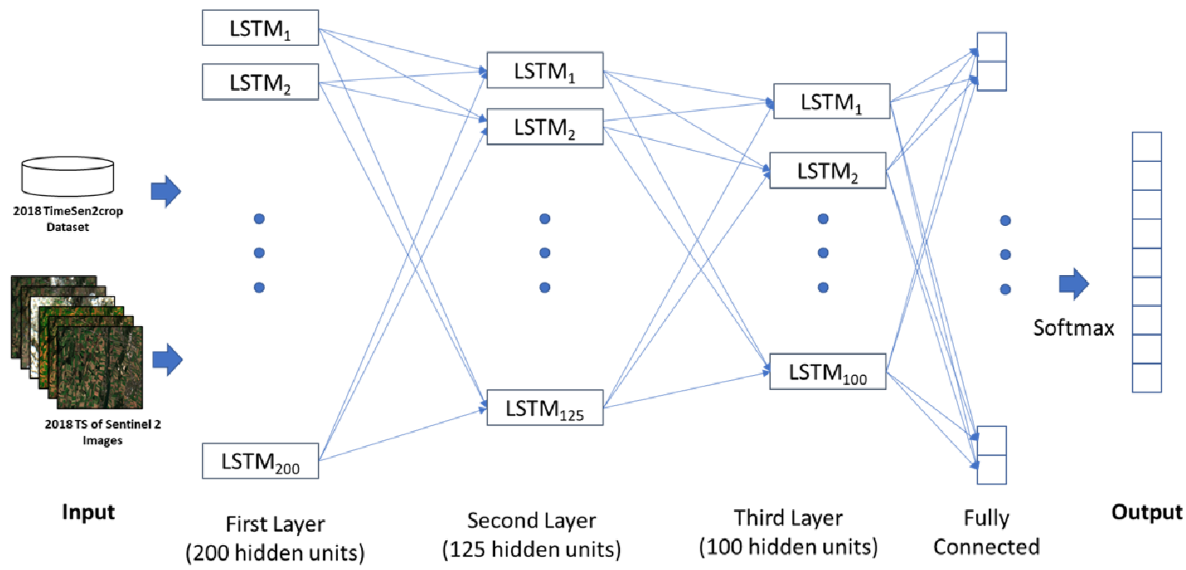

Figure 2 Implementation of the multitemporal deep learning model defined for the Food Security Use Case.

2.2.1. Single year crop type mapping

Crop type classification using remote sensing data is a challenging task especially with multispectral data where spectral information is not sufficient at the single date to discriminate the different crops. Indeed, one of the key discriminants is the phenological behavior of the different crops during the year, which is peculiar to each specific crop type. Such information can be captured by the time series of Sentinel 2 images to obtain accurate classification results. Accordingly, UNITN designed and developed a Deep Learning architecture which is based on the LSTM architecture. This model has been selected due to its internal feedback connections that are designed to model sequential data exploiting previous observations to analyze the current one [6]. Figure 2 shows the implementation of the deep learning architecture that takes as input:

- the 1 million labeled sample TimeSen2Crop database for the network training.
- the harmonized time series of Sentinel 2 composites.

It generates as output the crop type map that provides the crop label at the pixel level. Note that here a multilayer architecture is used in order to better model the time-series information. In greater detail, the model used is a Long-Short Term Memory (LSTM) made up of three layers having 200, 125 and 100 hidden units for the first, second and third layer, respectively, a fully connected layer and a softmax layer which provides the classification posteriors, which are converted into the classification result at pixel level. Additional details can be found in the Deliverable 2.6 [5].

2.2.2. Multi year crop type mapping

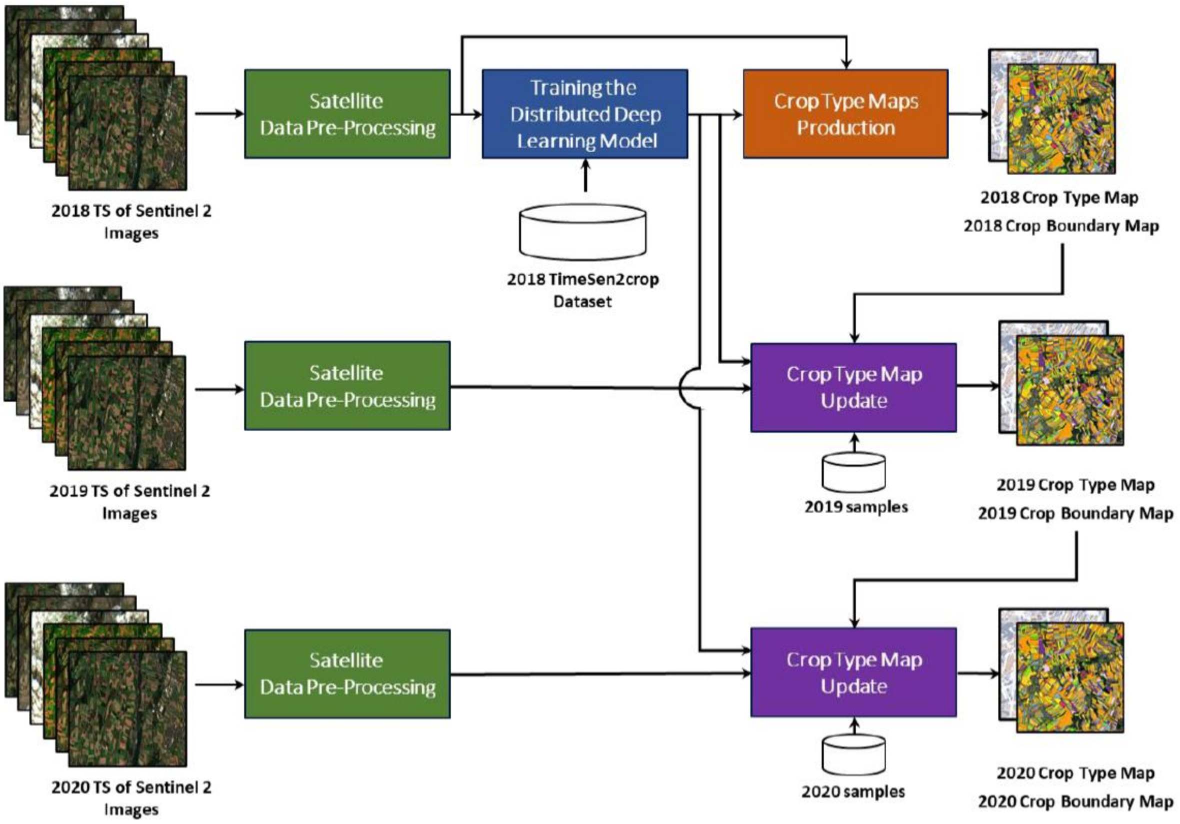

Figure 3 Workflow of the proposed system architecture implemented to generate annual crop type and crop boundaries maps at high spatial resolution.

To be effective in a real scenario, it is important that the network can be used to generate crop types maps also for different years with respect to the one on which it has been trained. Indeed, it is not reasonable to assume that a new model can be trained from scratch every year. However, due to changes in the image acquisition conditions, the crop phenology and the crop rotation practice, different years will show a significant variation of the class statistical distributions. Crop seasons in farming practice are not limited to the September to August period and can also be set outside this logic. This can lead to a strong decrease of performance if the model is applied to a different year without any modification [7]. To mitigate this issue, we exploit the fine-tuning strategy which is widely used to adapt a pre-trained network to a new target case using a small dataset [8]. This is done by freezing most of the layers of the network and training only the latest thus strongly reducing the number of parameters to be trained. Figure 3 shows the proposed multi-year crop type mapping architecture. Additional details can be found in the Deliverable 2.6 [5].

3. Training and Implementation of the Deep Architecture

The proposed architecture has been developed and trained on the distributed computing Hopsworks platform[2] while the complete processing chain is implemented on the Food Security TEP[3].

3.1. Architecture Training

The proposed architecture has been trained on the Hopswork platform. Hopsworks is an open-source platform for the development of machine learning and deep learning models. The training has been performed according to a distributed strategy to distribute the workload across multiple workers each having one GPU. The network has been trained considering both one GPU (i.e., one worker) and two GPUs. The training considering two GPUs is considerably faster than the single-worker training. Indeed, using a single GPU, the training was completed in ~1560 mins, while using two GPUs the training required ~910 mins, ca. 58% of the time (Table 2). Note that the distributed strategy can be easily scaled with no changes to the code allowing for the use of more GPUs thus further reducing the training time. Figure 4 shows the performance of the training, performed on the Hopswork according to a distributed strategy, in terms of epoch accuracy and epoch loss.

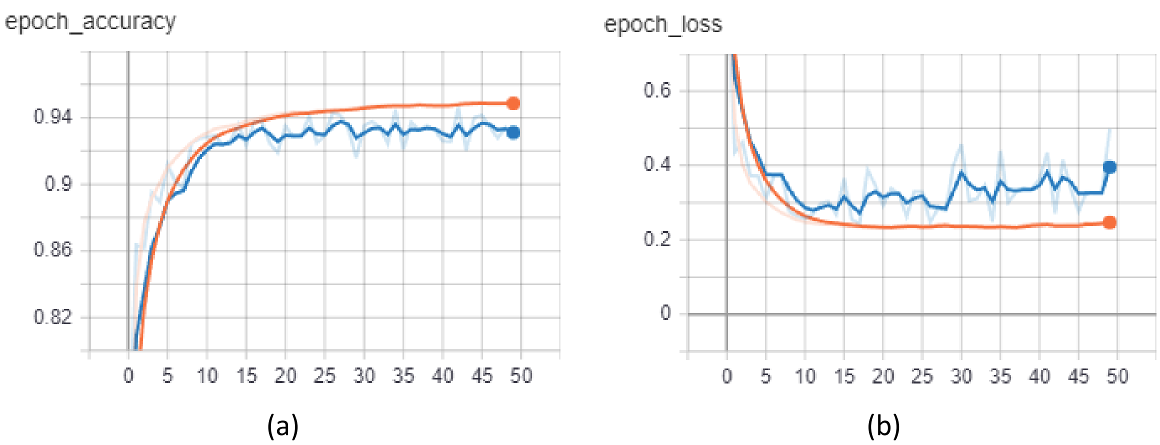

Figure 4 Training performance plots provided by the Hopsworks platform in terms of: (a) epoch accuracy, and (b) epoch loss.

[2] https://www.hopsworks.ai/
[3] https://foodsecurity-tep.net/

3.2. Full Processing Chain Implementation

The entire processing is implemented on the Food Security TEP. The FS TEP Platform provides easy access to EO data and product generation to both experts and non expert users with a focus on agriculture and aquaculture applications. It allows for the massive processing of big data at the regional and national level. Accordingly, it has been used to provide the trained architecture and the complete processing chain to the final user. To this end, we developed a set of services that can be accessed using the website Food Security TEP interface. Note that the basic pre-processing of the time series, including radiometric correction, cloud detection and generation of the Bottom of Atmosphere Reflectance (RefBOA) and Leaf Area Index (LAI) images, using VISTAs sophisticated processors on the TEP, has been performed using the available platform services during the project. Figure 5 shows how the pipeline has been implemented on the Food Security TEP. Since also the classification/inference to generate the crop map is performed on the TEP, the model trained on the Hopswork is retrieved using the Hops API [4]. Additionally, the inference is also available on the Hopsworks platform. The services run on Ubuntu OS in a virtualized environment defined by a docker image. Table 2 shows the average classification times for one tile and for the whole study area (36 tiles). Note that this is only an average as the classification time varies from tile to tile and depends on the number of pixels to be classified (i.e., crop pixels).

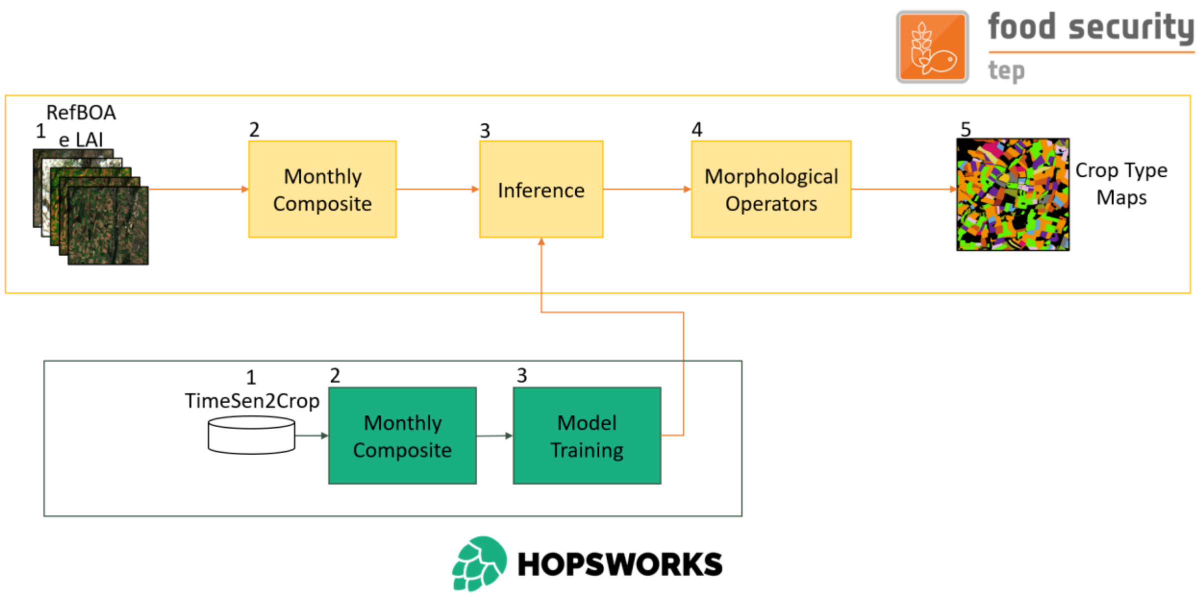

Figure 5 Processing Pipeline implemented on the FS TEP and the Hopswork.

[4] https://hops-py.logicalclocks.com/

	Training		Classification	
	1 GPU	2 GPUs	1 Tile	Whole area (36 Tiles)
Time [Minutes]	1560	910	~120	~4320

Table 2. Training and classification times of the proposed implementation.

4. Performance Evaluation and Objective Compliance

4.1. Study Area

The considered study area is in the Danube catchment, Europe's second largest river basin, with a total area of 801,463 km^2. 36 Sentinel 2 tiles covering Austria, Moravia, Hungary, Slovakia and part of Germany were considered. Each tile covers an area of 100 x 100 km. Figure 12 shows the considered area by presenting the 36 Sentinel 2 tiles considered. The 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 and the way big data EO analysis can offer a unique insight into large scale processes and challenges. Initial plans or additional coverage of wider extent of the training area had to be modified due to unavailability of appropriate ground truth data.

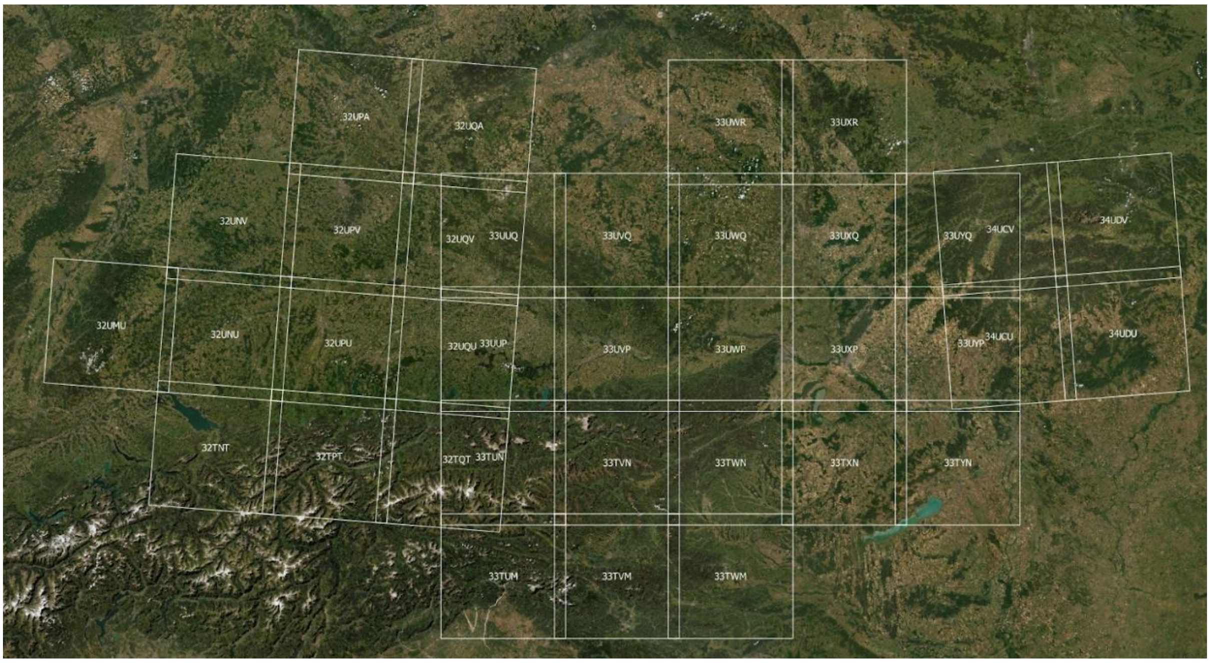

Figure 6 Study area located in the Danube Catchment made up 36 Sentinel 2 belonging to three spatial reference systems, namely EPSG 32632, 32633 and 32634.

The Sentinel 2 data acquired between September 1, 2017 and September 1, 2018 were collected by discarding only the data having cloud coverage higher than 80%. This condition allows us to model the whole agronomic year (i.e., the period from one year's harvest to the next one for agricultural commodities). To perform the multi-year crop type mapping, we also considered the Sentinel 2 data acquired between September 1, 2018 and September 1, 2019 as well as the data acquired between September 1, 2019 and September 1, 2020. The data were downloaded after the preprocessing from the Food Security Thematic Exploitation Platform (TEP) using an API access. The results of Sentinel 2 images made up of nine spectral bands are provided at 10 m spatial resolution, each having a size of 10980x10980 pixels. In particular, the blue (B2 - 490 nm), green (B3 - 560 nm), red (B4 – 665 nm), the four vegetation red edges (B5 - 705 nm, B6 – 740 nm, B7 - 0.783 nm and B8A - 865 nm) and the two short wave infrared (SWIR) (B11 - 1610 nm and B12 - 2190 nm) channels were considered. Band 8 was discarded because of its coarser spectral resolution compared to band 8A. The data had been atmospherically corrected by VISTAs Image Processing software VIA, using the radiative transfer model MODTRAN [11] and the spectral bands are provided at the highest spatial resolution of Sentinel 2, i.e., 10 m.

4.1.1. **Large Training Database and Validation**

The result of the database generation is TimeSen2Crop [2]. The dataset represents 15 crop type classes with samples distributed across 15 Sentinel 2 tiles thus representing a large geographical area. The database also contains samples extracted from the 33UVP tile for the successive year, to test the effectiveness of the network on a different agronomic year. Figure 7 shows the class distribution highlighting crop types having severely imbalanced prior probabilities.

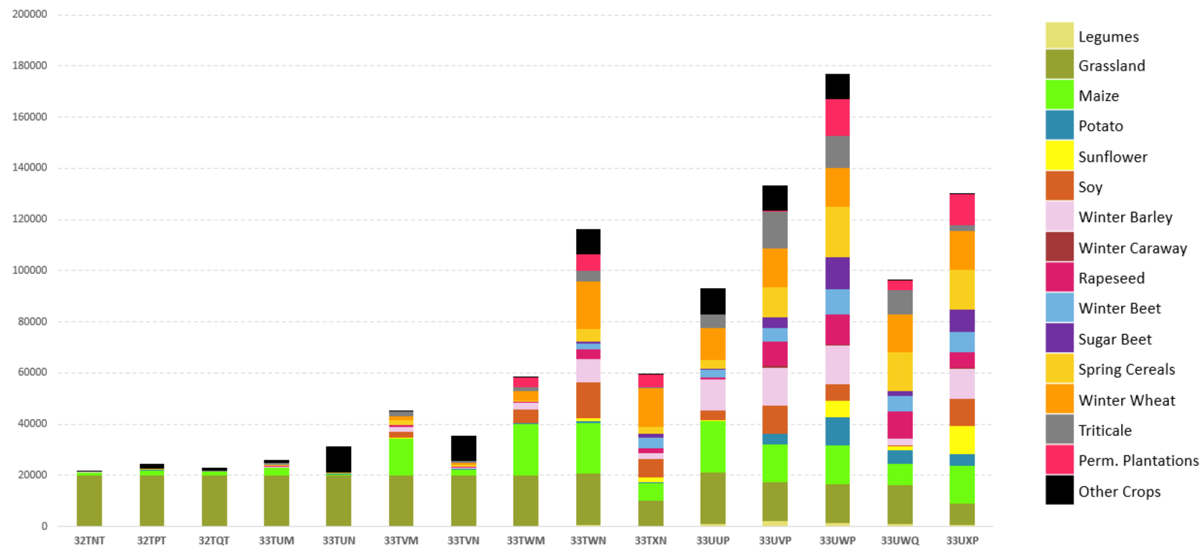

Figure 7. Sample distribution in the 16 classes across the covered Sentinel 2 tiles

Note that while the training has been performed using the TimeSen2Crop dataset, thus considering only the Austrian tiles, the validation for the 2017-2018 agronomic year has been performed considering all the 36 tiles of using the Land Use and Cover Area frame Statistical Survey (LUCAS)[5] as reference. This is a very important aspect as it allows us to test the generalization capabilities of the trained network. Figure 8 shows the LUCAS points used as reference for validation.

[5] https://land.copernicus.eu/imagery-in-situ/lucas

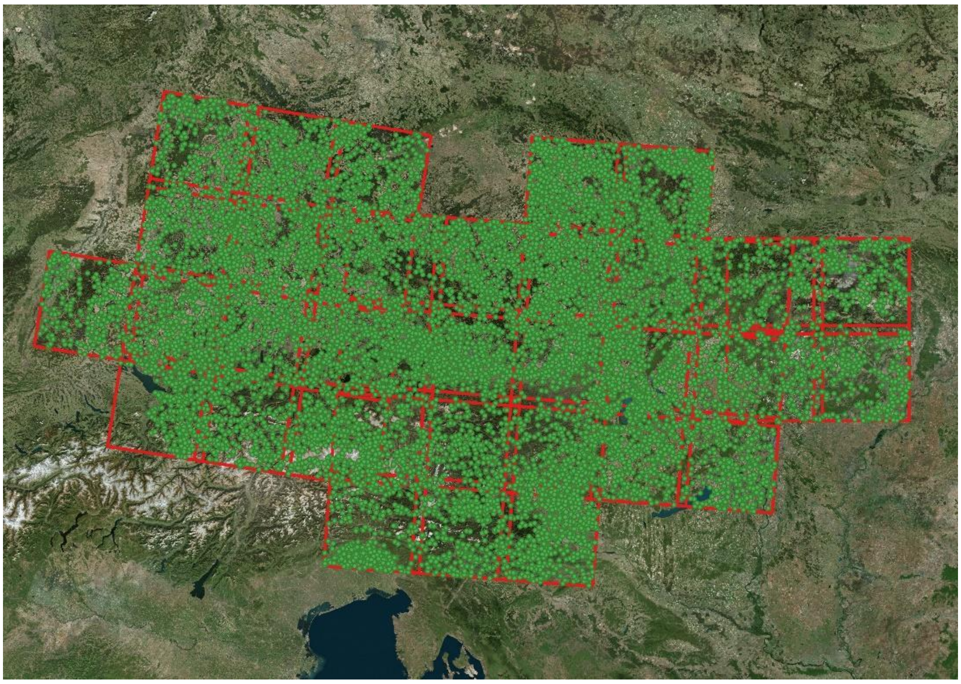

Figure 8 LUCAS reference points overlayed on the study area.

For the multi year mapping, the architecture update (fine tuning) and validation has been performed considering only the Austrian tiles since multi year reference data (INVEKOS) are available only for such areas. In detail, the selection of the validation samples has been performed using patches of images spatially uncorrelated from the patches used for the fine tuning of the architecture.

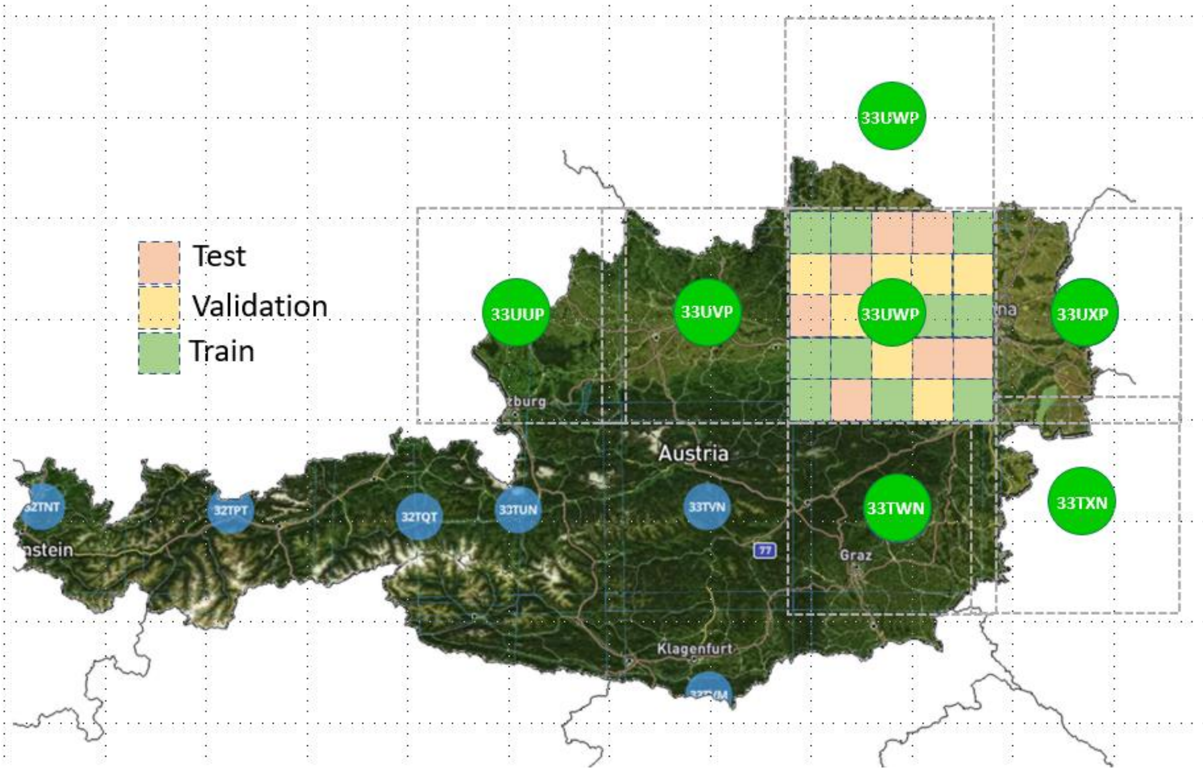

Figure 9 Qualitative examples of the fine tuning and validation samples selection for the muti year mapping.

4.1.2. **Data Volume**

	RefBOA	LAITif	Monthly Composites	Inference	Crop Type Maps	Total
Single Scene	60 GB/tile	7 GB/tile	24 GB/tile	350 MB/tile	10 MB	91.36 GB
Single Year (36 tile)	2.16 TB	252 GB	864 GB	12.6 GB	360 MB	3.28 TB
Multi Year (108 tiles)	6.5 TB	756 GB	2.5 TB	37.8 GB	1.08 GB	9.79 TB

Table 3. Estimated Data Volume

Table 3 shows the estimated data volumes for both the single and multi-year mapping. The table shows that in the context of the food security use case we analyzed big data. This was possible also due to the use of online computing platforms such as the Hopsworks and the Food Security TEP. Another aspect shown in the table is the significant advantage of the monthly composite that allows for almost 3x reduction of the initial data volume.

4.2. Numerical Results

4.2.1. Single Year Mapping

	TimeSen2Crop TestSet		LUCAS	
	#Samples	F1%	#Samples	F1%
Legumes	2031	94.01	-	-
Grassland	15080	98.78	2832	92.72
Maize	15001	99.57	1661	95.94
Potato	4015	95.90	88	72.20
Sunflower	240	89.28	140	85.82
Soy	10712	99.05	131	84.44
Barley	15001	97.89	817	74.75
Winter Caraway	577	95.12	-	-
Rye	9701	86.04	142	40.38
Rapeseed	5086	99.59	733	92.03
Beet	4212	99.44	181	92.05
Spring Cereals	11987	96.40	-	-
Winter Wheat	15001	98.01	1705	80.98
Triticale	14363	86.15	117	18.32
Perm. Plantations	411	81.11	170	61.49
OA%		95.78		85.20
Median F1		96.40		82.71

Table 4. Numerical results obtained with the TimeSen2Crop test set (Austria) and the LUCAS database (Danube basin) for the 2017-2018 agronomic year.

Table 4 shows the numerical results obtained on the 36 tiles of the Danube basin for the 2017-2018 year. The results showed that the proposed architecture achieved good performances both in terms of Overall Accuracy (OA) and median F score (F1). This is true for the results on the TimeSen2Crop and LUCAS datasets. In detail, the TimeSen2Crop test reached an accuracy of 95.78% while the LUCAS test of 85.2%. This proves the generalization capabilities of the proposed architecture that, while trained on the Austrian tiles, performs well on the whole

Danube basin which is characterized by significantly different geographic regions. Focusing on individual classes, the two tests reached similar results with the most significant decrease of performances associated with the rye, which is confused with the wheat-rye hybrid triticale, and permanent plantations classes. Note that these are mostly minority classes and that the permanent plantation class is characterized by a high variability across the study area. A qualitative analysis of the crop type map obtained on a local area is shown in Figure 10. Note that, even if the architecture proposed performs a pixel-wise classification, the resulting product is consistent. The methodologies have been extended to the whole Danube basin and the complete crop type maps generated can be seen in Figure 11.

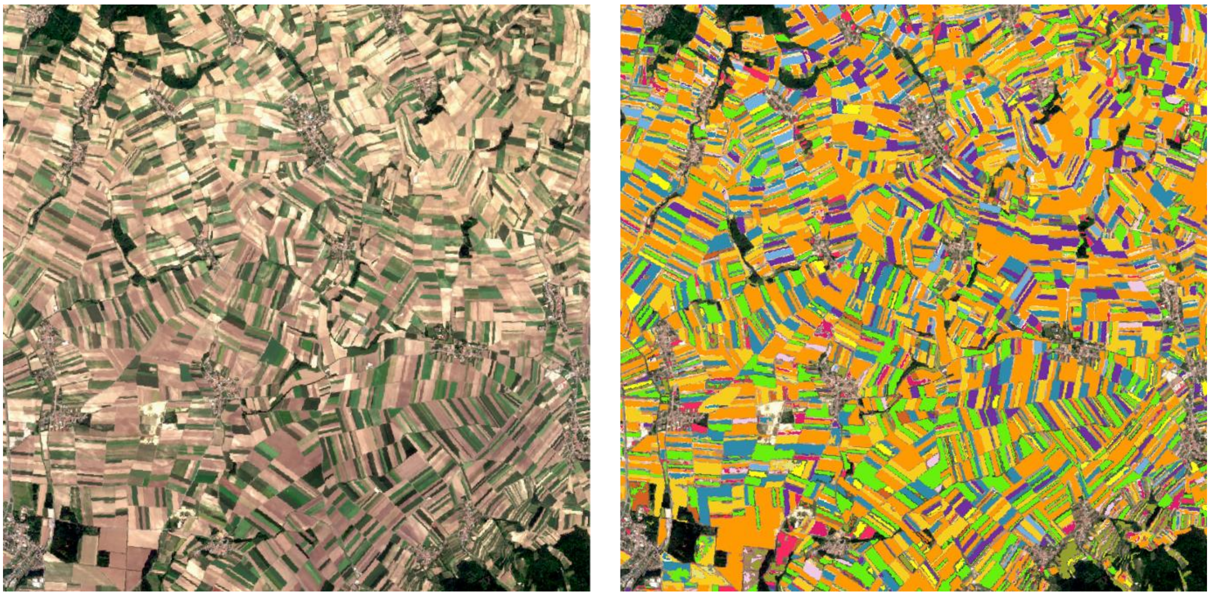

Figure 10. Comparison of a Sentinel 2 acquisition of 4th August 2018 and the crop type map generated

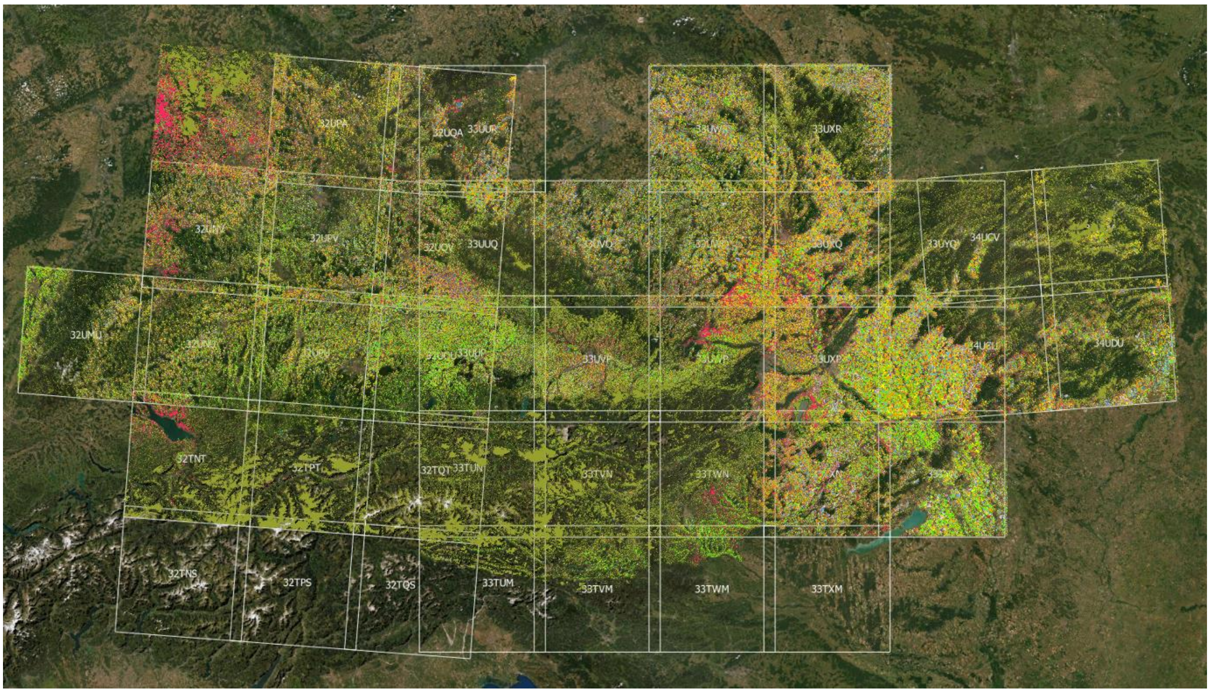

Figure 11. Superimposition of the crop type map generated in the year 2018 on the Danube basin.

4.2.2. **Multi Year Mapping**

	2018	2019		2020	
		No Adaptation	FT (15000 samples)	No Adaptation	FT (15000 samples)
	F1%	F1%	F1%	F1%	F1%
Legumes	94.01	73.16	83.63	69.45	81.69
Grassland	98.78	67.90	76.38	65.44	79.75
Maize	99.57	87.22	91.83	82.39	85.66
Potato	95.90	44.71	61.24	55.28	72.10
Sunflower	89.28	49.47	73.47	42.77	76.40
Soy	99.05	80.04	87.36	75.16	86.49
Barley	97.89	42.56	88.84	19.51	83.58
Winter Caraway	95.12	59.48	72.06	28.18	71.06

Rye	86.04	49.23	67.73	49.94	60.96
Rapeseed	99.59	93.26	96.96	92.11	95.80
Beet	99.44	75.77	86.69	67.77	90.35
Spring Cereals	96.40	62.50	80.46	64.99	79.74
Winter Wheat	98.01	53.72	76.24	43.92	69.81
Triticale	86.15	34.75	61.70	33.09	59.37
Perm. Plantations	81.11	56.57	68.45	58.72	82.52
OA%	95.78	63.25	81.29	60.07	78.79
Median F1%	96.40	61.15	81.99	61.26	80.65

Table 5. Numerical results obtained for the three agronomic years.

Table 5 shows the multi-year mapping numerical results for the 2019 and 2020 years compared with the 2018 (the year on which the network has been trained). The results for 2019 and 2020 are shown for both the 2018 network with no adaptation and with the fine tuning. The median F1 and overall accuracy shows a significant improvement with respect to the case where no adaptation is employed. This shows that proposed architecture can be applied on time series with different temporal and radiometric characteristics with respect to the one used for training. Moreover, the network can be effectively adapted to the unique conditions (e.g., due to crop rotation practices) of each year, as can be seen in Figure 12. The numerical results show relatively stable results from 2019 to 2020 proving that the fine tuning is effective even when the time interval from the year of training becomes significant.

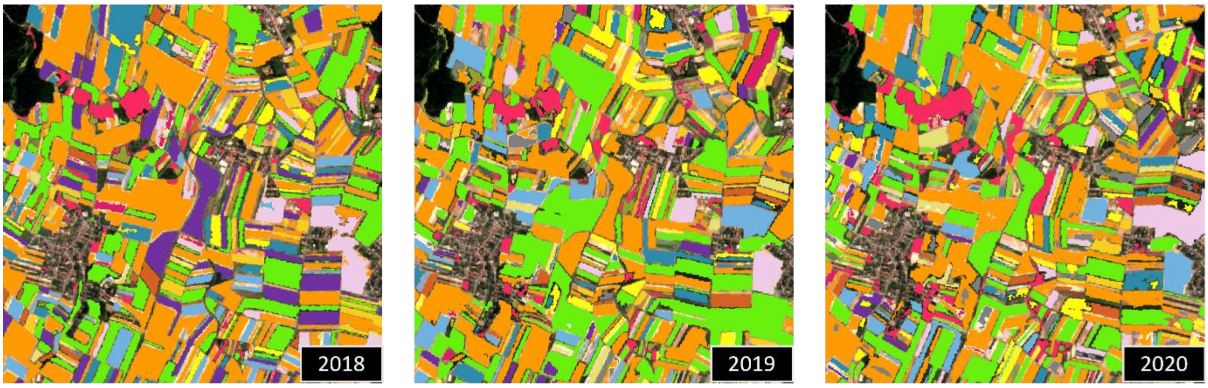

Figure 12. Crop type maps produced in the three target years considered.

4.2.3. "Invekos" Validation

To further validate the single and multi-year results, we extended the Austrian validation to the Austrian tiles containing the biggest variety of crop types using the INVEKOS maps, as reference (i.e., '33TWN', '33TXN', '33UUP', '33UVP', '33UWP', '33UWQ', '33UXP'), thus discarding the Austrian tiles mainly composed by grassland. While it is true that the training database has been generated using the Invekos maps and thus this is not a fully uncorrelated validation, note that by considering all the different tiles and all the available pixels we are significantly expanding the test set. Table 6 shows the obtained numerical results. The results show that all the crop types are classified with good Overall Accuracy and Fscore on all the years. The proposed architecture can generalize well over neighboring tiles and can adapt well on the target years. Most importantly, we can see stable results across the different years confirming the results of Table 5. The most critical classes are Winter Caraway, Triticale and Rye, as discussed in the Single Year Mapping session.

	Samples 2018	**F1% 2018**	**Samples 2019**	**F1% 2019**	**Samples 2020**	**F1% 2020**
Legumes	571689	70.65	368639	63.18	340416	68.12
Grassland	51303200	89.71	15210298	89.60	13744181	85.62
Maize	23516291	93.93	21531831	94.82	19950607	94.79
Potato	2002816	77.11	1752755	78.83	1720180	82.48
Sunflower	1993073	79.11	1682262	70.89	1958104	69.70
Soy	5618872	86.40	5418531	88.84	5472900	87.47
Barley	7751633	87.73	7599399	91.67	7409855	90.33
Winter Caraway	102898	52.40	59824	33.51	67529	34.36
Rye	3501974	64.64	2748134	67.93	2520765	63.76
Rapeseed	3810026	95.61	3228564	95.84	2888543	95.71
Beet	3254119	92.73	2521550	94.81	2450972	92.60
Spring Cereals	7866020	82.53	4697081	85.41	4182017	85.04
Winter Wheat	24517683	89.14	20937790	89.74	20314358	86.68
Triticale	3983221	50.91	3196163	56.23	2834587	48.40
Perm. Plantations	5342051	61.77	4186860	67.07	4570997	59.39
OA%	-	88.99	-	89.41	-	86.20
Median F1	-	85.65	-	86.73	-	84.80

Table 6. Numerical results obtained for the three agronomic years using the Invekos maps as validation.

4.3. Objectives Compliance

In this section we analyze the outcomes of the activities of UNITN for the Food Security Use case (WP2) in terms of objectives, the related user requirements, and quality of the generated products. In Section 1, we revised the main objectives and user requirements.

The first objective was the definition of the training database. This objective has been achieved with the generation of the publicly available TimeSen2Crop dataset. The dataset represents 16 crop types, and it is composed of a million of labeled samples collected over the entirety of Austria. Most importantly, the samples are collected from spatially disjoint tiles to generate the training, test and validation sets while guaranteeing statistical independence. The classes have been tailored to the spectral/temporal properties of the Sentinel 2 time-series to guarantee an effective training and to the simulation / PROMET requirements so that the resulting crop type maps can be effectively used by the partner VISTA to generate the water demand analysis and e.g. irrigation recommendation products.

The second objective was the design and implementation of a deep learning architecture to generate crop type maps. This objective has been achieved with the proposed network that has several important properties. Indeed, due to the use of Sentinel 2 images, the network generates crop type maps at the required geometrical details (i.e., 10m) defined by the user requirements. The network can distinguish the 15 crop types that are required by the PROMET model thus generating products that can be effectively used in the following steps (e.g., water demand maps generation). Moreover, according to the user requirement, the proposed network can generate multi-year crop type maps, for three consecutive years, namely 2018, 2019 and 2020. This is a critical aspect as it allows us to model the temporal changes related both to the crop rotation practice and climate.

This analysis showed that all the objectives and related user requirements for the Food Security Use Case part of WP2 have been achieved. In terms of product and architecture accessibility, the generated database is freely available while all the services can be accessed by means of the Food Security TEP. The mechanisms of using Hopsworks based models for EO classifications had also been successfully implemented on the Food Security TEP.

5. Publication Lists

Here the publications, related to the Food Security use in the project, case are listed:

[1] Paris, Claudia, Giulio Weikmann, and Lorenzo Bruzzone. "Monitoring of agricultural areas by using Sentinel 2 image time series and deep learning techniques." Image and

Signal Processing for Remote Sensing XXVI. Vol. 11533. International Society for Optics and Photonics, 2020.

[2] Migdall, Silke, et al. "Water stress assessment in Austria based on deep learning and crop growth modelling." Proc. Conf. Big Data Space. 2021.

[3] Weikmann, Giulio, Claudia Paris, and Lorenzo Bruzzone. "TimeSen2Crop: A Million Labeled Samples Dataset of Sentinel 2 Image Time Series for Crop-Type Classification." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 14 (2021): 4699-4708.

[4] Migdall, Silke, et al. "Water stress assessment in Austria based on deep learning and crop growth modelling." Proc. Conf. Big Data Space. 2021.

[5] Weikmann, Giulio, Claudia Paris, and Lorenzo Bruzzone. "Multi-year crop type mapping using pre-trained deep long-short term memory and Sentinel 2 image time series." Image and Signal Processing for Remote Sensing XXVII. Vol. 11862. SPIE, 2021.

6. References

[1] Florian Appel, Silke Migdall, Julia Stockamp, Anja Rösel and Heike Bach, “The food security use case - User requirements analysis”, Deliverable 4.1 of the Extreme Earth Project (2019).

[2] Weikmann, Giulio, Claudia Paris, and Lorenzo Bruzzone. "TimeSen2Crop: A Million Labeled Samples Dataset of Sentinel 2 Image Time Series for Crop-Type Classification." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 14 (2021): 4699-4708.

[3] Claudia Paris, Lorenzo Bruzzone, Torbjørn Eltoft, Thomas Kræmer, Andrea Marinoni, Salman Khaleghian, Corneliu Octavian Dumitru, Mihai Datcu, “Large Training Database”, Deliverable 2.1 of the Extreme Earth Project (2019).

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[5] Claudia Paris, Giulio Weikmann, Daniel Marinelli, Lorenzo Bruzzone, “Deep architectures implementation for the Food Security use case”, Deliverable 2.6 of the Extreme Earth Project (2021).

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[8] X. Liu, M. Chi, Y. Zhang and Y. Qin, "Classifying High Resolution Remote Sensing Images by Fine-Tuned VGG Deep Networks," IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium, 2018, pp. 7137-7140.

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[10] Online, [Accessed November 2021] https://foodsecurity-tep.net/

[11] Berk, G. P. Anderson, L. S. Bernstein, P. K. Acharya, H. Dothe, M.W. Matthew, S. M. Adler-Golden, J. H. Chetwynd Jr, S. C. Richtsmeier, B. Pukall et al., “Modtran4 radiative transfer modeling for atmospheric correction,” in Optical spectroscopic techniques and instrumentation for atmospheric and space research III, vol. 3756. International Society for Optics and Photonics, 1999, pp. 348–353.