Global Water Partnership
Central and Eastern Europe

Integrated Drought Management
Programme in Central and Eastern Europe

Activity 5.5. Policy oriented study on remote sensing agricultural drought monitoring methods

Output 2: Signaling and intervention levels of drought based on remote sensing datasets

(11/12/2014)

1. Basic information

Name of the milestone report	Signaling and intervention levels of drought based on remote sensing datasets
Activity leader	Prof. Dr. János Tamás
Participating partners	University of Debrecen, Hungary Institute of Hydrology of the Slovak Academy of Sciences, Slovakia University of Oradea, Romania
Duration	01/01/2014 – 30/06/2014
Chairman of the CWP	Dr. József Gayer

*Milestone report is information about the progress made within this activity from previous milestone report for GWP CEE Regional Secretariat, Programme Manager, Peer Review Group and partners involved into IDMP CEE. It is not intended for further distribution.

2. Activity Report

2.1. Short summary of the milestone report (max 2500 characters); *What have been done after the previous milestone report(s)?*

The Activity 5.5. "Policy oriented study on remote sensing agricultural drought monitoring methods" case study focuses on identification of agricultural drought characteristics and elaborates a monitoring method (with application of remote sensing data), which could result in appropriate early warning of droughts before irreversible yield loss and/or quality degradation occur. The spatial decision supporting system to be developed will help the farmers in reducing drought risk of the different regions by plant specific calibrated drought indexes. In the frame of this innovation such a data link and integration, missing from decision process of IDMP, are established, which can facilitate the rapid spatial and temporal monitoring of meteorological, agricultural drought phenomena and its economic relations, increasing the time factors effectiveness of decision support system. This methodology will be extendable for other Central European countries when country specific data are available and entered into the system.

Output 2 focuses on determination of drought effects on watersheds from remote sensed spectral data. For the investigations normalized difference vegetation index (NDVI) was used calculated from 16 day moving average chlorophyll intensity and biomass quantity data. The study area was the lowland part of the Tisza River Basin, which is located in Central Europe within the Carpathian Basin. The current Output 2 report is a toolbox with the concrete identification of remote sensing and GIS data tools for agricultural drought monitoring and yield loss forecast, which eventually provides information on physical implementation of drought risk levels. As a result, five drought risk levels were developed to identify the effect of drought on yields: Watch, Early Warning, Warning, Alert and Catastrophe.

In the frame of Milestone 1 databases which are from meteorological, soil physical, plant production, GIS and RS point of view homogenous were produced for the Tisza river basin for the recent years. In Milestone 2 using GIS geoprocessing and time series analysis drought maps were generated based on the established drought risk levels.

2.2. Describe the progress to the objectives of your activity

The identification of those available and most appropriate remote sensing data and GIS transformation, calibration tools were carried out, with which remote sensing based agricultural drought monitoring and yield loss forecast can be implemented. These tools are synthetized into one huge toolbox including landuse, soil physical, meteorological and satellite data integrating them into a model, which can be a feasible tool for plant specific drought risk evaluation. This model contains several steps from data acquisition, through processing and calibration to risk mapping and evaluation (Figure 3.). There are three main steps:

I. data acquisition and processing, (database homogeneity)
II. identification and calibration of drought risk levels (geoprocessing, time series analysis, GIS toolbox)
III. drought risk evaluation and mapping. (improved high accurate drought maps on Tisza watershed)

2.3.	**The expected final output (s). At what stage you are now in the process of producing the final output(s)?**

Final output: Integration of RS and GIS tools and intervention levels into agricultural drought monitoring system

The case study has three important steps, milestones, which correspond and relate to each other in hierarchical way. First, the green and brown water resources should be analyzed on the examined watersheds in order to gather information on water utilization of a site. These data are necessary for the second step, the calibration and validation of remote sensing data. Our activity is in the end of the second phase, so green and brown water were identified, and the calibration of remote sensing data was done. The third milestone, which is the implementation of the signaling levels of drought is based on the results of the integrated data of step 1 and step 2 in order to develop drought indicators and integrate them into a drought monitoring system.

A specific data integration process were managed to set with which the other conventional drought indices can specified and refined by actual yield loss data based on the calibration of remote sensing based maps. Such models and scripts were generated, which can be used by other user for other drought risk affected areas. This digital IDMP geoprocessing framework toolbox make it possible to access and share this knowledge tool for users and stakeholders.

In the next phase of the activity the GIS toolbox will be tested in the case of different scenarios. Testing of this integrated agricultural drought management system will focus on the impact of the spatial and temporal, yield loss based drought mapping on the economic relations and indicators of drought, eventually on decision making.

2.4. Have you introduced any change in the original plan as outlined in the Activity List?

No changes has been done.

2.5. Identify links with other IDMP CEE activities

Activity 2.1: Guideline for Drought Management Plan - Our MODIS NDVI based agricultural drought mapping method can be one of the support guideline n preparation of the Drought maps.

Activity 5.1: Experimental field research on increasing of soil-water holding capacity in agriculture and **Activity 5.6: Upgrading agricultural drought monitoring and forecasting: the case of Ukraine and Moldova -** Soil water capacity mapping, described in this Output can support the identification of soil water holding capacity in regional scale.

Activity 5.4: Drought Risk Management Scheme: a decision support system - Yield calibrated drought risk levels can decrease the risk of uncertainty and increase the feasibility of other recently available of decision support system by the visualization and communication the probability of occurrence of different phases of droughts.

Activity 6.2: Capacity building trainings - Participation on capacity building trainings with interpreting how to implement NDVI based yield calibrated imagery in drought mapping and yield loss forecast.

Activity 7.1: Development of the Compendium of Good Practices - Review of remote sensing in agricultural drought monitoring and yield loss forecast for decision support system.

2.6. Other issues (problems during the implementation, how they were solved, etc.)

There were no critical problems to be solved

2.7. List if National Reports have been used, and if so, provide details on the National Reports (title, authors, publication data and location)

National reports were not used, instead statistical data of several parameters obtained from Hungarian Central Statistics Office (www.ksh.hu) and National Institute of Statistics in Romania (www.insse.ro)

3. Attachments

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Integrated Drought Management Programme

Global Water Partnership Central and Eastern Europe

Signaling and intervention levels of drought based on remote sensing datasets

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Contents

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1. Introduction

In the hydrological cycle of a watershed the soil covering biomass quantity, its activity as well as the biomass spatial-temporal pattern play a significant role. Biomass is not only affects the water resources through evapotranspiration, but the interception reduces the intensity of soil reaching rainfall, reduces the intensity of run-off, infiltration and erosion. Notwithstanding, following from the wide range of agricultural practices, such as growing numerous crop species, applying crop rotations and technologies (plant nutrition, cultivation, plant protection, irrigation, mechanization) innumerable changes occur in the related hydrological parameters, which could be determined only by approximate methods. Arable field experimental data have significant limitations in hydrological calculations and modelling when they are applied on other areas. Over the past decade, the number of Earth observation satellites increased by several orders of magnitude and the spectral and spatial resolution of data they collected have improved. In particular, since 2000 new opportunities for better data for calculations can be gained from the MODIS Aqua and Terra satellites, which provide free 36-band number, with 1 day repeating cycle and 250 to 500 m pixel size time series data sets.

The Activity 5.5. “Policy oriented study on remote sensing agricultural drought monitoring methods” case study focuses on identification of agricultural drought characteristics and elaborates a monitoring method (with application of remote sensing data), which could result in appropriate early warning of droughts before irreversible yield loss and/or quality degradation occur. The spatial decision supporting system to be developed will help the farmers in reducing drought risk of the different regions by plant specific calibrated drought indexes. This methodology will be extendable for other Central European countries when country specific data are available and entered into the system.

Output 2 focuses on determination of drought effects on watersheds from remote sensed spectral data. For the investigations normalized difference vegetation index (NDVI) was used calculated from 16 day moving average chlorophyll intensity and biomass quantity data. The study area was the lowland part of the Tisza River Basin, which is located in Central Europe within the Carpathian Basin. Hydrologically the Carpathian Basin is one of the most closed basins on Earth and the investigated lowland has semi-arid to arid character. In this region there is intensive agricultural activity where the ratio of arable land is 72%.

The methods and databases to be explored include employment of remote sensing data on land use, as well as biomass production, soil characteristics for better integration and understanding of cropping patterns influenced by hydrology and soil types. Internationally available land use remote sensing data (CORINE database, topographic maps), MODIS NDVI spectral indices, soil data (agro topographic map, soil water management properties, map of water management properties of soils), hydrology (soil water table), digital elevation models were processed and integrated to determine soil water holding capacities, water content and consumption of the concerned cultivated plants at different soil types.

The current Output 2 report is a toolbox with the concrete identification of remote sensing and GIS data tools for agricultural drought monitoring and yield loss forecast, which eventually provides information on physical implementation of drought risk levels. As a result, five drought risk levels are developed to identify the effect of drought on yields:

1. *Watch*: When plant water stress is observed in sensitive phenological phases
2. *Early Warning*: When relevant plant water stress is observed. The available soil moisture is close to critical, and it is suggested for farmers to start preparation of intervention. Predicted potential yield loss is up to 10%.
3. *Warning*: When plant stress translates into significant biomass damage, and there is time to start the intervention actions. Potential yield loss is up to 20%.

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4. *Alert*: When farmers expect irreversible vegetation damage with real negative profit, and they have to consider to give up additional cultivation actions in crop production in that actual vegetation period. Potential yield loss is up to 30%.
5. *Catastrophe*: When serious damages and profit loss mitigation is necessary. Potential yield loss is up to 40%.

Within the deliverables of this output 2 the purpose of the toolbox is to present:

- identify droughts and the characteristics of drought sensitive areas in an early stage,
- predict area-specific yield forecasts,
- calculate possible yield loss
- mapping of drought related soil moisture regime.

2. Dissemination of drought indexing methods and their purposes

Drought indices have been developed by several generations of researchers during the 20th century in the domains of meteorology, hydrology, agricultural research and application, remote sensing, and water resources management. More than 80 drought indices have been identified by the authors, and probably the total number of drought indexes ever published exceeds 160. Reviews and classifications of drought indices have been produced regularly during the last decades, thus providing a good overview on the period's state of art and development (Niemeyer, 2008).

Meteorological drought indices

Some decades ago drought indices relied on meteorological variables that were observed at meteorological stations. Examples:

- Rainfall Anomaly Index (RAI) (van Rooy, 1965),
- Bhalme and Mooley Drought Index (BMDI) (Bhalme and Mooley, 1980). The Bhalme and Mooley Drought Index (BMDI) is an empirical index that uses monthly rainfall as the sole climatological input.
- Standardized Anomaly Index of Katz and Glantz (1986),
- Pálfai Aridity Index (PAI) developed and applied predominantly for Hungarian conditions (Pálfai, 1991). This index characterizes the strength of the drought for an agricultural year with one numerical value, which has a strong correspondence with crop failure. However, in the formula of PAI the determination of three correction factors, based on daily temperature and precipitation values, as well as groundwater levels is difficult. In the frame of the DMCSEE project for easier practical use, a new simpler method was developed for the calculation of these factors, which is based on monthly mean air temperature and monthly sum of precipitation. The equation for the new method, base-value of the modified index, named Pálfai's Drought Index (PaDI) (Herceg, 2012).
- The Drought Severity Index (DSI) often used in the UK (Bryant *et al.*, 1992),
- The most widespread Standardized Precipitation Index (SPI) (McKee *et al.*, 1993). The Standardized Precipitation Index is a probability index that considers only precipitation. The SPI is based on the probability of recording a given amount of precipitation, and the probabilities are standardized so that an index of zero indicates the median precipitation amount (half of the historical precipitation

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amounts are below the median, and half are above the median). The index is negative for drought, and positive for wet conditions. As the dry or wet conditions become more severe, the index becomes more negative or positive.

- Effective Drought Index (EDI) considers effective precipitation (Byun and Wilhite, 1999), The EDI is an attempt to more accurately determine the exact start and end of a drought period. The EDI is a function of 'precipitation needed for a return to normal' conditions (or to recover from the accumulated deficit since the beginning of a drought)
- Reconnaissance Drought Index (RDI) by Tsakiris *et al.* (2007). This drought index is based both on cumulative precipitation (P) and potential evapotranspiration (PET). That is one measured and one calculated determinant. Therefore, it is of great interest to assess the effect of the PET calculation method on the results of RDI.

Agricultural drought indices

Starting from the PDSI and specializing on soil moisture and actual evapotranspiration led to the development of explicit agricultural drought indices, such as

- Crop Moisture Index (CMI) (Palmer, 1968) The Crop Moisture Index (CMI) uses a meteorological approach to monitor week-to-week crop conditions. Whereas the PDSI monitors long-term meteorological wet and dry spells, the CMI was designed to evaluate short-term moisture conditions across major crop-producing regions (Hayes,, 1999),
- Soil Moisture Drought Index (SMDI) (Hollinger *et al.*, 1993),
- Crop Specific Drought Index (CSDI) (Meyer *et al.*, 1993).

Recently, two new agricultural drought indices have been proposed by Narasimhan and Srinivasan (2005).

- Soil Moisture Deficit Index (SMDI) is computed as the weekly soil moisture normalized by long-term statistics. Weekly values are then added on an incremental basis to account for the duration of a drought. The SMDI is computed separately for different soil depths in order to consider the varying rooting depth for different crops and stages of plant development.
- The Evapotranspiration Deficit Index (ETDI) is computed similar to the SMDI, but it considers the water stress ratio of potential to actual evapotranspiration instead of soil moisture.

Agricultural Drought Index (DTx) (Marletto et al., 2005) was created for regional application. It is based on the daily transpiration deficit as computed by a water balance model, and describes the integrated deficit of transpiration of a crop for a period of x days; e.g. DT180 indicates the deficit of the 180 precedent days (Niemeyer, 2008).

Hydrological drought indices

From the entire water cycle perspective, hydrology-oriented drought indices have been developed in order to characterize the water balance in a catchment area for water management purposes, with special focus on discharge producing processes such as snow accumulation and melt.

Threshold level method for defining drought events is the most frequently applied quantitative method where it is essential to define the beginning and the end of a drought. It is based on defining a threshold, below which the river flow is considered as a drought (Yevjevich, 1967).

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The Palmer Hydrological Drought Index that considers hydrological impacts on reservoirs or groundwater levels that have a longer time dimension than the original PDSI. , and the moisture anomaly or

The Surface Water Supply Index (SWSI) of Shafer and Dezman (1982) accounts for snow accumulation. This incorporates snowpack, streamflow, precipitation, and reservoir storage. Designed for snowpack-dominated basins. The SWSI is probably the best-known example of a hydrological drought index.

Reclamation Drought Index (RDI) is calculated at a river basin level, and it incorporates the supply components of precipitation, snowpack, streamflow, and reservoir levels. The RDI differs from the SWSI in that it builds a temperature-based demand component and a duration into the index (Hayes, 1999).

Comprehensive drought indices

The Palmer Drought Severity Index (PDSI) (Palmer, 1965) is the most prominent index of meteorological drought used in the United States (Heim, 2000). For this type of drought index, besides meteorological parameters, typically information on soil moisture - in case of PDSI the available water content of the soil - was added.

Palmer Modified Drought Index (PMDI) developed for the US National Weather Service for operational real-time application.

Z-index measures short-term drought on a monthly scale and is lacking the back-looking procedure of the PDSI and is considering the moisture conditions of the current month as compared to the average conditions only.

Aggregate Drought Index (ADI) (Keyantash and Dracup, 2004) describes the meteorological, hydrological, and agricultural aspects of drought on a climate-divisional basis, using fluctuations in the values of five variables associated with the hydrologic cycle and available water: precipitation, evaporation, streamflow, reservoir storage, and soil moisture (Niemeyer, 2008).

Anomalies of precipitation (SPI-3), soil moisture and fAPAR are used as the basic indicators to design a prototype of the so-called Combined Drought Indicator (CDI), characterising the different stages of the agricultural drought cause–effect relationship (Sepulcre-Canto et al., 2012).

These drought indices indicate the effect of weather conditions (most commonly the temperature and precipitation) on the intensity of drought. The hydrological drought is associated with the extreme reduction of water resources, while agricultural drought indicates crop loss or vegetation water stress condition. Despite the fact that there is a close quality connection among the harmful level of all three indicators, the numerical scale of the relationships among them is unclear. Thus, different areas or the same area with different forms of drought cannot be compared. For example, it cannot be stated from the evaluation of meteorological drought standardized precipitation index (SPI) values of a river basin, how many tonnes of maize will be lost during a given forecasting period. However, the expected rate of yield loss would be very important information for the planned intervention in terms of time and cost.

3. Presently available remote sensing indexing methods of vegetation and agricultural drought

One of the best way for monitoring of Earth's surface is to measure the reflectance of the incoming electromagnetic radiation. Electromagnetic radiation (EM radiation or EMR) is a fundamental phenomenon of electromagnetism, behaving as waves propagating through space, and also as photon particles traveling through space, carrying radiant energy. The electromagnetic spectrum is the distribution of electromagnetic radiation according to energy (or equivalently, by virtue of the relations in the previous section, according to

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frequency or wavelength). Different materials and surfaces have characteristic spectra, often showing characteristic absorption maxima or minima at particular wavelengths. The complexity of these spectra means that there is a need to derive simplified approaches that can be used to determine key biophysical parameters of vegetation. *Spectral indices* are new variables generated by mathematical combination of two or more of the original spectral bands chosen in such a way that the new indices are more clearly related to biophysical parameters of interest such as canopy leaf-area index, chlorophyll than are any of the original bands. This principle of deriving spectral indices from measurements at two (or more) wavelengths is widely adopted in remote sensing, especially in the use of *vegetation indices (VI)* for studying vegetation cover.

Vegetation indices are usually dimensionless measures derived from radiometric data that are primarily used to indicate the amount of green vegetation present in a view. Most vegetation indices are based on the sharp increase in reflectance from vegetation that occurs around 700 nm (the red-edge), a change that is characteristic of green vegetation and not found for most other natural surfaces that show relatively slow changes of reflectance with wavelength over this region (Jones and Vaughan, 2010). Vegetation Indices (VIs) are combinations of surface reflectance at two or more wavelengths designed to highlight a particular property of vegetation. They are derived using the reflectance properties of vegetation. Each of the VIs is designed to accentuate a particular vegetation property. More than 150 VIs have been published in scientific literature, but only a small subset have substantial biophysical basis or have been systematically tested. Selection of the most important vegetation categories and the best representative indices within each category was performed by Dr. Gregory P. Asner of the Carnegie Institution of Washington, Department of Global Ecology. The selections were based upon robustness, scientific basis, and general applicability. Many of these indices are currently unknown or under-used in the commercial, government, and scientific communities. The indices are grouped into categories that calculate similar properties (www.exelisvis.com/docs/VegetationIndices.html).

Broadband Greenness

The broadband greenness VIs are among the simplest measures of the general quantity and vigor of green vegetation. They are combinations of reflectance measurements that are sensitive to the combined effects of foliage chlorophyll concentration, canopy leaf area, foliage clumping, and canopy architecture. These VIs are designed to provide a measure of the overall amount and quality of photosynthetic material in vegetation, which is essential for understanding the state of vegetation for any purpose. These VIs are an integrative measurement of these factors and are well correlated with the fractional absorption of photosynthetically active radiation (fAPAR) in plant canopies and vegetated pixels. They do not provide quantitative information on any one biological or environmental factor contributing to the fAPAR, but broad correlations have been found between the broadband greenness VIs and canopy leaf area index (LAI).

Broadband greenness VIs compare reflectance measurements from the reflectance peak of vegetation in the near-infrared range to another measurement taken in the red range, where chlorophyll absorbs photons to store into energy through photosynthesis. Use of near-infrared measurements, with much greater penetration depth through the canopy than red, allows sounding of the total amount of green vegetation in the column until the signal saturates at very high levels. Because these features are spectrally quite broad, many of the broadband greenness indices can work effectively, even with image data collected from broadband multispectral sensors, such as AVHRR, Landsat TM, and QuickBird. Applications include vegetation phenology (growth) studies, land-use and climatological impact assessments, and vegetation productivity modeling. The broadband greenness equations in the next sections represent the surface reflectance in an image band with a center wavelength as follows: rNIR = 800 nm, rRED = 680 nm, and rBLUE = 450 nm. Increases in leaf chlorophyll concentration or leaf area, decreases in foliage clumping, and changes in canopy architecture each can contribute to rNIR decrease and rRED increase, thereby causing an

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increase in the broadband greenness values.

Narrowband Greenness

Narrowband greenness VIs are a combination of reflectance measurements sensitive to the combined effects of foliage chlorophyll concentration, canopy leaf area, foliage clumping, and canopy architecture. Similar to the broadband greenness VIs, narrowband greenness VIs are designed to provide a measure of the overall amount and quality of photosynthetic material in vegetation, which is essential for understanding the state of vegetation. These VIs use reflectance measurements in the red and near-infrared regions to sample the red edge portion of the reflectance curve. The red edge is a name used to describe the steeply sloped region of the vegetation reflectance curve between 690 nm and 740 nm that is caused by the transition from chlorophyll absorption and near-infrared leaf scattering. Use of near-infrared measurements, with much greater penetration depth through the canopy than red measurements, allows estimation of the total amount of green material in the column. Narrowband greenness VIs are more sophisticated measures of general quantity and vigor of green vegetation than the broadband greenness VIs. Making narrowband measurements in the red edge allows these indices to be more sensitive to smaller changes in vegetation health than the broadband greenness VIs, particularly in conditions of dense vegetation where the broadband measures can saturate. Narrowband greenness VIs are intended for use with high spectral resolution imaging data, such as that acquired by hyperspectral sensors.

Light Use Efficiency

The light use efficiency VIs are designed to provide a measure of the efficiency with which vegetation is able to use incident light for photosynthesis. Light use efficiency is highly related to carbon uptake efficiency and vegetative growth rates, and is somewhat related to fractional absorption of photosynthetically active radiation (fAPAR). These VIs help to estimate growth rate and production, which is useful in precision agriculture. These VIs use reflectance measurements in the visible spectrum to take advantage of relationships between different pigment types to assess the overall light use efficiency of the vegetation.

Dry or Senescent Carbon

The dry or senescent carbon VIs are designed to provide an estimate of the amount of carbon in dry states of lignin and cellulose Lignin is a carbon-based molecule used by plants for structural components; cellulose is primarily used in the construction of cell walls in plant tissues. Dry carbon molecules are present in large amounts in woody materials and senescent, dead, or dormant vegetation. These materials are highly flammable when dry. Increases in these materials can indicate when vegetation is undergoing senescence. See Carbon for more information. You can use these VIs for fire fuel analysis and detection of surface litter. They use reflectance measurements in the shortwave infrared range to take advantage of known absorption features of cellulose and lignin. These indices provide suspect results in wet environments, or when the dry materials are obscured by a green canopy.

Leaf Pigments

The leaf pigment VIs are designed to provide a measure of stress-related pigments present in vegetation. Stress-related pigments include carotenoids and anthocyanins, which are present in higher concentrations in weakened vegetation. These VIs do not measure chlorophyll, which is measured using the greenness indices. Carotenoids function in light absorption processes in plants, as well as in protecting plants from the harmful effects of high light conditions. Anthocyanins are water-soluble pigments abundant in newly forming leaves

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and leaves undergoing senescence. Applications for leaf pigment VIs include crop monitoring, ecosystem studies, analyses of canopy stress, and precision agriculture. Stress pigments can indicate the presence of vegetation stress, often before it is observable using the unaided eye. The pigments are described in greater detail in Pigments. The VIs use reflectance measurements in the visible spectrum to take advantage of the absorption signatures of stress-related pigments. For leaf pigment indices, reflectance needs to be scaled between 0 and 1. If reflectance data are scaled, use the Reflectance Scale Factor field in the Header Info dialog instead of creating a copy of your data.

Canopy Water Content

The canopy water content VIs are designed to provide a measure of the amount of water contained in the foliage canopy. Water content is an important quantity of vegetation because higher water content indicates healthier vegetation that is likely to grow faster and be more fire-resistant. Canopy water content VIs use reflectance measurements in the near-infrared and shortwave infrared regions to take advantage of known absorption features of water and the penetration depth of light in the near-infrared region to make integrated measurements of total column water content.

Thermographic index

Canopy temperature acts as a good indicator of plant water status. Infrared thermography is considered for the identification of plant water stress and is also used as a tool for irrigation scheduling method (Wang and Gartung, 2010). If plant water stress increases, transpiration decreases and plant temperature may exceed air temperature. On the other hand, non-stressed plants will have canopy temperatures less than air temperature, particularly when vapour pressure deficit (VPD) is not greater than 4 kPa (Olivo et al., 2009). The crop water stress index (CWSI) relates canopy–air temperature difference to net radiation, wind speed and vapour pressure deficit (Jackson et al., 1981). However, a surrogate measure is calculable from the temperatures of the canopy and reference leaf surfaces corresponding to fully transpiring and non-transpiring canopies (Jones, 1999; Moller et al., 2007). Thus, by monitoring plant canopy temperature and the temperatures of wet and dry leaves, it is possible to estimate the underlying plant water stress status and therefore, intelligently control the related irrigation process.

Each category of indices typically provides multiple techniques to estimate the absence or presence of a single vegetation property. For different properties and field conditions, some indices within a category provide results with higher validity than others. By comparing the results of different VIs in a category, and correlating these to field conditions measured on site, you can assess which indices in a particular category do the best job of modelling the variability in your scene. By using the VI in any category that best models the measured field conditions for a few measurements, you can significantly increase the quality of the results from any further processing. The VIs are not designed to quantify the exact concentration or abundance of any given vegetation component. Instead, they are intended for use in geographically mapping relative amounts of vegetation components, which can then be interpreted in terms of ecosystem conditions. All VIs require high-quality reflectance measurements from either multispectral or hyperspectral sensors. Measurements in radiance units that have not been atmospherically corrected are unsuitable, and typically provide poor results. The VIs that can be calculated on a specific dataset are determined by the spectral bands sampled in the input dataset. A certain VI is available for the dataset if all spectral bands required for a specific index are available. For example, an input dataset from a sensor that matches only the near-infrared and red spectral bands (such as AVHRR, TM, and others) is only able to calculate two of the indices: the NDVI (Normalized Difference Vegetation Index) and SR (Simple Ratio). In contrast, for a high spectral resolution input dataset, such as AVIRIS, 25 of the indices will be available.

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4. Multi- and hyper-spectral remote sensing methods in vegetation-drought indexing

The development of Earth observation satellites from the 1980s onwards equipped with sensors mainly in the optical domain opened a new road for drought monitoring and detection. The new technologies allowed for the derivation of truly spatial information at global or regional coverage with a consistent method and a high repetition rate. Numerous indices were developed to describe the state of the land surface, mainly of vegetation, with the potential to detect and monitor anomalies such as droughts. A good overview on the first generation of remote sensing based drought monitoring is given in Gutman (1990), while Kogan (1997) provides an update almost one decade later. Presently, the development of fast information technology gives our hand such methods like global positioning system (GPS), geographic information system (GIS), remote sensing (RS). Hyper- and multispectral remote sensing technology is widely used in agriculture and environmental protection, and is appropriate for vegetation analysis (Clark, 1999; Kruse et al., 2003; Milics et al., 2008; Polder & van der Heijden, 2001; Sabins, 1997). Remote sensing is the science of acquiring, processing, and interpreting images and related data, acquired from aircraft and satellites, which record the interaction between matter and electromagnetic energy (Sabins, 1997). Small bandwidths distinguish hyperspectral sensors from multispectral sensors, acquiring spectral information of materials usually over several hundreds of narrow contiguous spectral bands, with high spectral resolution on the order of 20 nm or narrower (Polder & van der Heijden, 2001). As such, they allow identification of specific materials, whereas broadband multispectral data only allow discrimination between classes of materials (Kruse et al., 2003). Hyperspectral remote sensing combines imaging and spectroscopy in a discrete system, which often includes large datasets. Hyperspectral datasets are generally composed of 100 to 200 spectral bands with relatively narrow bandwidths (5–10 nm), whereas multispectral data sets are usually composed of about five to ten bands with relatively large bandwidths (70–400 nm). The contiguous, narrow-bandwidth characteristics of hyperspectral data enable an in-depth examination of surface features on the ground, features which otherwise would be ‘lost’ within the relatively coarse bandwidths acquired by the multispectral scanners.

Over the past decade, extensive research and development has been carried out in the field of hyperspectral remote sensing. Now, with commercial airborne hyperspectral imagers such as CASI, Hymap, and the Hungarian Aisa Dual System, plus the launch of satellite-based sensors such as Hyperion, hyperspectral imaging is progressing rapidly in the fields of mainstream remote sensing and applied remote-sensing research. Hyperspectral images have also many applications in water-resource management, agriculture and environmental monitoring (Tamás et al., 2005; Kardeván et al., 2003; Plaza et al., 2009). It is important to know that the difference is not necessarily in the spatial resolution between hyperspectral and multispectral data, but rather in their spectral resolutions. The analysis and classification of the hyperspectral image is suitable for the identification of different objects and features (Lefcourt et al., 2006; Plaza et al., 2009). Covered and uncovered ground can be quickly, accurately and cost effectively examined on large area (Burai, 2007). This ternary technology integrates and complementary in geospatial sciences and researches. From the precision agriculture point of view, the number of services become more widespread, which were not available in the past, because of their speed, complexity or price. The high accuracy high-tech instruments provide opportunity to elaborate several agrotechnics, such as fruit production, which aim is creating and operating water and energy safe quality fruit production systems. The chlorophyll content is one of the indicators of the state of health (Burai et al., 2009), which affect the reflectance spectra of the vegetation and the vegetation indices, as well. Minimum at the visible spectral range is related to pigments in plant leaves. Chlorophyll absorbs markedly spectral range between 450 – 670 nm. Reaching infrared spectral range, the reflectance of healthy vegetation increases rapidly. Healthy vegetation reflects the 40-50% of the incoming energy between 700-1300 nm spectral ranges due to the internal structure of the canopy. In this way, the measured reflectance plays an important role in distinguishing different plant species, even if these species are seems to be similar based on visible spectral range (Berke et al., 2004). The reflectance value of the vegetation without any stress is high at NIR intervals, but low at red wavelength interval. The chlorophyll content is one of the indicators of the state of health before ripening term (Tamás et al. 2009).

Recently, Ghulam *et al.* (2007a, b) tried to exploit the relationship between NDVI and broad-band albedo, replacing LST, and applied their methodologies to data derived from the Enhanced Thematic Mapper Plus (ETM+) and Moderate Resolution Imaging Spectrometer (MODIS) sensors. Ghulam *et al.* (2007a) proposed the Vegetation Condition Albedo Drought Index (VCDAI), but stated some considerable problems related to the amount and variety of input data needed to define the entire NDVI/albedo spectral space for dry and wet as well as for densely and hardly vegetated surfaces. Then Ghulam *et al.* (2007b) proposed the Perpendicular Drought Index (PDI) that is again exploiting the near-infrared and red spectral reflectance space. This index is derived directly from the atmospherically corrected reflectances in the near infrared and red band and a perpendicular geometrical construction on the two bands' reflectance space. The PDI was then improved by Ghulam *et al.* (2007c) into the Modified Perpendicular Drought Index (MPDI) in that it included the fraction of vegetation of a pixel that accounted for soil moisture and vegetation growth. Consequently, according to the authors, the MPDI outperformed the PDI on vegetated surfaces.

Based on multi-band capabilities of e.g. the MODIS sensor on board Terra/Aqua satellites, Normalized Multi-Band Drought Index (NMDI) was proposed by Wang and Qu (2007). The NMDI is based on one near infrared and two short-wave infrared channels, exploiting the slope of the two water-sensitive absorption bands 6 and 7 of MODIS. A fairly different approach to exploit remote sensing data to construct a drought index has been presented very recently by Liu *et al.* (2008). The authors proposed a Remote Sensing Drought Risk Index (RDRI) on the basis of a linear combination of three cloud indices that describe the length of the continuous absence of clouds (hence no precipitation), the ratio between cloudy and non-cloudy days, and the length of the longest continuous cloud cover.

The Fraction of Absorbed Photosynthetically Active ,Radiation (FAPAR) plays a critical role in the energy balance of ecosystems and in the estimation of the carbon balance over a range of temporal and spatial resolutions. Spatially-explicit descriptions of FAPAR provide information about the relative strength and location of terrestrial carbon pools and fluxes. It is one of the surface parameters that can be used in quantifying CO_2 assimilation by plants and the release of water through evapotranspiration. The systematic observation of FAPAR is suitable to reliably monitor the seasonal cycle and inter-annual variability of vegetation photosynthetic activity over terrestrial surfaces. Current operational remotely sensed FAPAR products are mainly derived from medium resolution satellite observations instruments (e.g. MERIS, MODIS and MISR) to provide regional and global operational FAPAR products at a variety of spatial (from hundreds meters to half degrees) and temporal (from daily to monthly) resolutions. In addition to these operational space agency products, various national and international projects, like JRC-FAPAR, GLOBCARBON and LANDSAF, to name but a few, provide additional collections of products using data streams derived from other sensors (such as SeaWiFS, ATSR, VEGETATION or SEVIRI) over up to several years, at the continental or global scale (Gobron and Verstraete, 2009).

The principal objective of the SMOS mission is to provide maps of soil moisture and ocean salinity of specified accuracy, sensitivity, spatial resolution, spatial coverage and temporal coverage. In addition, the mission is expected to provide useful data for cryosphere studies. A novel instrument has been especially developed to make these observations and the objective is also therefore to demonstrate the use of a new radiometer that is capable of observing both soil moisture and ocean salinity by capturing images of emitted microwave radiation around the frequency of 1.4 GHz (L-band). Moisture is a measure of the amount of water within a given volume of material and is usually expressed as a percentage. From space, the SMOS instrument can measure as little as 4% moisture in soil on the surface of the Earth - which is about the same as being able to detect less than one teaspoonful of water mixed into a handful of dry soil (www.esa.int). SMOS produces images with spatial resolution 35-50 km and its revisit time 1-3 days.

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5. Identification of remote sensing based drought monitoring and intervention levels

The goal of this Output 2. is to identify those available and most appropriate remote sensing data and GIS transformation, calibration tools, with which remote sensing based agricultural drought monitoring and yield loss forecast can be implemented. These tools are synthetized into one huge toolbox including landuse, soil physical, meteorological and satellite data integrating them into a model, which can be a feasible tool for plant specific drought risk evaluation.

This model contains several steps from data acquisition, through processing and calibration to risk mapping and evaluation (Figure 1.). There are three main steps:

I. data acquisition and processing,
II. identification and calibration of drought risk levels
III. drought risk evaluation and mapping.

Data acquisition and processing describes how to prepare and transform MODIS NDVI images from raw data for calibration. The calibration is based on yield data and results exact drought risk levels for the concerned plant species. The NDVI data were validated against the regional meteorological drought index values (SPI), and soil physical data related soil water content. The last step is the imagery of the results, implementing of drought risk results on MODIS NDVI images.

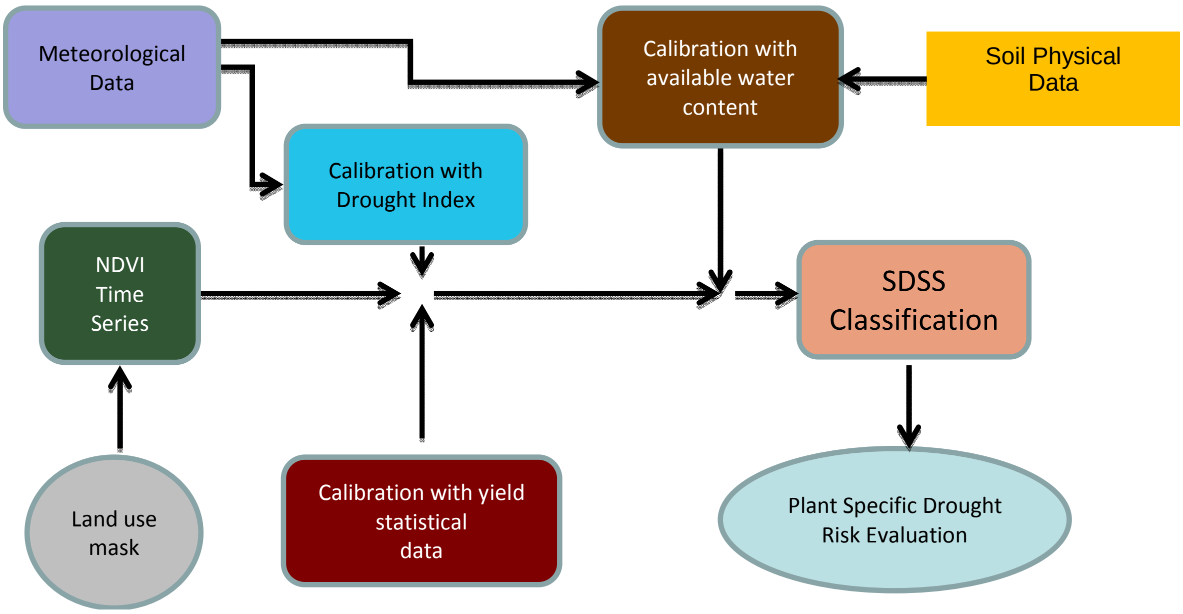

Figure 1. Steps of the process for Plant Specific Drought Risk Evaluation

I. Data processing and transformation

In the case of data processing and transformations five major steps should be done in order to make the NDVI calibration:

- *Reprojection* of MODIS data
- *Mask building* for data extraction
- *Extraction of MODIS NDVI* time series by masks

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- Acquiring *data matrix* from NDVI images
- *Normalization* of extracted NDVI data matrix and yield data

As it was discussed in Output 1, after *reprojection* of the MODIS NDVI data time series, a complex models for mask building and data extraction were established in order to select and delineate arable lands and orchards from the whole Charpathian basin. The reason for selecting the concerned sites was to eliminate the disturbing effect of other landuse categories on NDVI values. ArcGIS 10.2 software was used to create models for the data processing of NDVI images. Boolean mask images were produced for the selection of plain fields and arable lands or orchards with which the MODIS data set can be extracted. The Boolean masks were made based on the CORINE Land Cover (CLC2006) and SRTM 90 m DEM data. After creating these masks, a set of models were created for the extraction of MODIS NDVI datasets. (More details concerning the models can be found in Output 1., Chapter 4.2.)

The models resulted NDVI images, representing arable lands or orchards on plains in a certain region. General result of these NDVI images is that, drought appears at the middle of June in the Southern part of the Tisza river basin, but in the case of East Slovakian Lowland the drought appears in the middle of July and higher NDVI values were detected representing good water supply circumstances in wet years. NDVI values were about 0.5-0.6 in 2003, meanwhile 0.6-0.8 in 2010 in July, and the difference in NDVI values was 0.3- 0.4 in August. Beside the generalities, extracted NDVI images of orchards are suitable for further calibration by yield.

On the other hand the models described in Output, thus the extracted NDVI images cannot be used directly for maize and winter wheat yield loss calibration, because the images represent arable lands and not the production area of the maize and wheat. Therefore further data was needed concerning the production area. Since there is no available data for the exact localization of the production area of maize and wheat, further *mask* models were *built* to separate the winter grains (wheat) and maize from each other.

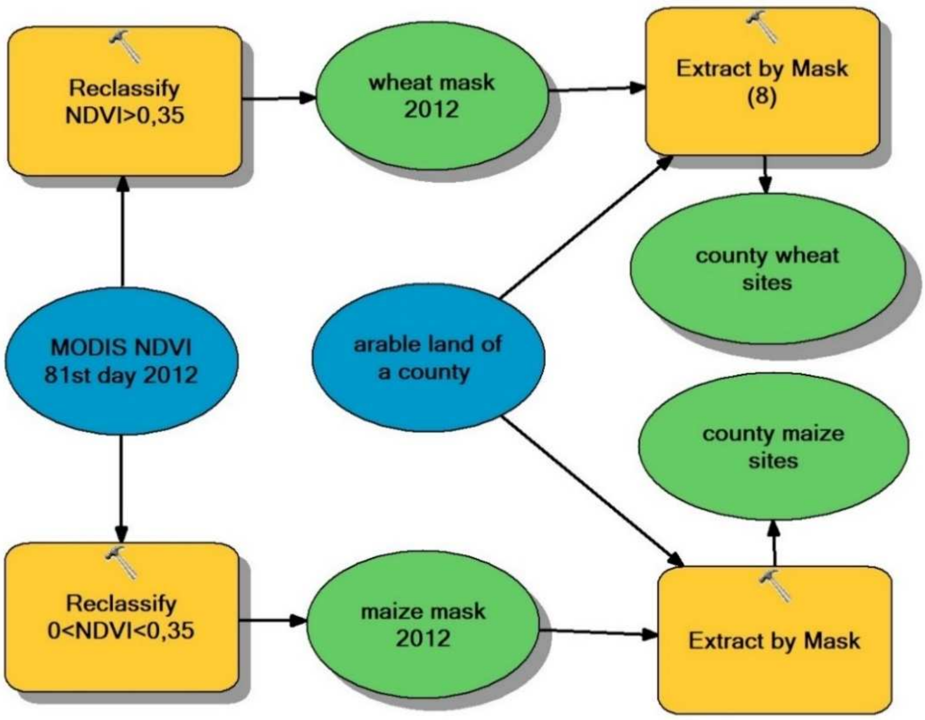

Figure 2. ArcGIS model for creating mask and extraction of wheat and maize site at a ROI

The bases of the mask models was that the winter wheat has ground cover in March, and fields dedicated to maize production is still bare, since the appropriate date for maize seeding is the middle of April on the Great Plain. Concerning crop rotation, NDVI classification process was made for every year, based on the NDVI images representing March, in our case the 81st day of the year. In the case of wheat, sites with 0.35-1 NDVI values were classified to wheat, and sites with 0-0.35 NDVI value were classified to maize. After the classification, two masks were obtained for one year, one for wheat, one for maize. After that these masks were used to extract the sites of a given crop from the county-arable land mask, - produced by model 1. in Output 1. County-arable land mask represents the arable lands of a certain region. As a result, wheat and maize mask were produced for every year for a certain county.

The masks for county wheat/maize sites were then used to *extract the MODIS NDVI images* to get NDVI data for the different crop sites. For masking, new models were built for each years (Figure 3.). The model describes the extraction processes of the MODIS NDVI images for a certain year. This model had to be built for every year and run for maize and wheat sites county by county.

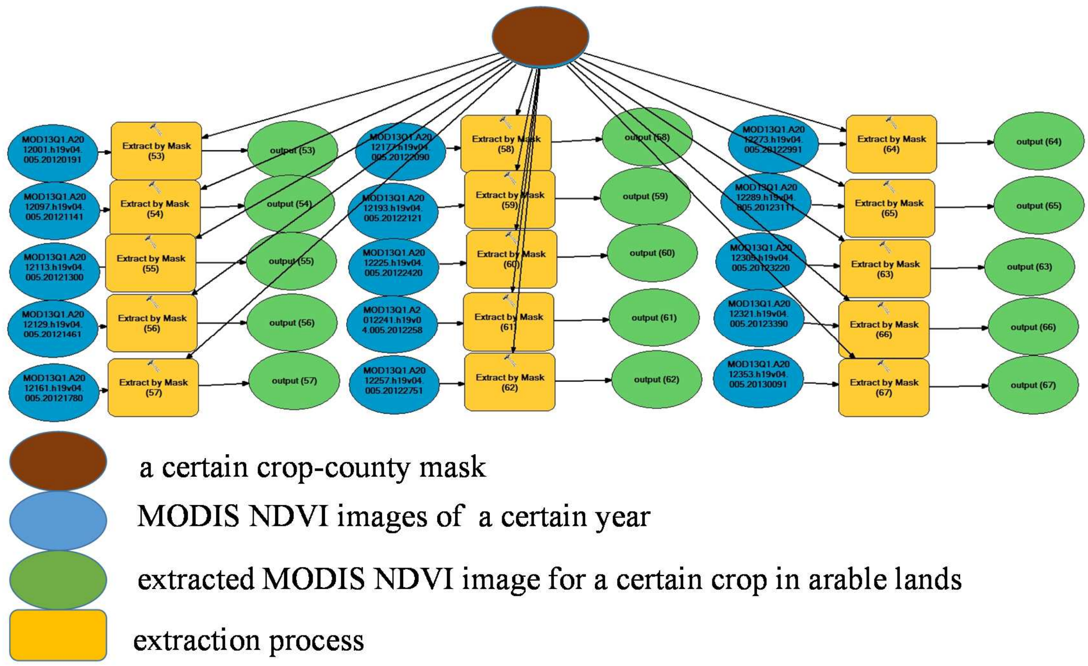

Figure 3. ArcGIS model for extraction process of a certain crop-county mask from MODIS NDVI images

After extractions the main aim was to create the *data matrix* of the mean NDVI values. The mean NDVI values were gathered from every extracted NDVI images, from the whole timescale concerning the ten examined counties (7 counties in Hungary, 2 counties in Slovakia and 1 county in Romania). The collection of mean NDVI values were made in ArcGIS 10.2 software ambient as well, by using band collection statistics tools. The data matrix of the mean NDVI values was the basis of the NDVI image calibration.

Next issue was to harmonize NDVI and yield data (t/ha) which was easily solved by the *normalization* of the datasets. In this way the two datasets became dimensionless between 0-1 values, so that statistics can be made. Normalization was made as follows:

$$\text{Normalized value} = (\text{Value} - \text{Value}_{min})/(\text{Value}_{max} - \text{Value}_{min})$$

where in the case of NDVI images the subscripts max and min refer to the values for dense vegetation and for the lowest vegetation cover. During normalization maximum and minimum values were chosen from the whole NDVI dataset regardless regions of interest. This provides us data uniformity for the whole river basin.

II. Identification and calibration of drought risk levels:

As it was described earlier NDVI based drought risk levels were calibrated by yield and meteorological data. As well as MODIS NDVI time series dataset, yield data is also available from 2000 – 2012. Concerning the yield dataset, in the case of maize and wheat severe yield loss were detected in 2000, 2002, 2003, 2007, and 2012, remarkable yield amount were detected in 2001, 2005, 2006, and average in 2010 and 2011 (Figure 4.).

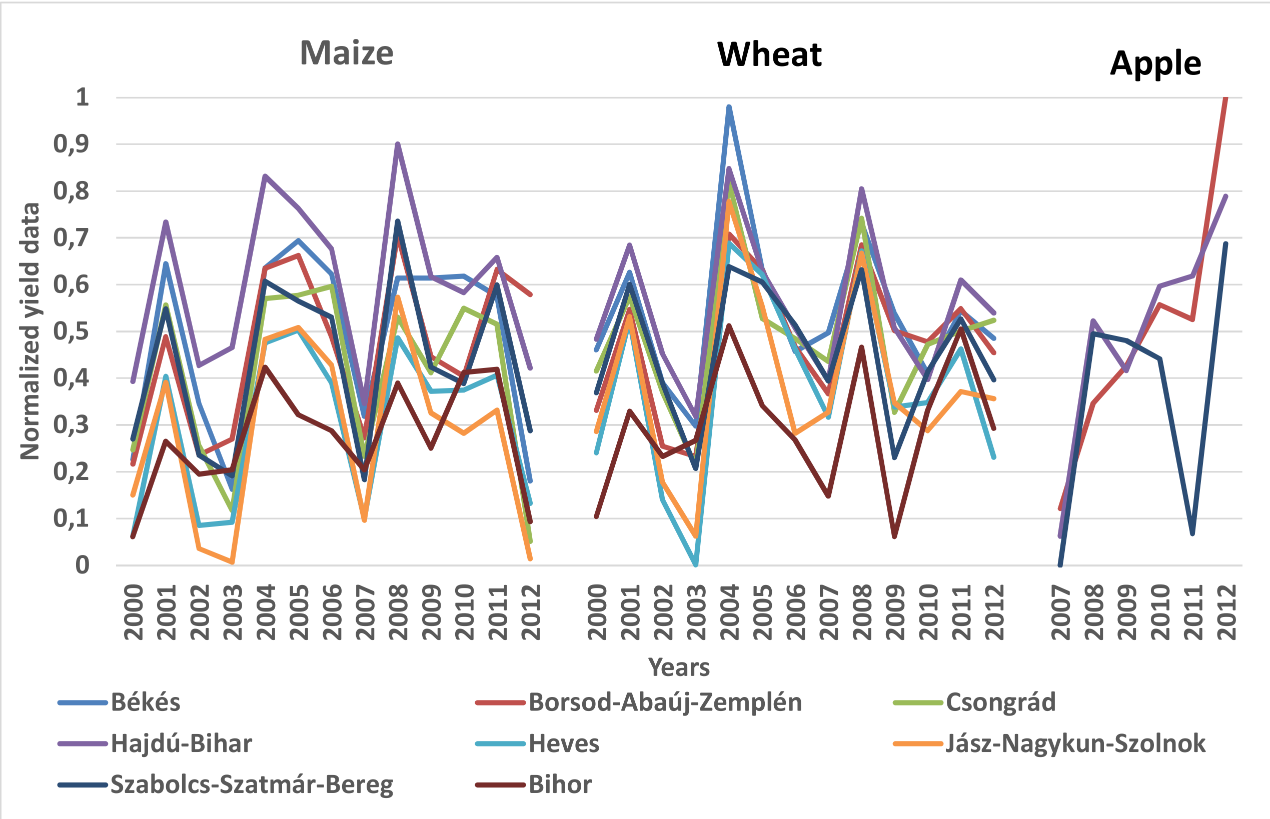

Figure 4. Yield changes of maize, wheat, 2000-2012 and apple 2007-2012 (based on KSH and INSSE data)

These findings are strongly related to the SPI and meteorological data (see as an example in Figure 2.), except for year 2010, when extreme amount of precipitation (900-1300 mm) fell on the plains of the Tisza river basin and due to the surplus water occurrences and diseases the quantity of the yields remained average. Furthermore the weather contributed to the spread of weed coverage. Although drought has very negative effect on apple production, there was no correlation between yield production and drought situation in other years, due to other factor (spring frost or hail damages, diseases).

Beside the fluctuation of yield, yield differences also detected between counties. Regardless the drought situation the largest maize and wheat yield production levels reveal generally in Hajdú-Bihar and Békés counties out of the examined counties, while Jász-Nagykun-Szolnok, Heves and Bihor (Romania) counties showed the worst yield results. The reason for this is the differences in soil characteristics. Hajdú and Békés counties have the highest rates of chernozem soils with very good water management characteristics, while Heves and Szolnok counties have relatively more clay and loamy clay soils, which are very sensitive to drought (Figure 5.).

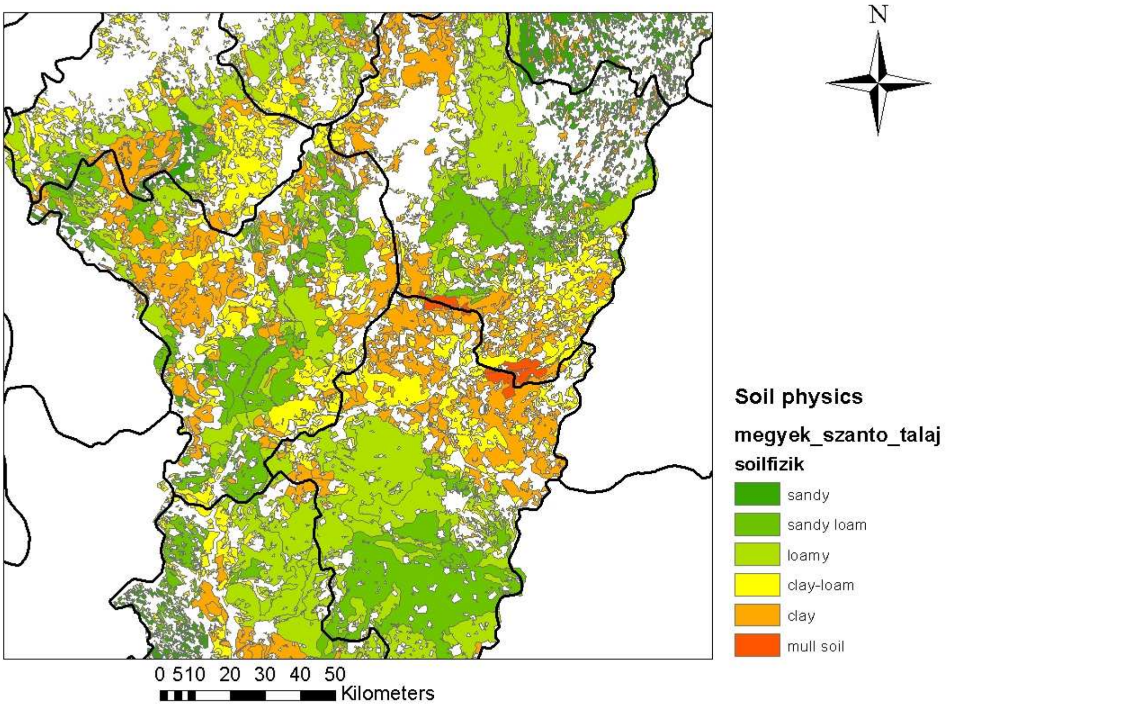

Figure 5. Soils of the concerned counties in Tisza river basin (based on the agro-topographic map of Hungary)

The calibration of NDVI dataset were carried out by calculating correlation and regression between yield and NDVI datasets. Since we had one yield value for one year for each county, but several mean NDVI values could be revealed within a year, first the collected and normalized NDVI datasets had to be grouped. The basis of the grouping was the date within a year, than all the data were arranged to one matrix with data of 13 year. The matrix contained variables for normalized NDVI data in certain dates (the number of variables were different for each plant species based on the vegetation period of the certain crop or fruit) and one variable for the yield. The reason for establishing these matrices was to select those significant normalized NDVI time scale or interval, which can be used for reliable yield or yield loss forecasting. Based on the results significant correlation were found between normalized NDVI values and maize yield from the middle of June, to the end of August, including the most drought sensitive blooming period (July) of this crop. In the case of wheat, only June is found to be reliable for yield prediction and forecasting (Table 1.). These results also suggest, that the effect of soil on yield through the NDVI values appears, if it is not the case, significant correlation cannot be detected at all. On the other hand the fair and moderate correlation can also be explained by the effect of soil. Since we have yield data for counties, and not for catchments or polygons of soil types, yield data represents the effect of various soil type at the same time on the county yield data. The effect of the rate of the major soil type on yield can be detectable.

Table 1. Correlation between normalized NDVI values and yield in the case of wheat and maize

	9-Jun	25-Jun	11-Jul	27-Jul	12-Aug	28-Aug
Maize		0.65*	0.70*	0.69*	0.68*	0.54*
Wheat	0.51*	0.63*				

*significant ($p<0.05$)

Based on the results of linear regressions, yield and descriptive statistics of normalized NDVI, reference spectral curves were generated in order to determine the Watch, Early warning, Warning, Alert

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and Catastrophe levels of normalized NDVI (Annex 1). After generating these reference curves, the normalized NDVI was back scaled and transformed into real NDVI values. As a result of this process, concrete NDVI levels and thresholds could be calculated for yield and yield loss. Since in the case of maize five, in the case of wheat, two dates were significant, NDVI thresholds and signing levels for drought monitoring and yield loss forecast can only be feasible from the middle of June to the end of August for maize, and in June for wheat (Table 2.).

Table 2. NDVI signing and intervention levels

NDVI signing levels	*Watch*	*Early Warning*	*Warning*	*Alert*	Catastrophe
	maize				
25-Jun	0.75	0.72	0.69	0.66	0.64
11-Jul	0.74	0.71	0.68	0.65	0.64
27-Jul	0.74	0.71	0.67	0.64	0.62
12-Aug	0.71	0.67	0.63	0.58	0.56
28-Aug	0.66	0.61	0.56	0.51	0.49
	Watch	*Early Warning*	*Warning*	*Alert*	Catastrophe
	wheat				
9-Jun	0.67	0.64	0.61	0.59	0.56
25-Jun	0.62	0.59	0.55	0.52	0.49
Yield loss	*0-10%*	*10-20%*	*20-30%*	*30-40%*	*40%<*

It has to be mentioned, that the genetic potential of different species or hybrids can highly influence yields. Earlier species of maize has less yield than those which mature in autumn (Table 3.). However, it has to take into consideration, that later ripening species or hybrids enhance the risk of yield loss, because their blooming period is directly in the middle of the most drought risk affected summer months.

Table 3. Ripening of different maize species and hybrids

Ripening group	FAO number	Length of vegetation period (day)	Ripening (month)
Very early	200-299	130-140	the end of Aug. - the beginning of Sept.
Early	300-399	140-150	middle of Sept.
Middle	400-499	150-160	the end of Sept. - the beginning of Oct.
Late	500-599	160-170	middle of Oct.

There is also a need to understand that why significant correlation can only be found in the middle of and the final phenological phase of the crops. The answer is in the recover ability of plants. The later the droughts appear, the less is the possibility of the recovery of a certain crop. For example if the emergence of wheat are weak or there is a period of drought in early spring with wet autumn, there is still a possibility to have good wheat yield, if there was enough rains in winter or in the e second half of spring.

In the case of apple production significant correlations were not found at any date between NDVI and yield between. On the other hand, the effect of drought on NDVI value decrease are obvious.. In July NDVI values were about 0.6-0.7 in 2007, meanwhile 0.7-0.8 in 2008, and in August the average difference NDVI was 0.05- 0.1. (Figure 6.). Thus NDVI images cannot be used for yield forecast and estimation of apple orchard, but can be feasible for general drought detection. The reason is very complex. Beside lack of precipitation several other factors can significantly influence the yield. These factors are mostly climatic. In some of the examined years there were severe freeze damages in early spring, which caused decrease in yield. Another typical problem in summer is the hail damages. These are hardly detectable through NDVI images because of the regeneration of the trees.

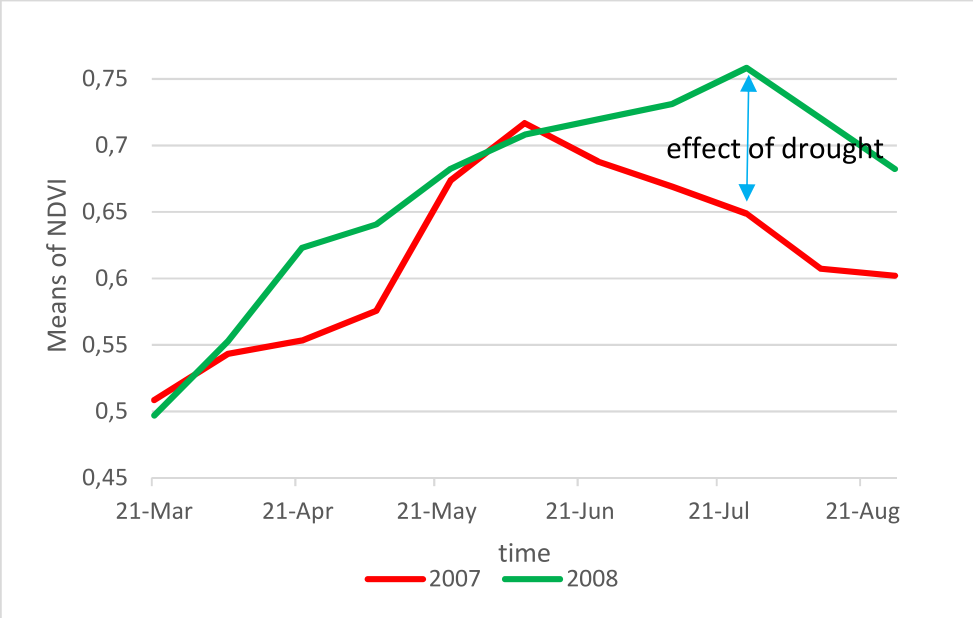

Figure 6. The effect of drought in orchards on NDVI (calculated based on own data)

There was special circumstance in 2010, when the amount of precipitation was nearly twice as much as the long term average annual precipitation, thus the excess water and pathogen agents had also negative effect. Beside this, the emerging weed coverage in the row spaces causes also a problem: it enhances the NDVI value strongly influencing the success of yield estimation. Furthermore, the spatial resolution of the MODIS image (250 m) is not able to represent the plantation structure of an orchard. Only images with large spatial resolution (<1m^2) can be a solution for orchard yield detection, monitoring and yield loss forecast.

After calibrating NDVI by yield, the validation was made by meteorological data as well. Higher yearly mean temperature and less precipitation (Annex 2.) cause an earlier vegetation cycle. Concerning this and regarding climate change, we can expect lower yearly average NDVI values in the future for Tisza river basin. The large NDVI values tend to occur in wet conditions, while low NDVI values imply warm-dry climate conditions. This phenomenon regarding to the NDVI values is mainly observable in August: i.e. average year, excess water and/or drought hazarded extreme year. From the agricultural point of view and because of being one of the input data of several drought indices, such as SPI, soil water content were used to calibrate NDVI data. According to the results, moderate significant correlation (r^2=0.62 p=0.008) was found between available soil water content and NDVI values. These moderate values highly due to the origin of soil moisture data, which were based on soil samples. Thus these point data cannot represent properly a site, or larger, heterogeneous area.

III. Drought risk evaluation and mapping

After the yield loss specified signaling levels of drought identified, the implementation the results were carried out. The evaluation of yield loss specific drought risk levels was generally based on classification and mapping of MODIS NDVI images and identification of the most drought effected region by calculating the area of the sites with different drought risk levels.

Within the drought risk evaluation and mapping deliverables the purpose of the results is suitable for identification of drought affected sites and the delineation of drought sensitive areas, forecasting of yields in the case of extreme drought situation at a certain place and calculation of possible yield loss.

Drought maps were generated by the classification of the NDVI image based on the drought risk levels. Mapping were made for a drought affected year with severe yield loss and for a year with good meteorological circumstances with average yield. Drought risk evaluation and mapping of yield loss were carried out for maize and wheat in 2003 and in 2008 (Annex 3. and Annex 4.). The yield loss forecast were based on the NDVI image from 6th of June for heat, and 1th of July for maize. The drought risk maps show the spatial distribution of yield loss pixel by pixel for the whole production area in Tisza catchment. There can be seen the severe different in yield loss between the drought affected, and not affected year. Since the drought risk map is raster, first the vectorization should be made, in order to calculate the area. Before area calculation sites with the same drought risk category has to be merged to achieve one polygon for each risk category. After that the rates (%) of different drought risk affected sites and yield loss were also calculated for both wheat and maize. (Table 4.).

Table 4. Rates (%) of different drought risk affected sites for wheat and maize (100% is the concerned investigated area

	2003 (drought affected)				**2008 (average year)**			
Risk levels	Tisza catchment (T.c.)	Hungarian part of T.c.	Jász-Nagykun-Szolnok	Hajdú-Bihar	Tisza catchment (T.c.)	Hungarian part of T.c.	Jász-Nagykun-Szolnok	Hajdú-Bihar
	Wheat (area %)							
Catastrophe	38.44	45.38	59.08	34.80	11.99	13.42	15.73	4.77
Alert	8.25	8.27	7.84	7.70	5.05	5.23	5.40	3.30
Warning	8.29	7.96	6.99	8.03	0.45	4.41	4.62	3.04
Early Warning	10.59	9.75	7.50	10.69	8.30	8.09	8.75	6.13
Watch	7.18	6.42	4.51	7.82	10.14	9.69	10.57	9.06
No yield loss	27.25	22.22	14.07	30.96	64.07	59.15	54.92	73.70
	Maize (area %)							
Catastrophe	51.77	51.86	66.06	20.92	24.54	19.85	21.24	10.74
Alert	2.94	8.06	2.11	1.80	2.78	1.90	2.15	1.27
Warning	8.93	8.11	6.62	7.03	9.92	6.87	6.92	4.97
Early Warning	8.93	7.83	6.46	8.92	11.90	8.83	9.73	6.77
Watch	8.38	2.51	5.99	10.18	12.46	10.61	11.52	9.54
No yield loss	19.05	21.63	12.76	51.16	38.39	51.94	48.44	66.70

In the case of wheat the exact rate of drought risk was calculated, thus the severe differences between the years can easily be identify numerically. This identification is also appropriate for detecting the differences between sites, or regions and even between catchment. In that case, we calculated the drought risk situation for Jász-Nagykun-Szolnok (JNSz) and Hajdú-Bihar (HB). The reason for selecting these counties is that even in drought affected years, Hajdú-Bihar had the best, and Jász-Nagykun-Szolnok gave the worst results for yield. The results of the risk map resulted the same, since in 2003 a little less than 60% of JNSz area had catastrophic wheat yield production (more than 40%), on the other hand “only” the 35% of the area of HB was catastrophic. The same results can be found in 2008 as well, and HB has far better results in “No yield loss” in both years. This statement can be made in the case of maize as well, but the differences between the counties are much larger, than in the case of wheat. The reason for this is the differences in soil characteristics; the rate of sandy and very often salt effected clay soils with bad water management and waterholding capacities are huge in JNSz, and much less in HB. The soil caracteristics appears in biomass, thus in NDVI value. The result suggest, that JNSz county is much more sensitive for droughts, than other counties. In this way, drought sensitive sites can be easily selected based on NDVI data.

This new drought risk monitoring and yield loss forecasting method is an improvement for hydrologists, meteorologists and farmers, allowing to set up a complex drought monitoring system, where for a given period and respective catchment area the expected yield loss can be predicted, and the role of vegetation in the hydrological cycle could be more precisely quantified. Based on the results more water-saving agricultural land use alternatives could be planned on drought areas.

6. Drought related soil moisture regime

Beside soil taxonomic data, analogous and digital conventional soil maps contains several indirect parameters (e.g. organic material content, clay content, particles distribution, pH), which are important from agriculture and water management point of view, but these parameters cannot be used for direct investigation of agricultural drought (Klute, 1965; Buzás, 1993; Fulajtár, 1998). On the other hand soil maps are necessary to know the physical characteristics of drought effected sites.

The soil map is generally 2 dimensional surface model abstraction of real soils, where depth represented by point based soil boreholes (Tóth et al., 2013). This mean volumetric approaches is ignored or limited by soil scientist and water content of root zones have not been mapped directly. If we like to know water content volumetric storage capacity of soil layers, we need modelling and calculate on watershed level. It was real pioneer task, because till now this important hydrological parameter data was only estimated. Of course we consider all applicable information and methods to build our integrated GIS data to calculate drought related soil moisture regime.

The first scientist were called Russian school (Mendelejev, Dokuchaev, Sibirtsev, Glinka) dated back XIX. century (Glinka, 1927). The soil maps of Central –European countries used this methods with special taxonomical nomenclature. This is an important limiting factor to build trans-border soil maps, which can describe soil water regime to analyze agricultural drought risk.

The modern soil (diagnostic) classification map systems from FAO-UNESCO system (FAO, 1994) are focusing on soil-forming factors-processes -diagnostic horizons and properties to describe a soil taxonomic unit.

The increasing need for internationally accepted rules and systems of soil description and soil classification led to the development of various soil classification concepts, e.g. the FAO–UNESCO Legend for the Soil Map of the World (FAO, 1998) and USDA Soil Taxonomy (Soil Survey Staff, 2003), and soil maps, e.g. SOTER (SOTER, 1995) Soil Atlas of Europe (eusoils.jrc/ec/Europa/eu). The FAO guidelines provide a complete procedure for soil description and for collecting field data necessary for classification according to second edition of the World Reference Base for Soil Resources (WRB) (WRB, 2006).

The term Reference Base is connotative of the common denominator function that the WRB assumes. Its units have sufficient width to stimulate harmonization and correlation of existing national systems. The Reference Base is not meant to substitute for national soil classification systems but rather to serve as a common denominator for communication at an international level. This implies that lower-level categories, possibly a third category of the WRB, could accommodate local diversity at country level. Concurrently, the lower levels emphasize soil features that are important for land use and management (FAO, 2006).

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Based on the abovementioned, it is obvious, that the transformation of national soil maps and their digital renewals to international word soil maps is a very complex strongly because of different explanations results various representations and translations of soil data.

In this project the pilot phase of digital transformation of four countries (Romania, Hungary, Slovakia and Ukraine) to WRB system was performed. On the other hand we had the opportunity to use the guidelines of JRC to calculate the soil moisture regime for the whole Tisza river basin. This method will be used for the calculation of the soil moisture regime of other CEE country.

Similarly to other countries in EU, attributive data for mapping of agricultural drought risk and decision support are available, but many preparation is needed to accomplish a uniform GIS environment, since these data and maps are generated in different scale with various soil bonitation methods. In correspondence the certainty of these data differs from each other. Hungarian soil classification is based on soil genesis and geography. We described our main soil types with the WRB2006 reference soil groups' names. Digital Soil Mapping technology is widely use GIS method to modeling 3D soil environment however identification, understanding and unification of different colour codes and annotations is a further challenge. The differences between projections of maps has to unify as well to UTM or WGS-84 system.

During the GIS work of soil mapping those investments, results and data were used, which were published by the European Soil Portal in ArcMap and Google Earth software environment. This insures that our databases will be compatible harmonized and joined to other European databases, and can be shared with other users through the data server of European Soil Bureau Network.

The European Soil Portal is the joint contribution of the European Commission and European Soil Bureau Network (ESBN), is the place in which all relevant data and information regarding soils at European level has been located. The activities (as well our activities too) related to this portal are in line the INSPIRE (Infrastructure for Spatial Information in Europe) initiative. INSPIRE deals, among others, with difficulties to identify, access and use available drought related spatial information in Europe. On the Figure 7. the interpretation of the Tisza catchment and the INSPIRE compatible metadata of a map can be seen.

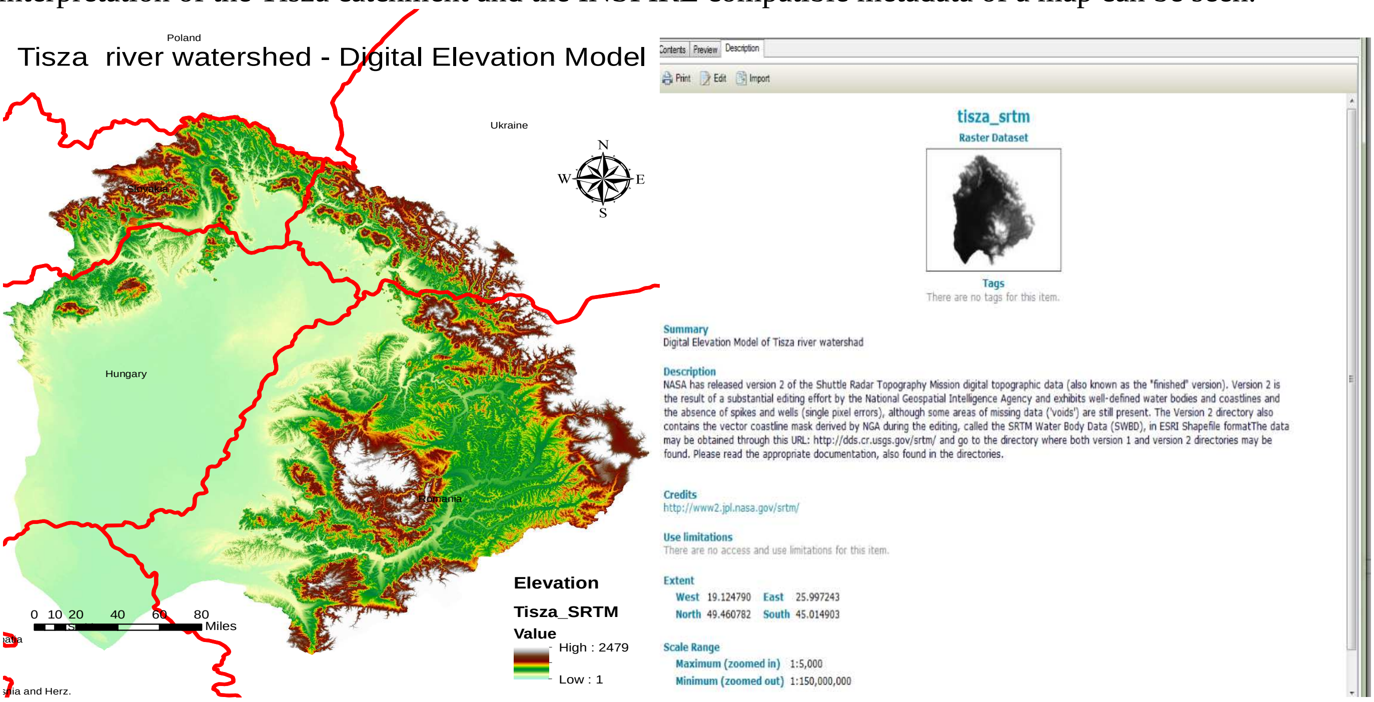

Figure 7. The study area and INSPIRE compatible spatial metadata

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As it was mentioned earlier that conventional soil maps cannot be used for direct investigation of agricultural drought. Recalculations and estimations should be made for unify data based on similar taxonomic parameters, The soil genetic maps considers the depth of soils on the basis of soil surveying results of the main reference soil types in the soil vertical horizon. The latest pedo-transfer soil regression models uses the data of these sample horizon for the investigation of soil water management of not sampled soil plots as well. Although there are several differences among the algorithms concerning parameters or the way of applications (Ahuja et al., 1985; Lamorski et al. 2008; Nemes et al., 2008; Rajkai et al., 2004). The Joint Research Centre (JRC) of the European Commission published a soil science guideline of database construction for pedo-transfer calculations, which can be a used for construction of agricultural drought risk based on digital soil data (Tóth, 2013; Makó et al., 2007).

Regarding soil moisture calculations there is no obvious recommendations in agricultural water management for reference soil depth. In irrigation management root depth is conventional, which considers the rooting depth of a specific corp. However it is obvious from agro hydrological point of view, that the spatially and temporally continuously changing actual and real rooting depth, thus utilized soil volume can be determined with high uncertainty in a watershed due to the high variation of crop rotation and agrotechnical processes. Therefore, as a simplification, water resource is calculated for the soil layer of a specific soil type. This can be 0.5 or 1 m deep soil layer in the case of shallow soils, but most of the crops in a crop rotation has the ability to access water from the upper 2 meters depth layer from deeper soils. Therefore 2 meters depth soil layer is recommended to be reference depth.

In our study, the calculations for water resources and supply are also concerned to 2 m soil layer. This statement is confirmed by the fact, that as a cumulative effect of drought serial for years root of crops grow deeper and deeper for accessible water sources, and the depth of the drought effected soil layers grows at the same time. (Certainly this reference depth can be 5-10 m in forestry)

Since this upper 2 m layer is not homogenous, the types of sub layers has to be identified. Furthermore, hydraulic conductivity and the transport processes between layers are also important to know. On the other hand many local point based crop models (water capacity models) often consider reference soil layers as homogenous ones (Allen, 1998).

In our study 1:100 000, 1:500 000 digital soil maps (Fulajtár and Curlik, 1980; Svoboda, 1965; Hrasko et al., 1973; Florea, 1971) were used, where national soil nomenclatures of Central European countries were transformed into the European JRC WRB taxon. Figure 8. shows the attributive data of the Romanian soil map with WRB codes.

Table

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FID	Shape *	Denumire	Denumire 2	Denumirea	caracteris	caracter 1	material p	Relief	ClasaSol	ApaFreatic	ExpTextura
0	Polygon	Bors	Faeoziom	Cernoziom cambic		gleic	depozite fluviatile	campie	1. Cernosoluri	1 - 1.5 m	Lut argilos
1	Polygon	Bors	Gleiosol	Lacoviste	cambic	gleic	depozite fluviatile	campie	4. Hidrosoluri	1 - 1.5 m	Lut
2	Polygon	Bors	Cernoziom	Cernoziom		gleic	loess	campie	1. Cernosoluri	1 - 1.5 m	Lut argilos
3	Polygon	Bors	Faeoziom	Cernoziom cambic		gleic	loess	terasa	1. Cernosoluri	1.5 - 3 m	Lut
4	Polygon	Bors	Gleiosol	Lacoviste	cambic	gleic	depozite fluviatile	campie	4. Hidrosoluri	1 - 1.5 m	Lut
5	Polygon	Bors	Gleiosol	Gleic	mlastinos	gleic	depozite fluviatile	lunca	4. Hidrosoluri	< 1 m	Lut argilos
6	Polygon	Bors	Cernoziom	Cernoziom		gleic	loess	campie	1. Cernosoluri	1 - 1.5 m	Lut argilos
7	Polygon	Bors	Cernoziom	Cernoziom		gleic	depozite fluviatile	campie	1. Cernosoluri	1 - 1.5 m	Lut argilos

Figure 8. Attibutive data of the Romanian soil map with WRB codes (Denumarire2)

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Since the attributive data table of the both map types (JRC WRB and national maps) contained the code columns for soil types this column can be used secondary key to merge the tables together. Thus on row of this table includes the JRC WRB and national soil data of the concerned soil plot (Table 5.).

As a result of this data transformation, the higher spatial resolution of the national maps were preserved transforming them to a common nomenclature. Concerning the PTRDB values saturated water content (SWC) at pF 0, field capacity water content (FC) at pF 2.5, minimum water holding capacity MWC at pF 2 and water resources at wilting point (WP) at pF 4.2 were assigned to the soil plots. Hhydraulic conductivity (mm/d) were also assigned for the characterization of water transport between layers. These maps make the calculation water resources possible in different soil layers in different soil plots.

Table 5. Attributes of the JRC WRB map - PTRDB (Pedotransfer Rules Database) (http://eusoils.jrc.ec.europa.eu/)

AGLIM1NNI = Dominant limitation to agricultural use (without no information).	AGLIM2NNI = Secondary limitation to agricultural use (without no information).	ALT = Elevation
AT = Regrouped accumulated mean annual temperature class (ATC) (source: JRC-MARS)	AWC_SUB = Subsoil available water capacity.	AWC_TOP = Topsoil available water capacity.
BS_SUB = Base saturation of the subsoil.	BS_TOP = Base saturation of the topsoil.	CEC_TOP = Topsoil cation exchange capacity.
CRUSTING = Soil crusting class.	DGH = Depth to a gleyed horizon.	DIFF = Soil profile differentiation.
DIMP = Depth to an impermeable layer.	DR = Depth to rock.	EAWC_SUB = Subsoil easily available water capacity.
EAWC_TOP = Topsoil easily available water capacity.	ERODIBILITY = Soil erodibility class.	HG = Hydrogeological class.
MIN = Profile mineralogy.	MIN_SUB = Subsoil mineralogy.	MIN_TOP = Topsoil mineralogy.
OC_TOP = Topsoil organic carbon content	PD_SUB = Subsoil packing density.	PD_TOP = Topsoil packing density.
PEAT = Peat.	PHYS-CHIM = Physico-chemical factor of soil crusting & erodibility.	PMH = Parent material hydrogeological type.
STR_SUB = Subsoil structure.	STR_TOP = Topsoil structure.	TD = Rule infered subsoil texture.
TEXT = Dominant surface textural class (infered).	TEXT-CRUST = Textural factor of soil crusting.	TEXT-EROD = Textural factor of soil erodibility.
USE = Regrouped land use class.	VS = Volume of stones.	

The area of the soil plots were also calculated, thus the layer volume could be calculated as well. For this layer volumes SWC, WP, FC contents were calculated. After that the total available water content TAW was also calculated by SWC-FC (Figure 9.).

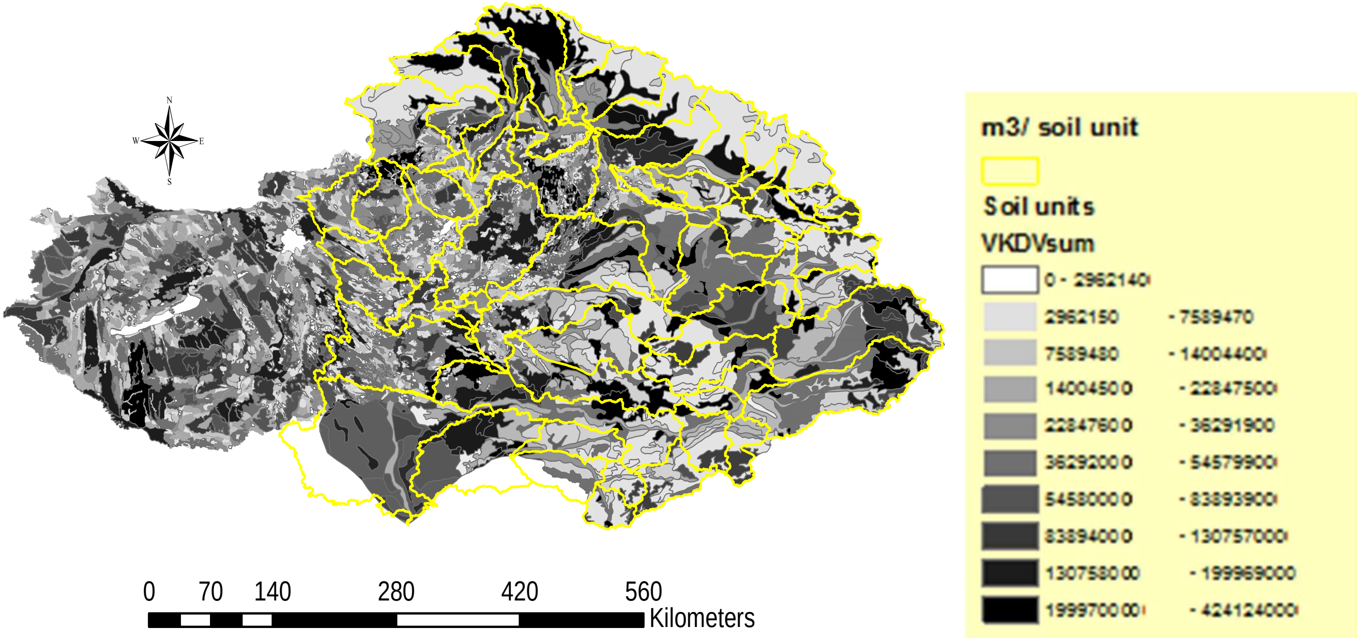

Figure 9. Available soil water content in 2 m depth soil layer

Eventually all of the water management parameters were totalized for 2 meters soil depth resulting a water resources map of Tisza watershed (157233,5 km^2) for concerned soil types (Table 6.). (Yellow lines indicate sub watersheds of Tisza.)

Table 6. Water resources of Tisza watershed

The volume of Tisza watershed of 2 m depth soil layer	Water resources of Tisza watershed (157233,5 km^2) in 2 m depth layer			
	MWC	FC	SWC	TAW
314,233,500,879 m^3	45,317,821,409 m^3	93,989,133,731 m^3	109,126,574,792 m^3	48,730,896,750 m^3
314 km^3	45.32 km^3	93.99 km^3	109.13 km^3	48.73 km^3
100%	14.4 %	29.9 %	34.7 %	15.5 %

As a result this is the first time to calculate the water resources and supply of watersheds or regions based on water management parameters of high resolution soil data by using different GIS SQLs. These information has been missing from hydrological calculations or evaluated them with high uncertainty. As a summary, the following steps were made:

- Transformation of national soil genetic codes to WRB
- Definition of soil layers
- Data upload of layers for 2m depth
- Upload of soil physical data of layers (with regard to impermeable layer)
- Calculating water resources of layers (SWC, WP, FC and TAW)
- Calculating totalized water resources for soil plots
- Spatial query of watersheds and regions
- Cartographic identifications (legend etc.)

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These data were fitted in a geographic information system, in which the data clearly showed that the impact of drought were more severe in extreme water management soils (for example sandy soils which have low water capacity, extreme heat management; and clay, heavy clay soils which have low available water content and high swelling - shrinking capacity). However loamy soils (with good water management) have enough available water content for plants in case of moderate severity of meteorological drought, which can buffer the yield loss due to the drought.

Our calculations can not take into account local differences caused by flash floods, permanent water cover, high salt content and stagnant groundwater or nearly impermeable or compacted clay layers. Due to the lack of detailed and local measurements of these local differences the error values can not be mapped considerably. In case of large-scale long-term droughts, local differences decreased the reliability of the calculations to a lesser degree. However, with further methodological development, the effect of these local differences can be reduced.

Considering the lack of data on soil water resource and capacity of watersheds, our calculations are significant development in better understanding of droughts risk from hidrological and soil characteristics point of view.

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Annexes

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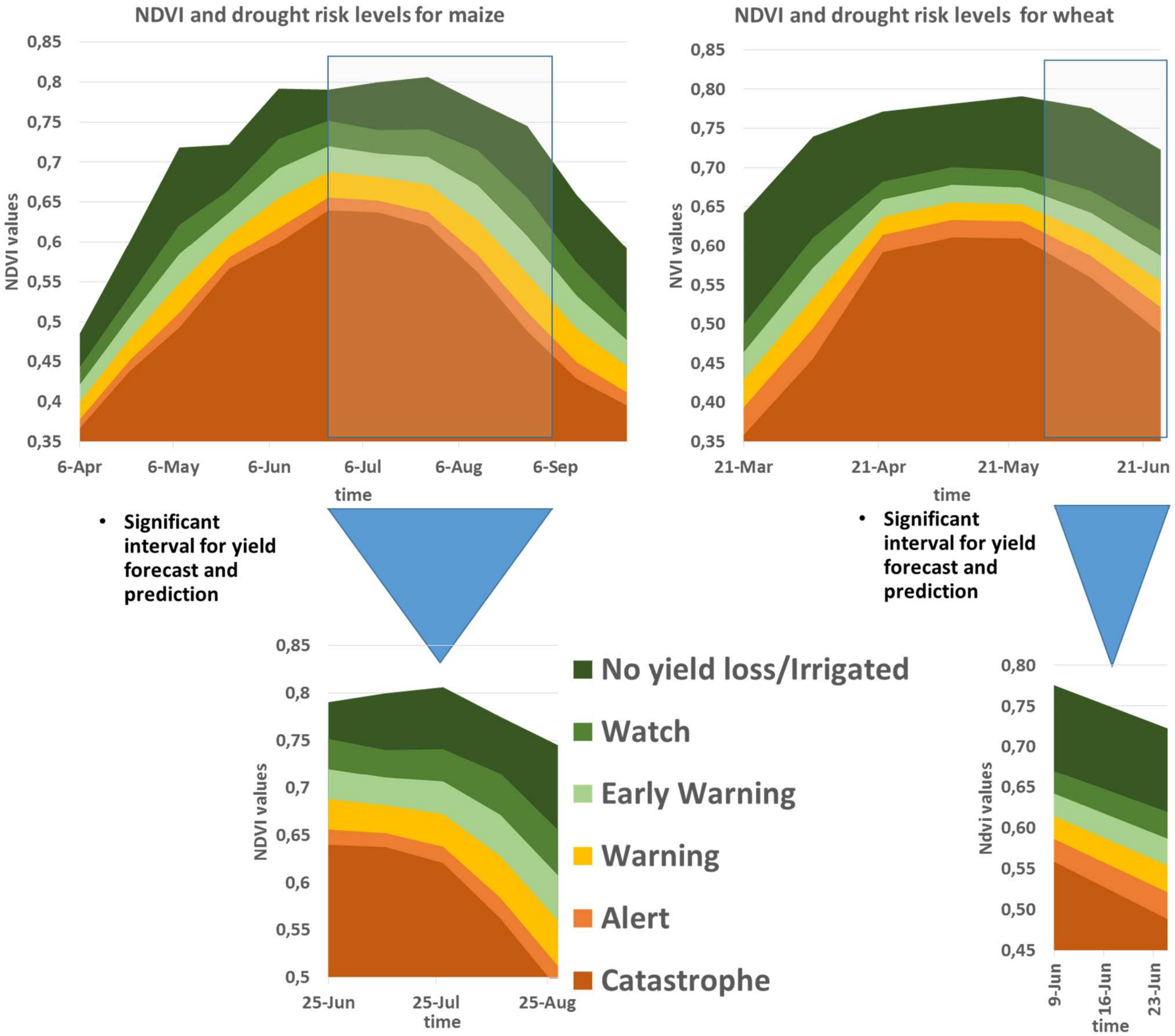

Annex 1. Drought risk and signaling NDVI levels for maize and wheat (calculated based on own-data)

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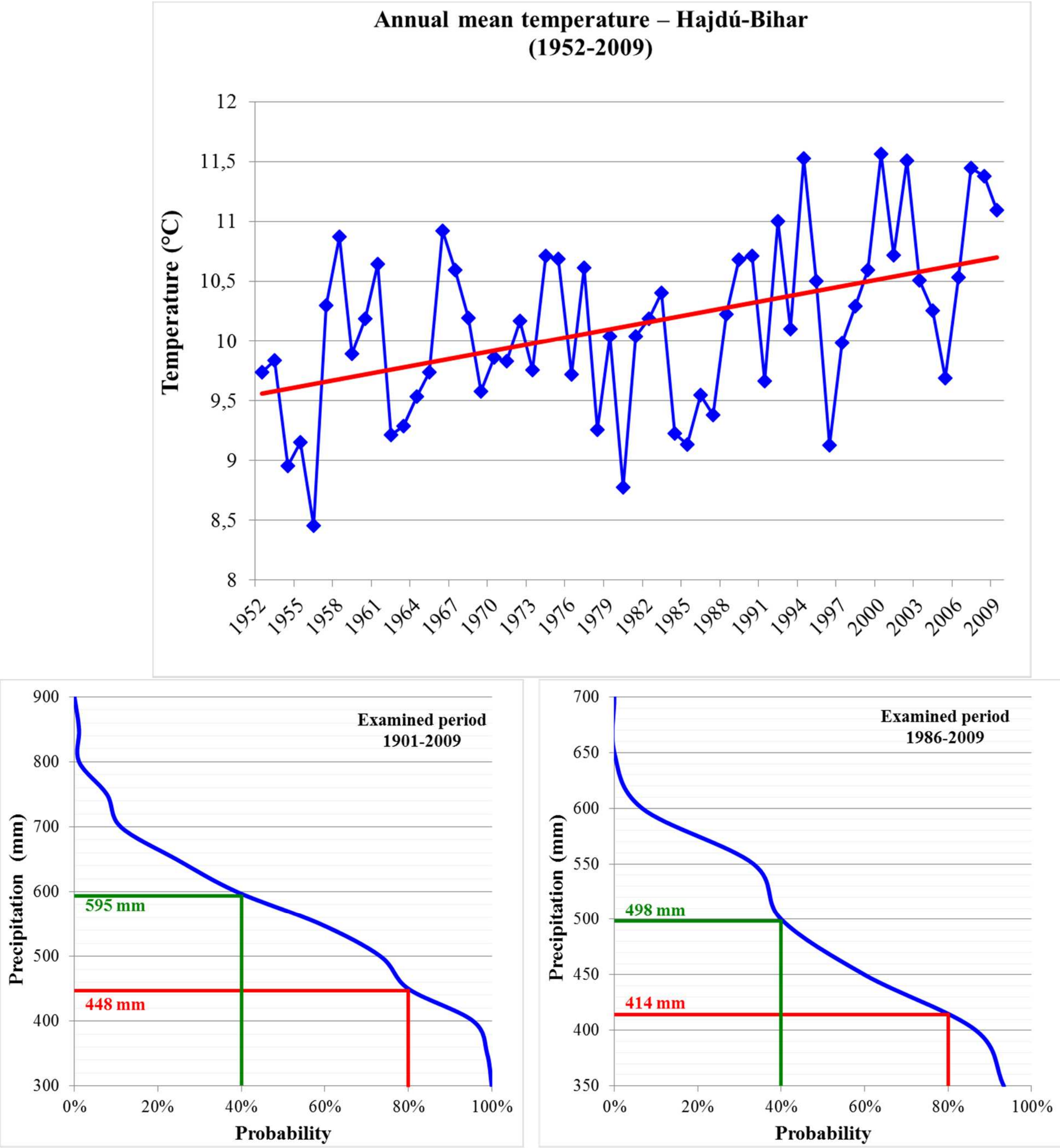
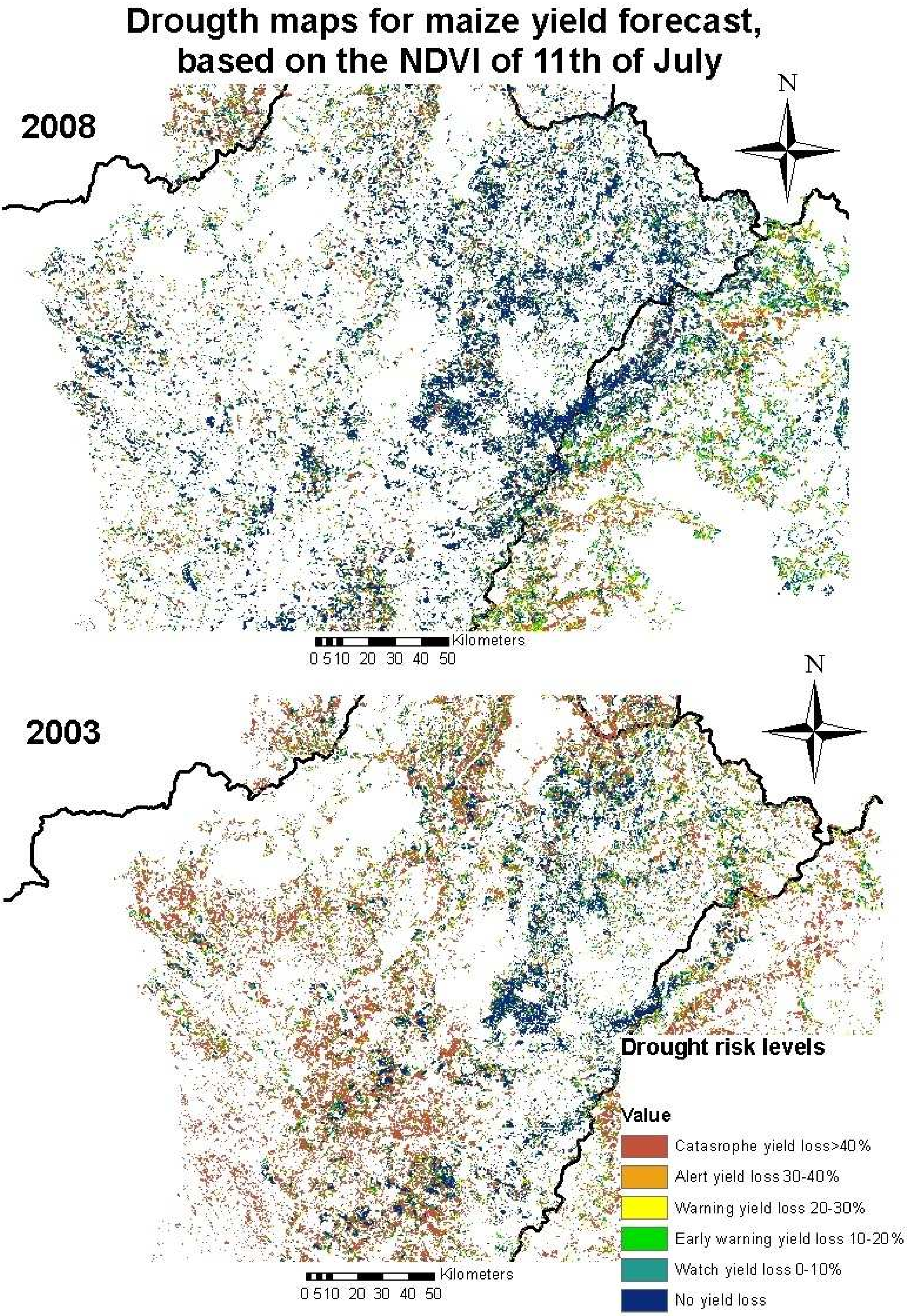


Annex 2. Changing average temperature and annual precipitation frequency in Tisza river basin (calculated based on OMSZ data)



Annex 3. Drought maps for maize in Tisza river basin (calculated and mapped based on yield calibrated MODIS NDVI)

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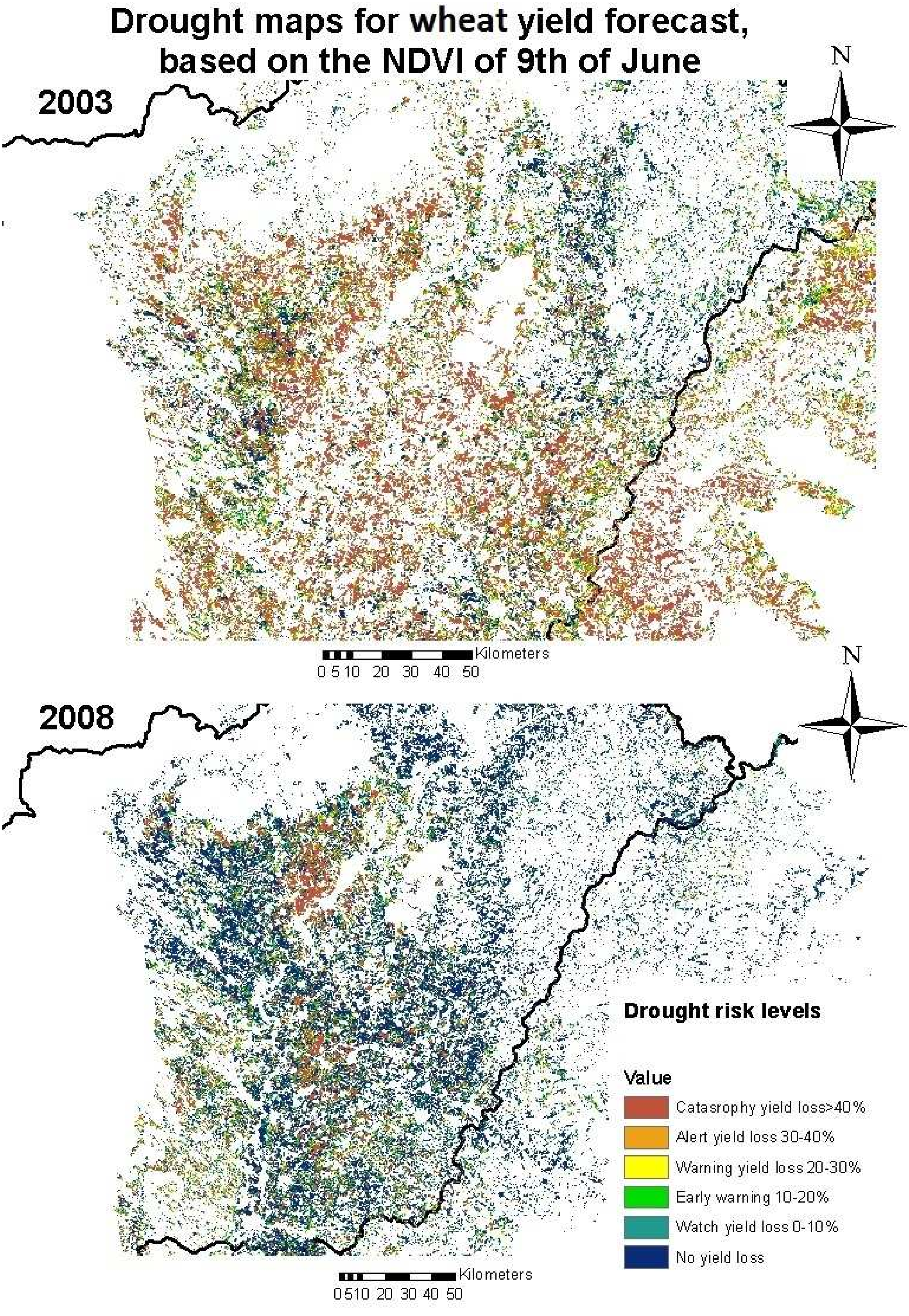

Annex 4. Drought maps for wheat in Tisza river basin (calculated and mapped based on yield calibrated MODIS NDVI)

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