Interreg
Danube Transnational Programme
DriDanube

Deliverable

4.2.2. Algorithm for impactforecast

WP	4
Activity	4.2
Activity leader	
Number and name of the deliverable/output	D. 4.4.2 ALGORITHM FOR DROUGHT IMPACTS FORECAST
Participating partners	CZECHGLOBE
Type of the deliverable/output (analysis, report, guideline, workshop, brochure, etc.)	REPORT INCLUDING METHODOLOGY
Purpose of the deliverable/output	PREPARE METHODOLOGY FOR ANALYSING IMPACTS
Connection with other deliverables	DELIVERABLES FROM ACTIVITY 4.1
Start date	01.03.2017
End date	30.06.2018

Contents

Introduction

The aim of the 4.2 activity is to prepare a common methodology for near real-time drought impact forecast and test it and introduce it to all participating countries. The methodology is based on an extensive database of drought impacts in the past (with special focus being paid to period from 2000). It is being developed to be closely linked to functionalities in the User Service for collecting impact data in near-real time. Methodology and consequently the manual is being verified in all countries. Existence of common methodology for reporting and forecasting impacts is essential for the establishment of drought impact monitoring and forecasting system.

Drought has been described as a natural phenomenon that results mainly from deficiencies in precipitation compared to the expected or normal amount (Wilhite 2005). When compared to other natural disasters, droughts have the largest spatial extent and longest duration (Sheffield and Wood 2011) and tend to develop slowly and persist over several years and can reach national (e.g. Zink et al. 2016) to continental spatial coverage (Svoboda et al. 2002, Samaniego et al. 2012). As described by Brázdil et al. (2016), droughts may have dramatic socio-economic consequences, including famine, epidemics, socio-political unrest and human migration (Heim 2002, Mishra & Singh 2010). The recent drought episodes in Russia in 2010 (Trenberth & Fasullo 2012), USA in 2011−2012 (Hoerling et al. 2014), China in 2013 and Brazil in 2014 were, for each particular year, among the 10 natural disasters worldwide with the highest recorded damage (Munich Re 2015). A series of recent droughts sparked widespread research activity leading to deployment of high resolution drought monitoring schemes in the Czech Republic (post 2012 drought), Germany, Austria and Slovakia (post 2015 drought). This is understandable as the economic damage caused by droughts is comparable with floods. These are the two most disastrous natural events that affect this region.

Droughts have impacts on many societal sectors including agriculture, forestry, water resources management, energy generation, and health. Their impacts can be divided into direct and indirect impacts (Wilhite et al. 2007) with direct impacts including among others reduced crop yield and forest productivity, increased forest fire hazard, reduced water levels, and increased mortality rates for livestock, wildlife and fish. The direct effects are usually driving a societal response (e.g. Brázdil et al. 2016) aimed at improving drought resilience of the particular region. Such events lead to response in terms of legislature (e.g. after the 1947 drought in the Central Europe (Brázdil et al. 2016) or the introduction of the drought monitoring systems such as the establishment of the U.S. Drought Monitor after major drought events in the late 1990´s (Svoboda et al. 2002)). An example of indirect drought impacts are volatile food prices, potentially exacerbated by market effects in the agricultural sector. As a result, it is difficult to estimate the total costs and losses at the regional and national levels. Indirect losses of droughts often exceed those of the direct ones (Wilhite et al. 2007), but they are more difficult to be linked with the particular event especially in the more affluent countries where direct impacts seem to attract the most attention.

Within DriDanube project activity we primarily focus on an effort to cover near real time monitoring of agricultural drought together with sings of meteorological and hydrological aspects of it.

Methods

Database of drought impacts

The database contains information about the impacts of drought episodes in all countries whose representatives have provided relevant background material. It is therefore a data from the following countries: Austria, Bulgaria, Czech Republic, Hungary, Montenegro, Croatia, Romania, Serbia, Slovakia and Slovenia. The data usually comes from two different sources - from newspaper articles in one selected national source and from one thematic journal. The tables summarize data from both available sources.

The table covers the period 1981 to 2017, but for most countries, information has been available since 2000. In each country, impacts are localized to the NUTS2 region level, and for each country a line for the cases where impacts have not been classified into a specific NUTS2 region or are generally valid for the whole country is also provided. Individual impacts were further categorized into 5 sectors (called “impact category” in the table) where drought is most common - i.e. agriculture, forestry, soil system, wildfires and hydrology. For each state, there is also a summary table (below the main table) where it can be found the total number of impacts in each sector.

Table 1. General overview of number of drought impacts in surveyed countries and periods for which data are available

Country	Data available		Number of impacts since 2000
	From	To	
Austria	1981	2017	82
Bosnia and Herzegovina	-	-	-
Bulgaria	1981	2016	44
Croatia	1981	2016	605
Czech Republic	2000	2017	160
Hungary	1988	2016	64
Montenegro	1981	2016	183
Romania	2000	2016	184
Serbia*	2000	2016	23
Slovakia	1981	2016	163
Slovenia	1981	2016	138

* This data has not yet been taken into account in the other outputs shown in this report due to their late delivery

Estimating drought impacts from SPEI and SWI data

The second approach is to use quantitative insights obtained from the relation between observed drought impacts and the SPEI and SWI (Fig. 2). To this end, we follow the approach of previous assessments (Gudmundsson *et al* 2014, Stagge *et al* in revision b), which related drought impact occurrence to drought indicators using binary logistic regression. Logistic regression predicts the likelihood of drought impact occurrence, LIO as

$$\log\left(\frac{\mathrm{LIO}}{1-\mathrm{LIO}}\right) = \alpha + \beta \cdot \mathrm{SPEI},$$

where the left hand side of the equation is known as the logit transformation. The model parameters α and β are estimated using standard regression techniques within the framework of generalized linear models (Harrel 2001, Venables and Ripley 2002, Zuur *et al* 2009). The LIO is hence a measure for the probability of drought impact occurrence, which is dependent on the drought hazard indicator (here SPEI). With this probabilistic model, the occurrence of drought impacts cannot not directly be predicted as 'impact' or 'no impact', but, the likelihood of drought impact occurrence gives estimates in a range from zero (0% probability of impact occurrence) to one (100% probability of impact occurrence).

In DriDanube the idea is to sample the binary response variable (i.e. the drought impact occurrence series) and the SPEI/SWI values of all NUTS regions. Due to the data sampling strategy, as well as the fact that droughts are by definition rare events the number of impact occurrences compared to the number of no-impact occurrences is generally low. However, in most cases, the distributions of impact and no impact occurrence along the predictor variable SPEI/SWI should be fairly well separated (figure X). The logistic regression models will be then fitted for each region and each impact category.

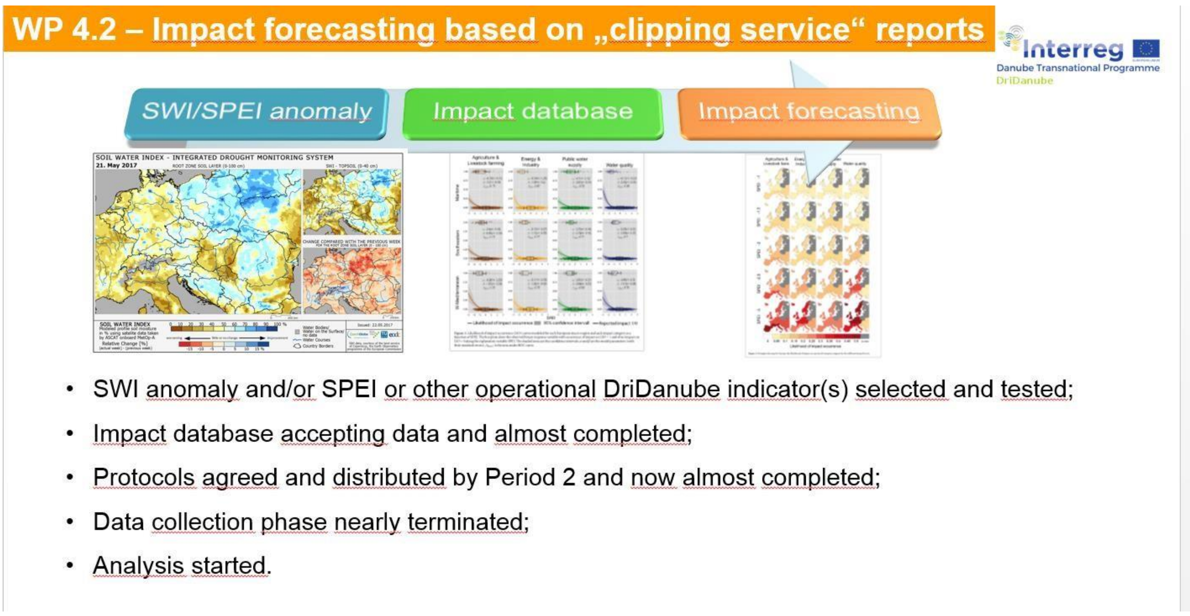

Fig. 1. Flow chart of the SWI/SPEI vs. impacts and the methodology

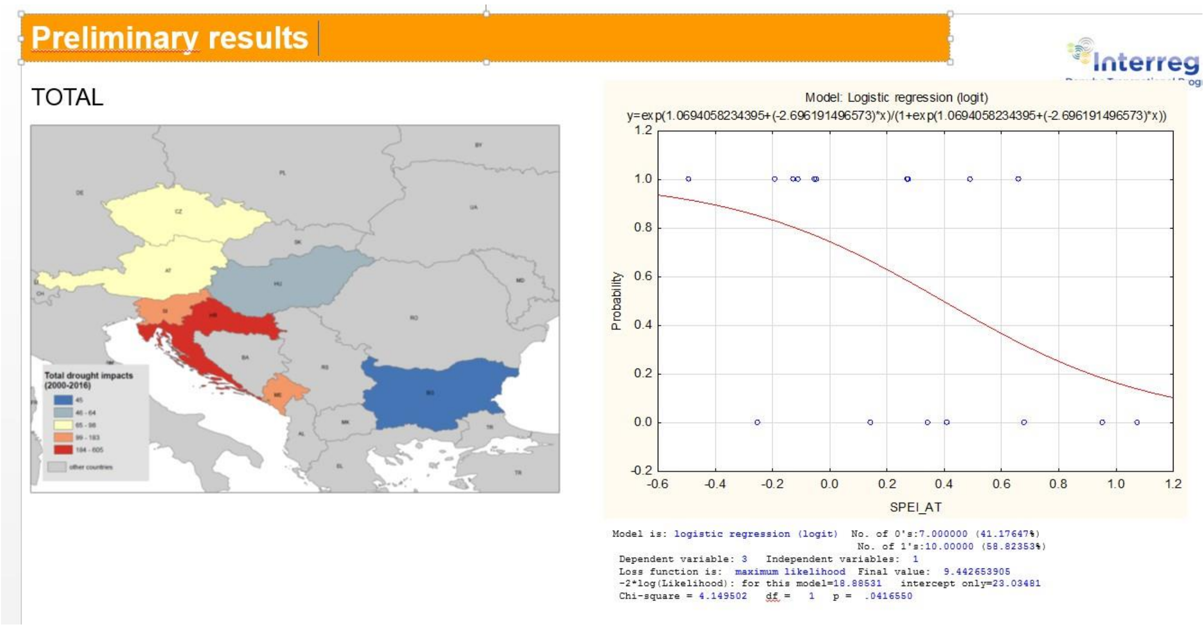

Fig. 2. Preliminary results of applying logistic regression using SPEI and reported drought impacts on agriculture over first version of the impact database.

Results

Initial analysis

In the first step, all recorded drought impacts in the selected countries (in the period since 2000) were analyzed, these impacts were divided into different categories depending on the specific sector affects. These data are now available for individual countries, but their higher resolution for NUTS 2 level is expected in the near future. An overview of these data and their map visualization for each sector is shown in the figures 3-8 and table 2.

Table 2. Number of drought impacts in all surveyed countries between 2000 and 2016, divided into five categories analysed

Country	Drought impact category / sector				
	AGR	FOR	SOI	WFR	HYD
AT	41	13	0	12	16
BG	11	16	0	0	17
CZ	36	6	4	35	79
HU	27	2	0	18	17
ME	77	1	1	74	30
HR	327	12	18	20	228
RO	161	11	12	0	0

SK	152	2	1	2	6
SI	110	1	25	2	0

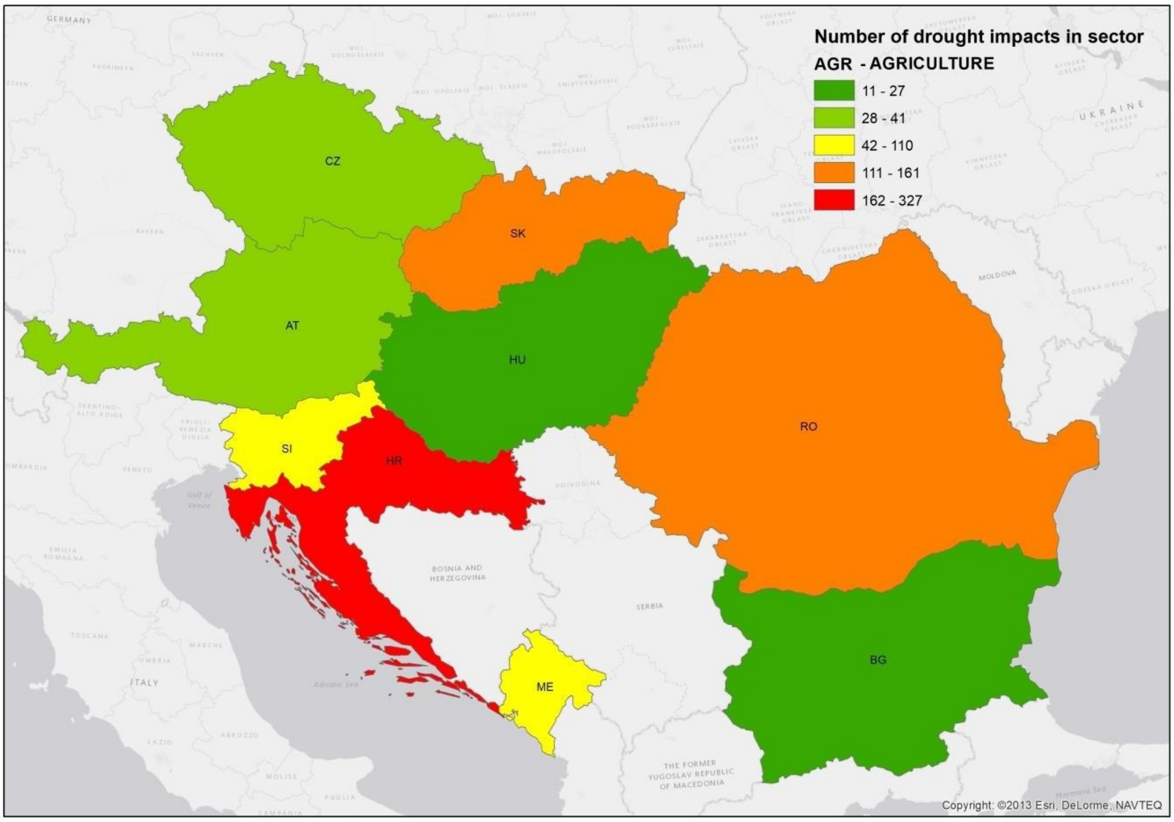

Fig. 3. Number of drought impacts in agriculture between 2000 and 2016

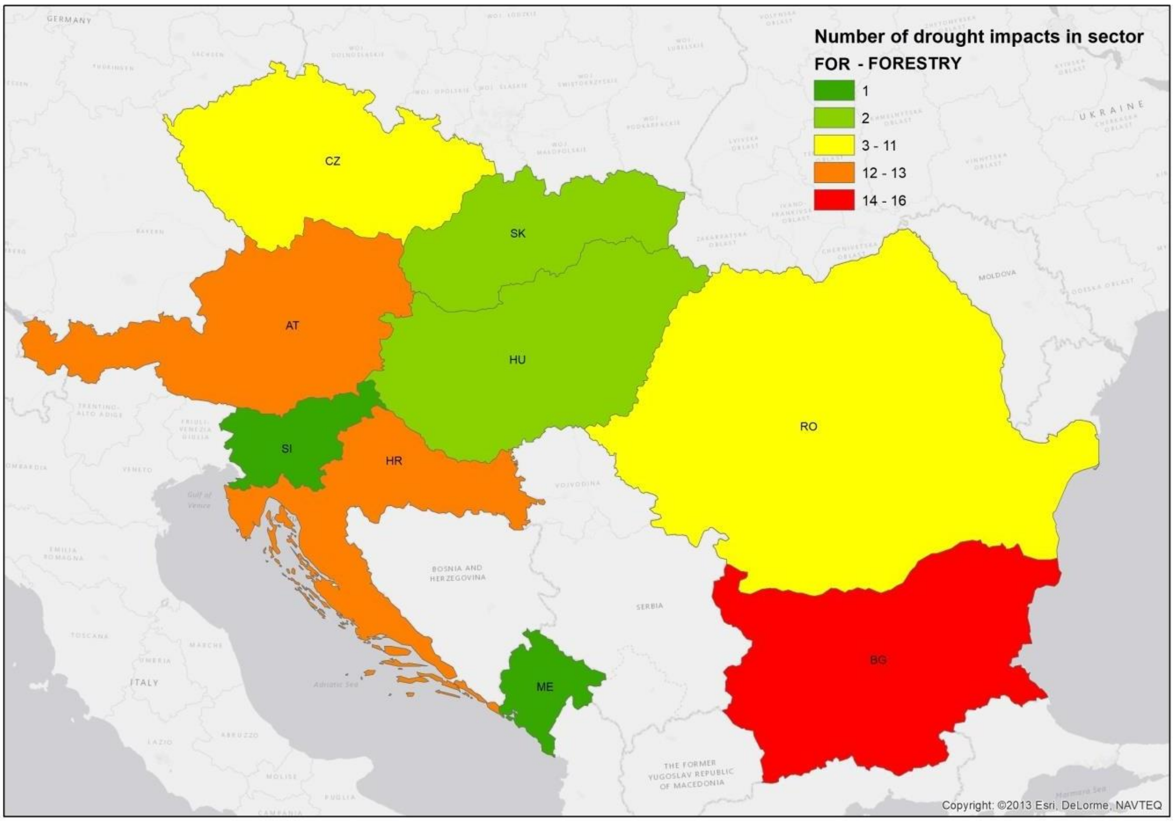

Fig. 4. Number of drought impacts in forestry between 2000 and 2016

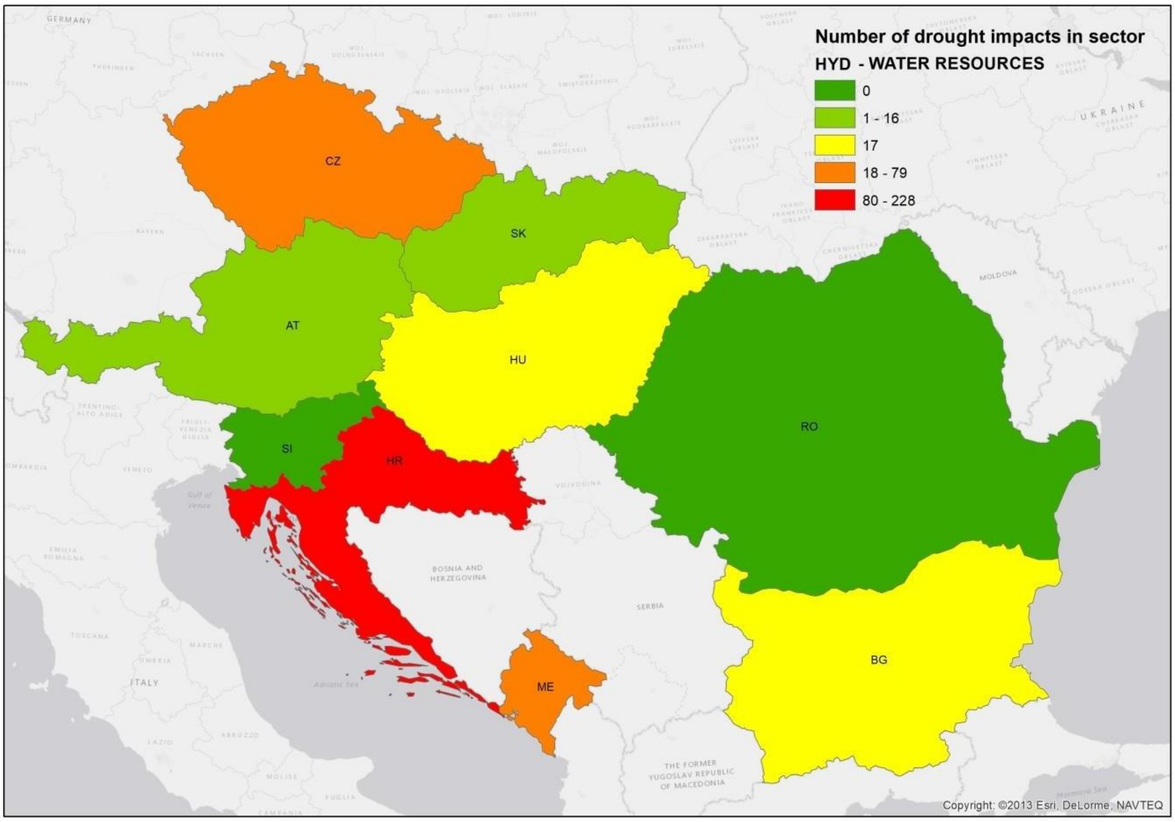

Fig. 5. Number of drought impacts in water resources between 2000 and 2016

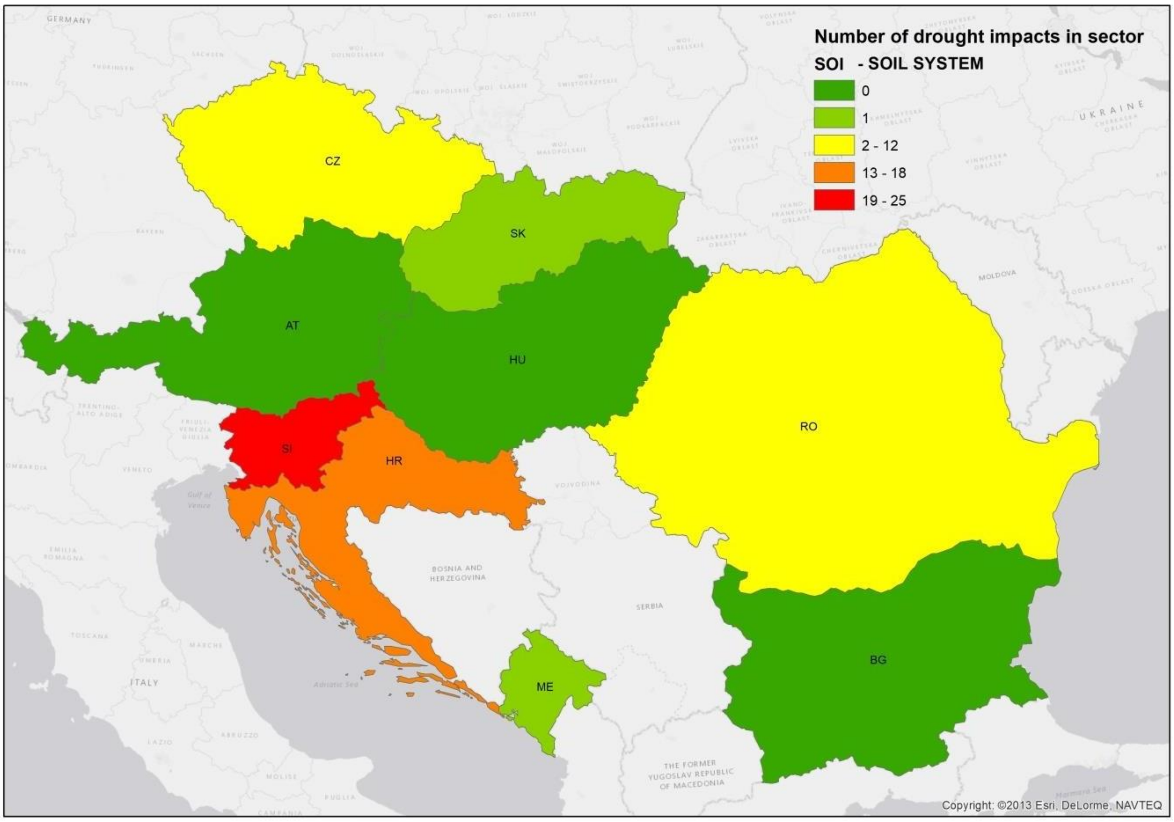

Fig. 6. Number of drought impacts in soil system between 2000 and 2016

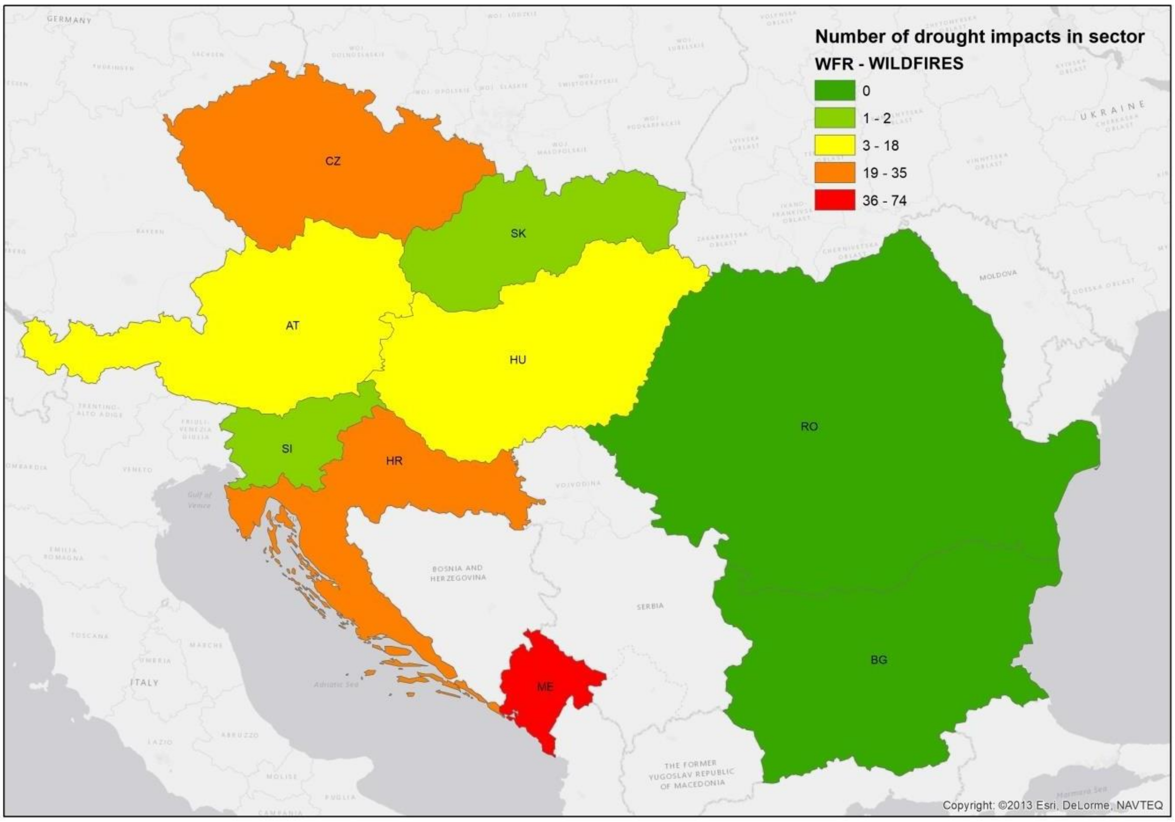

Fig. 7. Number of drought impacts in the form of wildfires between 2000 and 2016

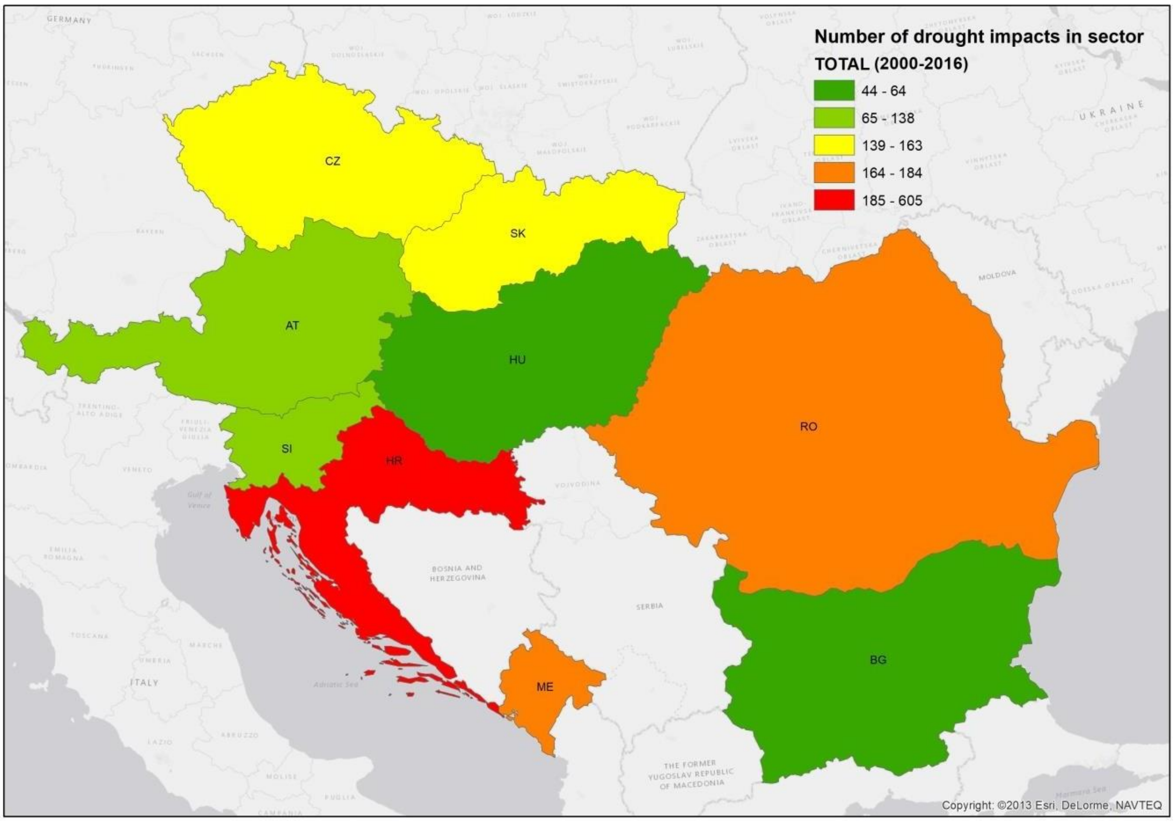

Fig. 8. Overall number of drought impacts in all analysed sectors between 2000 and 2016

Information about drought impacts categorized by sector and country, was then compared with the values of SPEI and SWI indexes described above. The analysis shows that there is a direct dependence between the number of drought impacts and index values only in some cases - the most significant dependence was found in case of Hungary, Croatia and Austria (valid both in SWI and SPEI). In these cases, it can be stated that with increasing drought intensity, the number of detected impacts increases proportionally. Overall, the greatest number of impacts was recorded mainly in the "agriculture" and "hydrology" categories, which may be due to the increased interest of the media in this type of impact to a certain extent. It's mostly due to the fact that these are the impacts which can significantly affect human society (e.g. by reduced crops or flood damages). On the other hand, for example impacts on the soil system are very harmful in long term, but the media usually do not pay such attention to these types of impacts. The results of the analysis of dependence between the number of drought impacts and the SPEI and SWI values are shown in Figures 9 and 10.

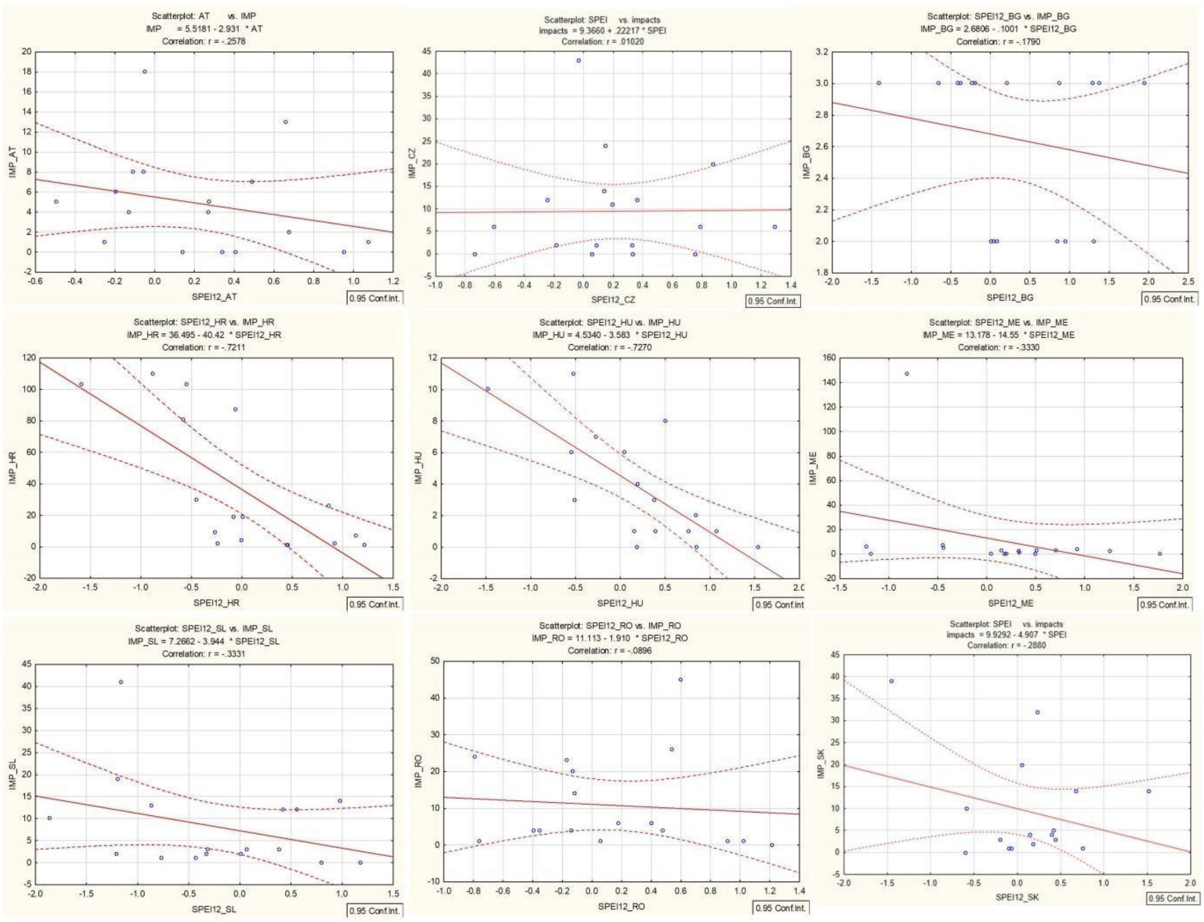

Fig. 9. Correlation field of dependence between the SPEI values and the number of drought impacts in all countries (from the upper left corner: Austria, Czech Republic, Bulgaria, Croatia, Hungary, Montenegro, Slovenia, Romania and Slovakia)

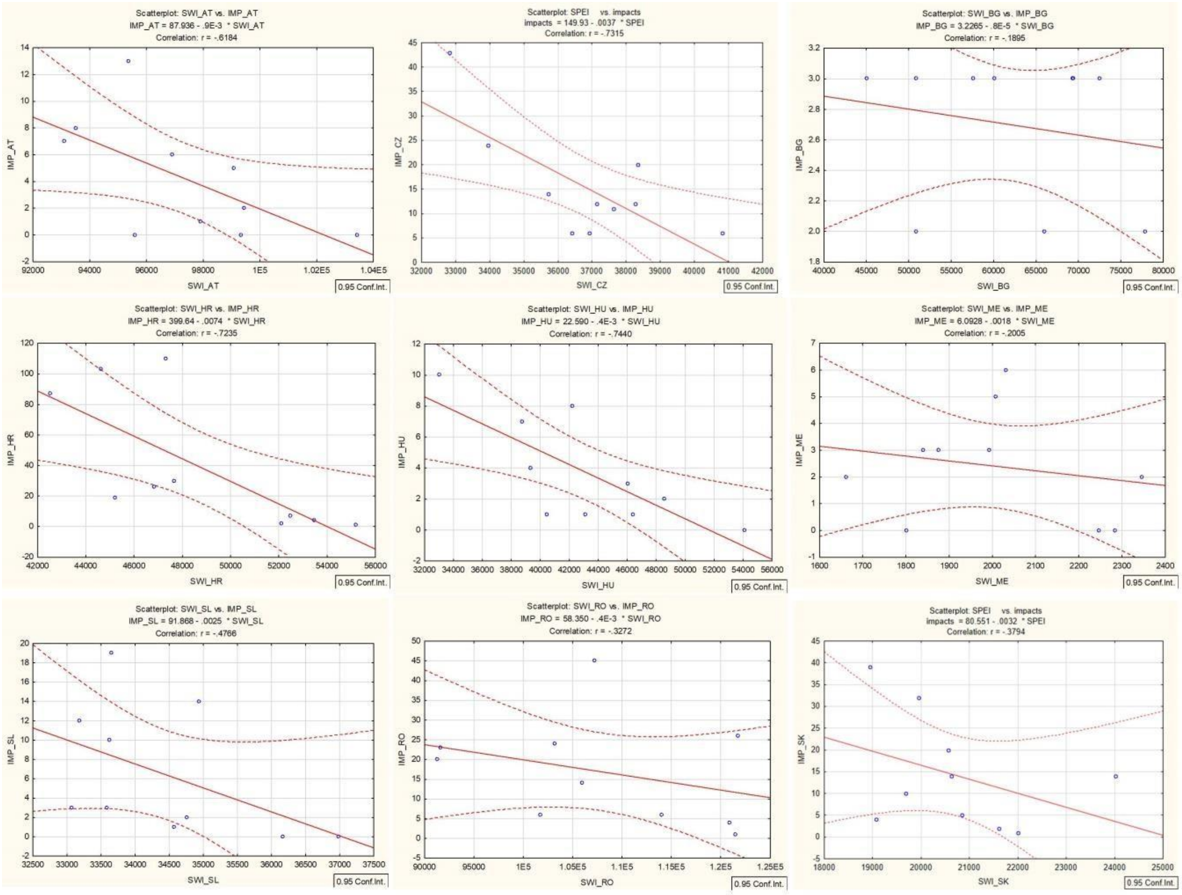

Fig. 10. Correlation field of dependence between the SWI values and the number of drought impacts in all countries (from the upper left corner: Austria, Czech Republic, Bulgaria, Croatia, Hungary, Montenegro, Slovenia, Romania and Slovakia)

Based on the comparison of SPEI, SWI and the drought impacts in all countries, a drought intensity scale has been established. However, it should be emphasized that this is a preliminary draft version, which will be clarified after the drought impacts will be differentiated at a more detailed level (into the NUTS 2 regions). In the current form (see Tables 3 and 4), the scale is based on the SPEI and SWI index values, but in the case of countries where there is no direct dependence between index values and the number of impacts, the categories are set only on the basis of the number of impacts that occurred in the given country and their significance (depending on the information contained in the underlying material). The scale created is very different for Croatia, as there have been enormous number of impacts compared to other countries. The determination of drought scale is problematic also in the case of Bulgaria, where only 2 or 3 impacts have been recorded in most of the years. The more precise specification of the input data and possible correction of the resulting scale will be made in the case of these countries additionally.

Table 3. Number of impacts determining the drought intensity in selected countries (draft version)

Drought intensity		AT*	BG*	CZ*	HU	ME*	HR	RO*	SK*	SI*
0	without drought	0–5	0–2.6	0–5	0–4	0–4	0–39	0–5	0–9	0–7
1	weak drought	6–8	2.7–2.8	6–15	5–7	5–6	40–59	6–15	10–15	8–10
2	moderate drought	9–13	2.9–3.0	16–29	8–9	7–8	60–79	16–25	16–28	11–14
3	significant drought	14–18	3.1–3.2	30–45	10–11	9–10	80–99	26–35	29–40	15–19
4	extreme drought	19+	3.3+	46+	12+	11+	100+	36+	41+	20+

* The correlation coefficient between SPEI and the number of drought impacts takes values less than 0.5, the resulting impact counts do not correspond to the SPEI found exactly and are derived rather on the basis of the values range.

Table 4. Drought intensity categories and corresponding SPEI values (used in cases of stronger dependence between these two characteristics only)

Drought intensity		SPEI
0	without drought	>-0.1
1	weak drought	<-0.2;-0.7>
2	moderate drought	<-0.8;-1.1>
3	significant drought	<-1.2;-1.5>
4	extreme drought	<-1.6

Table 5. SWI estimation for drought intensity categories defined in all countries (based on data between 2007 and 2016)

Drought intensity		AT	BG*	CZ*	HU	ME*	HR	RO*	SK*	SI*
0	without drought	> 105.0	> 80.0	> 110.0	> 104.0	> 90.0	> 100.0	> 110.0	> 112.0	> 115.0
1	weak drought	<104.9-102.0>	<79.9-73.0>	<109.9-103.0>	<103.9-91.0>	<89.9-83.0>	<99.9-93.0>	<109.9-102.0>	<111.9-105.0>	<114.9-110.0>
2	moderate drought	<101.9-100.0>	<72.9-67.0>	<102.9-96.0>	<90.9-79.0>	<82.9-75.0>	<92.9-86.0>	<101.9-94.0>	<104.9-98.0>	<109.9-105.0>
3	significant drought	<99.9-98.0>	<66.9-60.0>	<95.9-90.0>	<78.9-67.0>	<74.9-68.0>	<85.9-79.0>	<93.9-86.0>	<97.9-91.0>	<104.9-100.0>
4	extreme drought	< 97.9	< 59.9	< 89.9	< 66.9	< 67.9	< 78.9	< 85.9	< 90.9	< 99.9

* The correlation coefficient between SWI and the number of drought impacts takes values less than 0.5, the resulting impact counts do not correspond to the SWI found exactly and are derived rather on the basis of the values range.

The Soil Water Index values in Table 5 for each category of drought intensity roughly correspond to the numbers of impacts listed in Table 3. From the specific SWI values corresponding to the defined impact counts, it can be deduced that in some countries the scale is shifted relative to others - for example in the case of Bulgaria and Montenegro, the SWI values are significantly lower (extreme drought effects occur even at SWI values around 60.0). In contrast, in Austria and Slovenia, a comparable amount of drought impact already occurs at SWI 95.0 to 100.0.

Combined analysis approach

Based on the results of the initial analysis it has been decided to combine two predictors i.e. SWI and condition of vegetatation together using ansamble of Artificial neural networks. This approach allows to fully utilize the available data and train robust statistical models that are in theory capable of accounting for hiden interactions between the predictors. In this approach we at first trained 50 ANNs and then selected only the top 10, which performed the best during the "validation" phase and used their mean in order to predictor the number of impacts. The Figs. 11-13 are showing that both condition of vegetation (Fig. 11) and SWI (Fig. 12) are significantly related to the number of impacts but that combination of both predictors (Fig.13) leads to the best results. The complete set of results is available in the enclosed zip file containing complete results of the testing including the statistics. The results include all impacts (All) but also the individual sectorial impacts i.e. AGR = Agriculture; FOR = Forestry; HYD = Hydrology; WFR = Wildfires and SOI = Soil. Results are provided both for models working at the country and NUTS 3 levels as planned. As the system aims for predicting the impacts the ANNs were created for six specific prediction periods i.e. end of April;; end of May; end of June; end of July; end of August and end of September with the ANNs models predicting the total number of impacts till the end of the year. It is clear that the forecasting ability improves with the time and also that the predictions at the NUTS3 level (Fig. 14) are loaded with greater error and have lower variability explained compared to the national records which is primarily caused by comparatively smaller training sample on the NUTS3 level.

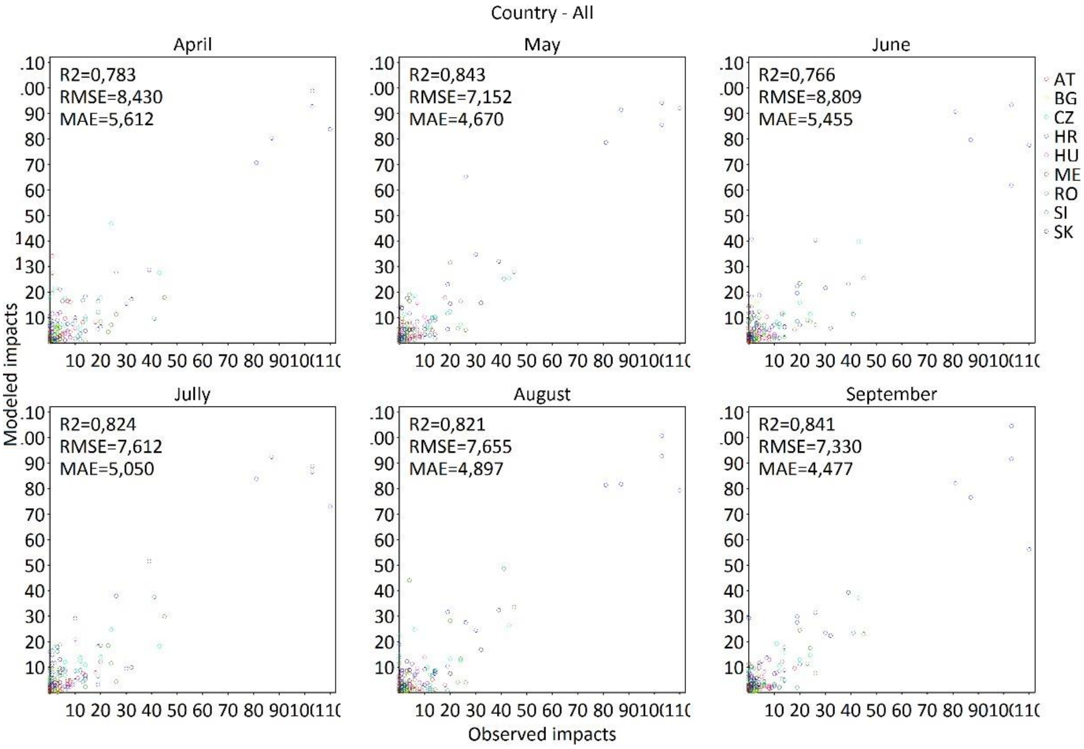

Fig. 11 Observed and estimated number of impacts for all sectors on the national level using the ensemble of ten best peforming ANN for impact preditions based on the **condition of vegetation** as the impact predictor**.** ***Note:*** *R2 = variability explained; RMSE = root mean square error of the estimate; MAE = mean absolute error of the estimate;*

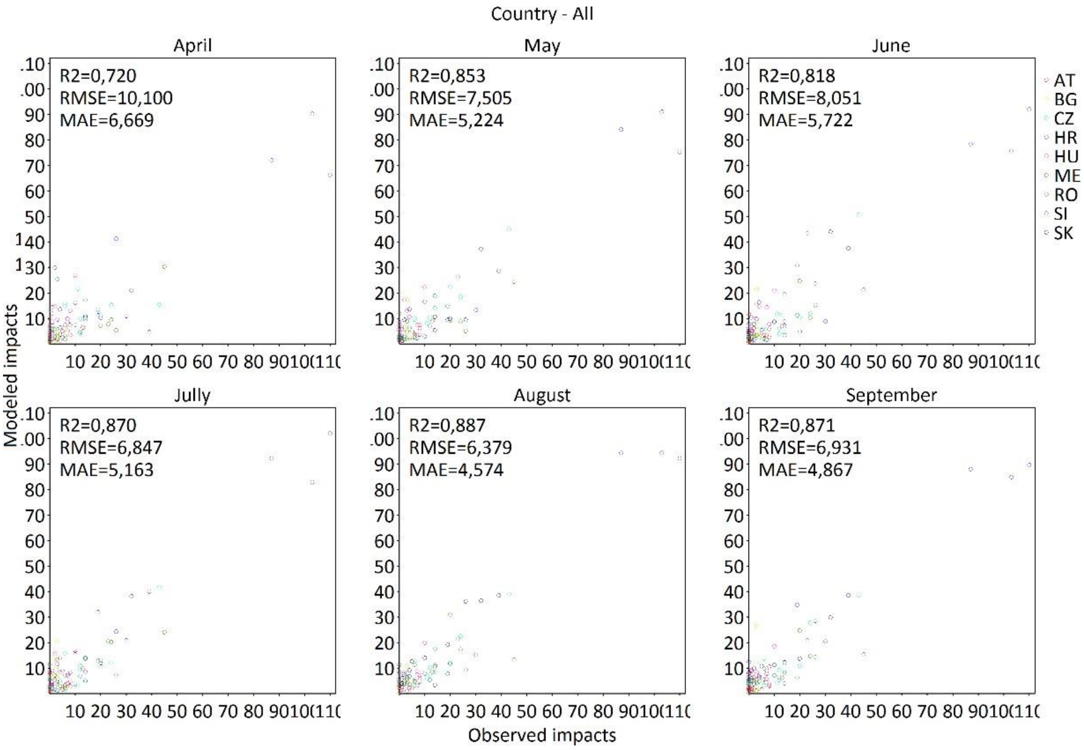

Fig. 12 Observed and estimated number of impacts for all sectors on the national level using the ensemble of ten best peforming ANN for impact preditions based on the **soil water index** as the impact predictor**.** ***Note:*** *R2 = variability explained; RMSE = root mean square error of the estimate; MAE = mean absolute error of the estimate;*

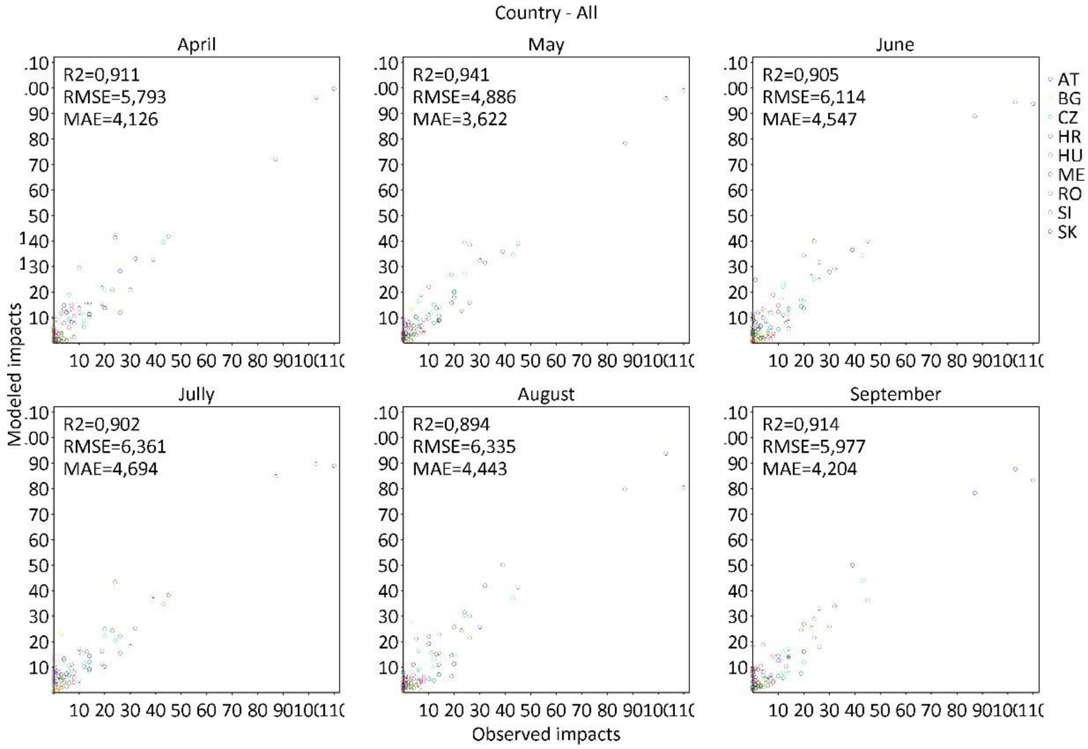

Fig. 13 Observed and estimated number of impacts for all sectors on the national level using the ensemble of ten best peforming ANN for impact preditions based on the **combination of vegetation condition and soil water index** as the impact predictor**.**

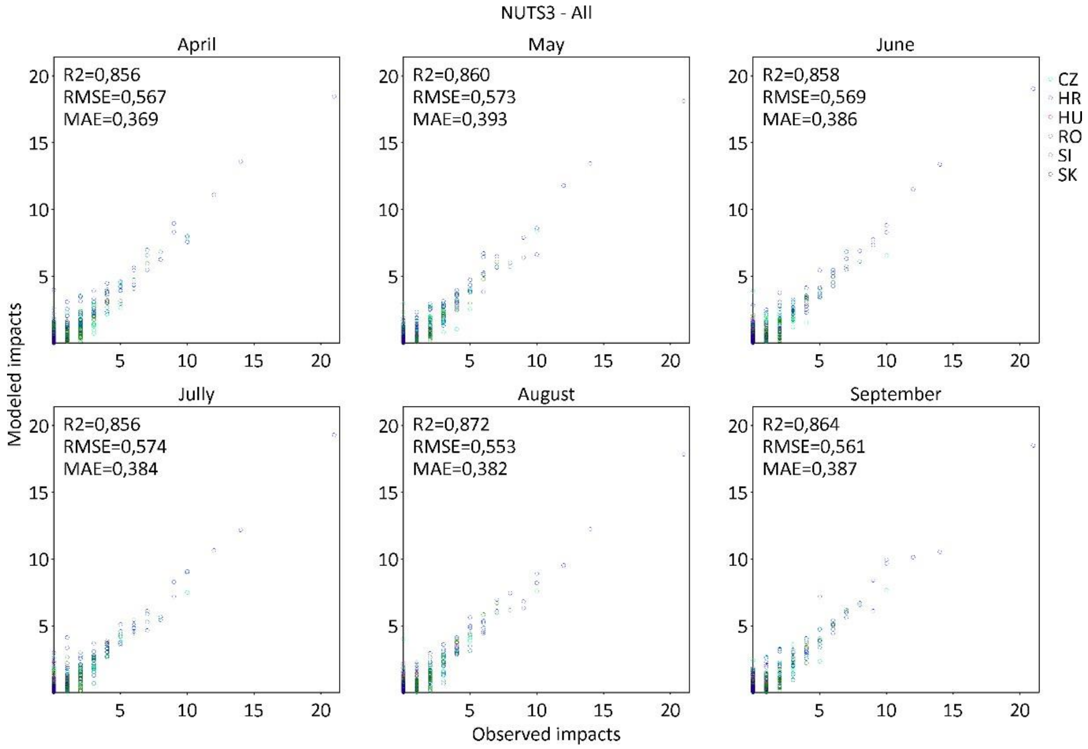

Fig. 13 Observed and estimated number of impacts for all sectors on the national level using the ensemble of ten best peforming ANN for impact preditions based on the **combination of vegetation condition and soil water index** as the impact predictor**.** ***Note:*** *R2 = variability explained; RMSE = root mean square error of the estimate; MAE = mean absolute error of the estimate;*

Conclusions

The results of the analysis show that combining the SWI and condition of the vegetation allows for fairly accurate estimate of the impacts on the country and NUTS3 level and that model have good predictive skill. It is also important to realiaze that there was disparity in the number of impacts used for training on the level of countries caused by differences in the impacts being reported in the used media. However still the approach seems to be applicable and is being transferred in to the DUS model. It is also highly important to stress that ideally the ANNs should be "re-trained" after each season to improve the accuracy and increase the robustness of the system. This will be done post 2018 season and should be made part of the planned DriDanube "sustainability" pact.

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