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MED-GOLD

Turning climate-related information into added value for traditional **MED**iterranean **G**rape, **OL**ive and **D**urum wheat food systems

Deliverable 4.3

Evaluation of the pilot

[Pilot service for durum wheat and pasta]

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Document Status Sheet

Deliverable Title	**Evaluation of the pilot**	
Brief Description	The present document shows methods and results to simulate several characteristics of the durum wheat crop dynamics. The document will also serve as a science-based information background that could mainstream the adoption of climate services in a wider user and decision making community.	
WP number	4	Co-design of pilot service for durum wheat/pasta
Lead Beneficiary	*CNR*	
Contributors (Alphabetical List)	*Bettati T., Calmanti S., Ceglar A., Di Giuseppe E., Manstretta V., Meriggi P., Monotti C., Pasqui M., Ruggeri M., Sanderson M. (Reviewer),Toreti A.,Toscano P., Zamperi M.*	
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Revision History Log

Version	Date	Created / Modified by	Pages	Comments
2.0	18-03-2021	CNR, JRC, HORTA, ENEA, BARILLA	45	Advanced Draft
2.1	29-03-2021	CNR, JRC, HORTA, ENEA, BARILLA METOFFICE.	51	Revised Draft

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1 EXECUTIVE SUMMARY

The present DEL4.3 shows methods and results to simulate several characteristics of the durum wheat crop dynamics, and it is a way to explain how to extract salient and authoritative information to tackle climate change impacts and to support agronomic transitions towards a more resilient agriculture in the Mediterranean basin. In particular, the collected results will serve as a science-based information background that could mainstream the adoption of climate services in a wider user and decision making community.

The key points described in the present document are:

- Using an innovative and robust numerical approach, the durum wheat sustainability estimate, at global scale, is presented for the decades to come. Suitable zones are projected to move further North in Europe and Central Asia. Results suggest emerging regional suitable areas in central and western parts of Europe. Negative impacts on winter-sown durum wheat suitability are expected in the North American Great Plain and Australia.
- A skill assessment of the Clisagri risk indicators for the entire arable land across Europe is shown. The skill and the reliability of the bias corrected ECMWF seasonal forecasting system, SEAS5, in predicting agro-climate indicators relevant for the European wheat farmers are also included. Prediction skills for different seasonal forecast initializations, areas and bioclimatic indices are shown in detail, producing an original large scale evaluation of seasonal forecast in the crop modelling sector.
- A new prototype functionality based on bias-corrected seasonal forecasts data has been developed for Granoduro.net®, which is the interactive web-based decision support system for sustainable wheat management of durum wheat crops. The new climate and risk indices functionalities now represent an unique gain of quality information to support decision making processes based on the MED-GOLD co-design and co-development processes.
- Functionalities of the well known modeling system DELPHI have been extended to include a bias-corrected seasonal forecasts component. A description of DELPHI skill performances is presented to showcase potential new benefits to the users.
- To explore longer (climatic) time scales durum wheat projection value, an innovative analysis, based on the CMIP5 Euro-Cordex climate projections under the high-end emission scenario RCP8.5, has been performed. It is focused on the current durum wheat areas. Results, which were made available through a web-service prototype, represent an innovative tool for developing and adopting targeted adaptation strategies and agro-management choices.

These results clearly confirm once more the key needs of sectoral climate services.

Finally, it is worth mentioning that the MED-GOLD project was flagged as one of the important R&I contributions in shaping the new EU Climate Adaptation Strategy in a recent EU factsheet.

2 OBJECTIVES

The main objectives of the present document are reported in the following scheme:

- to describe the WP4 activities results for building relevant information for climate service pilot for durum wheat and pasta;
- showcasing climate service pilot products for users in the durum wheat sector;
- showcasing GRANODURO.NET® developments and new features for users and farmers,
- reporting a science-based robustness and reliability of seasonal forecasts and long term projections to users;
- paving the way of further exploitation of climate services products to a wider community;

With this deliverable, the project has contributed to the achievement of the following objectives (DOA, Part B Table1.1):

No.	Objective	Yes
1	To co-design, co-develop, test, and assess the added value of proof-of-concept climate services for olive, grape, and durum wheat	X
2	To refine, validate, and upscale the three pilot services with the wider European and global user communities for olive, grape, and durum wheat	X
3	To ensure replicability of MED-GOLD climate services in other crops/climates (e.g., coffee) and to establish links to policy making globally	X
4	To implement a comprehensive communication and commercialization plan for MED-GOLD climate services to enhance market uptake	
5	To build better informed and connected end-user communities for the global olive oil, wine, and pasta food systems and related policy making	

3 IMPACT

This document reports processes and results of climate related information that the durum wheat and pasta pilot service will provide to aid the decision making strategy of users and stake-holders. In particular, this deliverable showcases the robustness, salient and scientific ground based information produced for the durum wheat and pasta pilot tool.

The deliverable fully describes the entire workflow adopted to build relevant climate information, providing a solid basis for further development and adoptions.

No.	Expected impact	Yes
1	Providing added-value for the decision-making process addressed by the project, in terms of effectiveness, value creation, optimised opportunities and minimise risk	X
2	Enhancing the potential for market uptake of climate services demonstrated by addressing the added value	
3	Ensuring the replicability of the methodological frameworks for value added climate services in potential end-user markets	
4	To implement a comprehensive communication and commercialization plan for MED-GOLD climate services to enhance market uptake	
5	To build better informed and connected en d-user communities for the global olive oil, wine, and pasta food systems and related policy making	

4 DEFINITIONS

Concepts and terms used in this document and needing a definition are included in the following table:

Concept / Term	Definition
Climate projections	Probabilistic estimates of the evolution of the climate in the future, from decades up to the end of the century.
Indicator	A parameter describing a reality, i.e., synthesizing the effects of climate with relevance to a specific sector and business.
Percentile	Division of the population distribution into 100 categories.
Reanalysis	A method similar to analysis, but performed in real time, and the background field is created by a numerical weather prediction model that does not change over the entire period of the reanalysis.
Seasonal forecasts	Predictions of the climatic conditions for the coming months.
(Predictive) Skill	A statistical measure of the accuracy of seasonal forecasts.
Tercile	Division of the population distribution into three categories.
Granoduro.net®	A Decision Support System (DSS) developed and maintained by HORTA, used by the durum wheat providers and producers in the BARILLA supply chain.
Anthesis	Flowering.
DELPHI	It is a model system based on a FORTRAN-based mechanistic model calibrated for durum wheat in Mediterranean conditions. Plant transpiration and soil evaporation, water and nitrogen soil-plant cycle are incorporated in the model.
Ideotype	The modelling correspondent of a specific plant variety.

Additional definitions of further temms can be found in the Concepts and terms used in https://www.med-gold.eu/glossary/

5 ACRONYMS

Acronyms used in this document and needing a definition are included in the following table:

Acronym	Definition
CIMMYT	International Maize and Wheat Improvement Center.
CMIP6	Coupled Model Intercomparison Project Phase 6.
ISIMIP	Inter-Sectoral Impact Model Intercomparison Project.
ERA5	ECMWF Re-Analysis version 5.
AgERA5	Daily surface meteorological data set for agronomic use, based on ERA5.
SSP585	Shared Socioeconomic Pathways (SSP) highest (5) emission scenario. It marks the upper edge of the SSP scenario spectrum with a high reference scenario in a high fossil-fuel development world throughout the 21st century.
SMOTE	Synthetic Minority Oversampling Technique,
CLISAGRI	It is a modelling system based on a set of dynamic agro-climatic indicators that bring key information to crop producers during different stages of the crop growth.

6 REFERENCES

The following documents, although not part of this document, amplify or clarify its contents. Reference documents are those not applicable and referenced within this document. They are referenced in this document in the form [RD.x]:

Ref.	Title	Code	Version	Date
[RD.1]	Climate change hotspots in the CMIP5 global climate model ensemble. Climatic Change 114, 813–822	Diffenbaugh, N. and Giorgi, F.	final	2012
[RD.2]	Wheat yield loss attributable to heat waves, drought and water excess at the global, national and subnational scales. Environmental Research Letters, 12(6), 064008.	Zampieri, M., Ceglar, A., Dentener, F., & Toreti, A.	final	2017
[RD.3]	Extreme heat waves under 1.5 and 2 degree global warming. Environmental Research Letters, 13 054006	Dosio, A., Mentaschi, L., Fischer, E. M. & Wyser, K.	final	2018
[RD.4]	How did the domestication of Fertile Crescent grain crops increase their yields? Functional Ecology, 31(2), 387–397	Preece, C., et al.	final	2017
[RD.5]	Trend-preserving bias adjustment and statistical downscaling with ISIMIP3BASD (v1.0), Geoscientific Model Development, 12, 3055–3070	Lange, S.	final	2020
[RD.6]	ISIMIP	Inter-Sectoral Impact Model Intercomparison Project		
[RD.7]	Global emissions pathways under different socioeconomic scenarios for use in CMIP6: A dataset of harmonized emissions trajectories through the end of the century. Geoscientific Model Development, 12, 1443–1475	Gidden, M. J. et al.	final	2019
[RD.8]	Clisagri: An R package for agro-climate services. in Climate Services, 20, 100197.	Ceglar, A. et al.	final	2020
[RD.9]	SEAS5: the new ECMWF seasonal forecast system. Geoscientific Model Development, 12, 1087–1117	Johnson, S. J.et al.	final	2019
[RD.10]	On the reliability of seasonal climate forecasts. Journal of The Royal Society Interface11, 20131162	Weisheimer, A. & Palmer, T. N.	final	2014
[RD.11]	Downscaling RCM precipitation to the station scale using statistical transformations; a comparison of methods. Hydrology and Earth System Sciences, 16, 3383–3390	Gudmundsson, L., Bremnes, J. B., Haugen, J. E. & Engen Skaugen, T. Technical Note.	final	2012
[RD.12]	Using reanalysis in crop monitoring and forecasting systems. Agric. Syst., 168, 144-153	Toreti, A. et al.	final	2019

[RD.13]	The Exceptional 2018 European Water Seesaw Calls for Action on Adaptation. Earth's Future	Toreti, A.et al.	final	2019
[RD.14]	A web-based decision support system for managing durum wheat crops. Advances in Decision Support Systems.	Rossi et al.	final	2010
[RD.15]	Granoduro.net®™: a web-based decision support system to improve durum wheat sustainability. MPU Workshop. Bari	Ruggeri et al.	final	2012
[RD.16]	A multicomponent decision support system to manage Fusarium head blight and mycotoxins in durum wheat. World Mycotoxin Journal.	Rossi, Manstretta et al.	final	2015
[RD.17]	First Feedback report from users on durum wheat pilot service development	D 4.6	final	2019
[RD.18]	Second Feedback report from users on durum wheat pilot service development	D 4.7	final	2020
[RD.19]	Report on the identified specific needs and opportunities	D 4.1	final	2018
[RD.20]	Design of innovative agro-climatic systems for durum wheat	D 4.2	final	2020
[RD.21]	A simulation model for the development of brown rust epidemics in winter wheat. European Journal of Plant Pathology.	Rossi et al.	final	1997
[RD.22]	Durum wheat quality prediction in Mediterranean environments: From local to regional scale. Eur. J. Agron. 2014, 61, 1–9.	Toscano, P.; Gioli, B.; Genesio, L.; Vaccari, F.P.; Miglietta, F.; Zaldei, A.; Crisci, A.; Ferrari, E.; Bertuzzi, F.; La Cava, P.; et al.	final	2014
[RD.23]	Durum wheat modeling: The Delphi system, 11 years of observations in Italy. Eur. J. Agron. 2012, 43, 108–118.	Toscano, P.; Ranieri, R.; Matese, A.; Vaccari, F.P.; Gioli, B.; Zaldei, A.; Silvestri, M.; Ronchi, C.; La Cava, P.; Porter, J.R.; et al	final	2012
[RD.24]	AFRCWHEAT2 A model of the growth and development of wheat incorporating responses to	Porter, J.R.; Porter, J.R.	final	1993

	water and nitrogen. Eur. J. Agron. 1993, 2, 69–82.			
[RD.25]	A Precision Agriculture Approach for Durum Wheat Yield Assessment Using Remote Sensing Data and Yield Mapping. Agronomy 2019, 9(8), 437; https://doi.org/10.3390/agronomy9080437	Toscano P., Castrignanò A., Di Gennaro S.F., Vonella A.V., Ventrella D., Matese A.	final	2019
[RD.26]	Seasonal climate forecast can inform European agricultural sector well in advance of harvesting.	Ceglar, A., Toreti, A.,	Under review	2021
[RD.27]	Global loss of suitable durum wheat areas in the future.	Ceglar, A. et al.	Under review	2021
[RD.28]	A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index. Journal of Climate 23,1696–1718	Vicente-Serrano, S. M., Beguera, S. & Lopez-Moreno, J. I.	final	2010
[RD.29]	Durum wheat projections for the Mediterranean region. Scientific Reports	Toreti A., S. Bassu, D. Fumagalli, M. Bratu, A. Ceglar, M. Zampieri, C. Royo.	In preparation	2021
[RD.30]	CroPS: a new crop growth model for large ensemble simulations. Geoscientific Model Development.	Toreti A., D. Fumagalli, M. Bratu, S. Bassu, A. Ceglar, M. Zampieri.	In preparation	2021
[RD.31]	Bassu S., Toreti A., D. Fumagalli, C. Royo.	Modelling heat stress at anthesis. Fields Crop research	In preparation	2021

7 DETAILED REPORT

7.1 Global durum wheat suitability

The global Mediterranean-like regions where durum wheat is currently grown are hot-spots of climate change, where temperature is warming faster than in other areas of the world (RD.1) and changes in precipitation regimes and extremes will pose additional threats to agricultural production (RD.2). Durum wheat is sensitive to heat stress and drought, which are projected to increase in areas currently suitable for durum wheat production (RD.3). Climate change might lead to completely unsuitable areas for durum wheat cultivation, as it has been anticipated for the “Fertile Crescent” in the Middle East, where wheat was domesticated (RD.4). Here we aim at assessing changes in climate suitability for durum wheat production driven by future projected climate change. We also assess the possibility of shifting cultivation over emerging suitable areas, as part of sustainable sectoral adaptation strategies.

7.1.1 Data and Methods

To model climate suitability, the current global arable land area is classified into two categories: suitable and non-suitable for durum wheat growth. Furthermore, durum wheat production is classified into winter-sown and spring-sown categories, with prevalence of rainfed or irrigated conditions (Fig. 1). The current spatial distribution of global durum wheat areas has been established based on the expert-driven information provided by Barilla and CIMMYT. The main production areas are concentrated around the Mediteranean, the Northern Great Plains of Northern America, Central Asia and Australia (Fig. 1). In North America durum wheat is also cultivated in California, Arizona and north-western Mexico, where it is mainly irrigated.

Daily data on maximum and minimum temperatures, precipitation, and global solar radiation for the reference period (1981-2015) have been obtained from the global high-resolution AgERA5 dataset, available on the Climate Data Store of the Copernicus Climate Change Service (https://cds.climate.copernicus.eu). Global climate change projections have been retrieved from five CMIP6 climate simulations, statistically downscaled and bias-adjusted in the framework of the Inter-Sectoral Impact Model Intercomparison Project (RD.5, RD.6). All the climate model simulations here used are based on the SSP585 scenario (RD.7).

The proposed climate suitability model builds on Support Vector Machines (SVM), a widely used classification algorithm for nonlinear binary classification (RD.26). The model is based on a set of 12 bio-climatic indicators (predictors) characterizing the conditions between durum wheat sowing and maturity (Table 1), i.e. along the entire growing season. As the global arable land is used for background sampling, the dataset is characterized by highly imbalanced data with the majority of arable land being not suitable for durum wheat (Fig. 1). To address this issue, we implemented a

hybrid multi-step approach: 1) a Different Error Cost SVM based on the imbalance ratio is performed, 2) a SMOTE-like oversampling is applied (RD.26).

Table 1: Description of bioclimatic variables to develop the suitability model.

Bioclimatic variable	Description	Aggregation period
BIO1	Average maximum temperature	sowing-anthesis
BIO2	Average minimum temperature	sowing-anthesis
BIO3	Average of global solar radiation	sowing-anthesis
BIO4	Average ref. evapotranspiration	sowing-anthesis
BIO5	Average precipitation	sowing-anthesis
BIO6	Average maximum temperature	anthesis-maturity
BIO7	Average minimum temperature	anthesis-maturity
BIO8	Average of global solar radiation	anthesis-maturity
BIO9	Average ref. evapotranspiration	anthesis-maturity
BIO10	Average precipitation	anthesis-maturity
BIO11	Maximum temperature of warmest month	sowing-maturity
BIO12	Minimum temperature of coldest month	sowing-maturity

7.1.2 MAIN RESULTS

The suitability model, trained and tested under the reference conditions (1981-2020) using the AgERA reanalysis dataset, is characterized by a good predictive performance. The proportion of suitable areas correctly identified by the derived suitability model is 87%. To assess the impact of climate change on future suitability, five different suitability models are developed, each trained by using different climate simulations as climate input data.

The most significant projected loss of suitability for winter-sown durum wheat in the middle of the 21st Century is estimated for eastern Ukraine, the European part of Russia, and Kazakhstan. Losses are also evident in southern France, Spain, northern Italy, Morocco, and southern Turkey (Fig. 2). Towards the end of the 21st Century, loss of suitability can be observed for southwestern

France, northern Italy, southern Turkey, and the Maghreb. Suitable zones are projected to move further North in Europe and central Asia. Our model suggests emerging regional suitable areas in central and western parts of Europe. Overall, the largest gain in suitability at mid-century is projected in the southwestern Siberian and southern Ural Russian districts.

As for the rest of the world, negative impacts on winter-sown durum wheat suitability are expected in the North American Great Plains and Australia. Simultaneously, a significantly smaller proportion of arable land could become suitable towards the second half of the century in these regions.

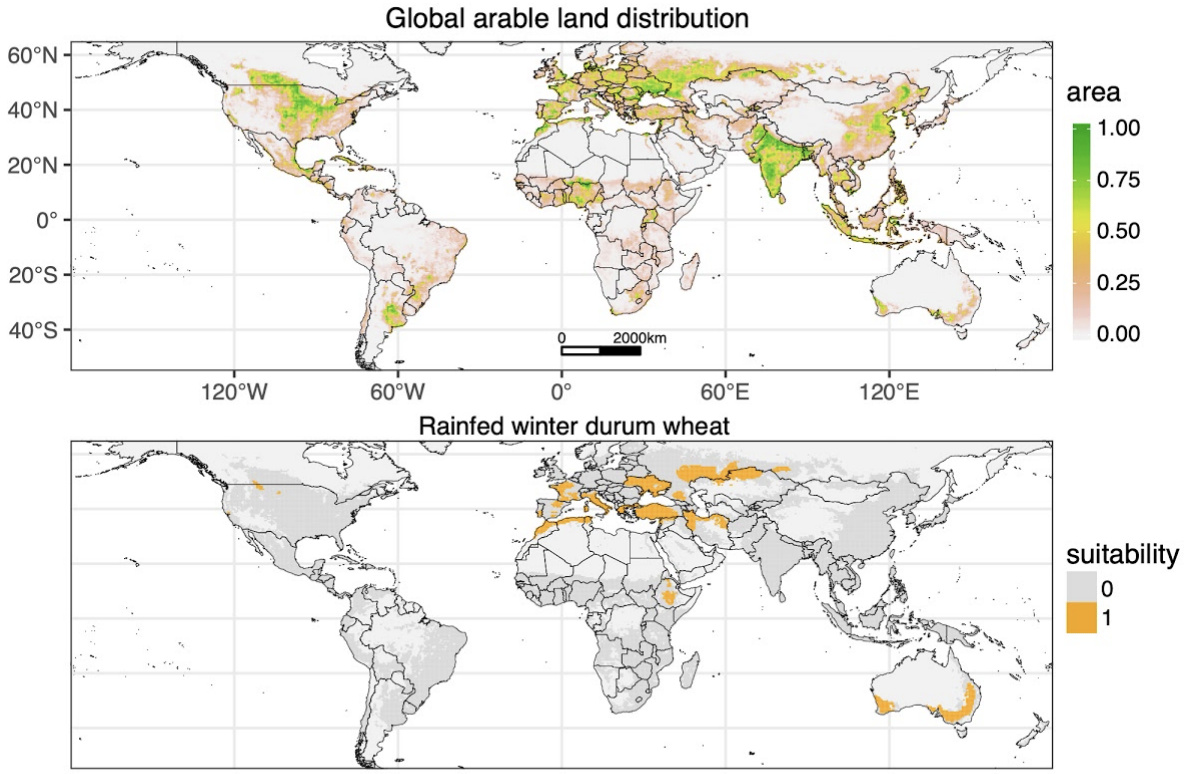


Figure 1: Upper Panel: global arable land distribution. Four different cropping systems of durum wheat are used in this analysis: rainfed winter-sown durum wheat, irrigated winter-sown durum wheat, rainfed spring-sown durum wheat, and irrigated spring-sown durum wheat. Lower Panel: spatial distribution of winter-sown rainfed durum wheat areas (in orange) obtained from the intersection of global durum wheat regions as given from Barilla and MIRCA2000 dataset. To train the suitability model, the orange areas were flagged as suitable and the light gray areas as not suitable.

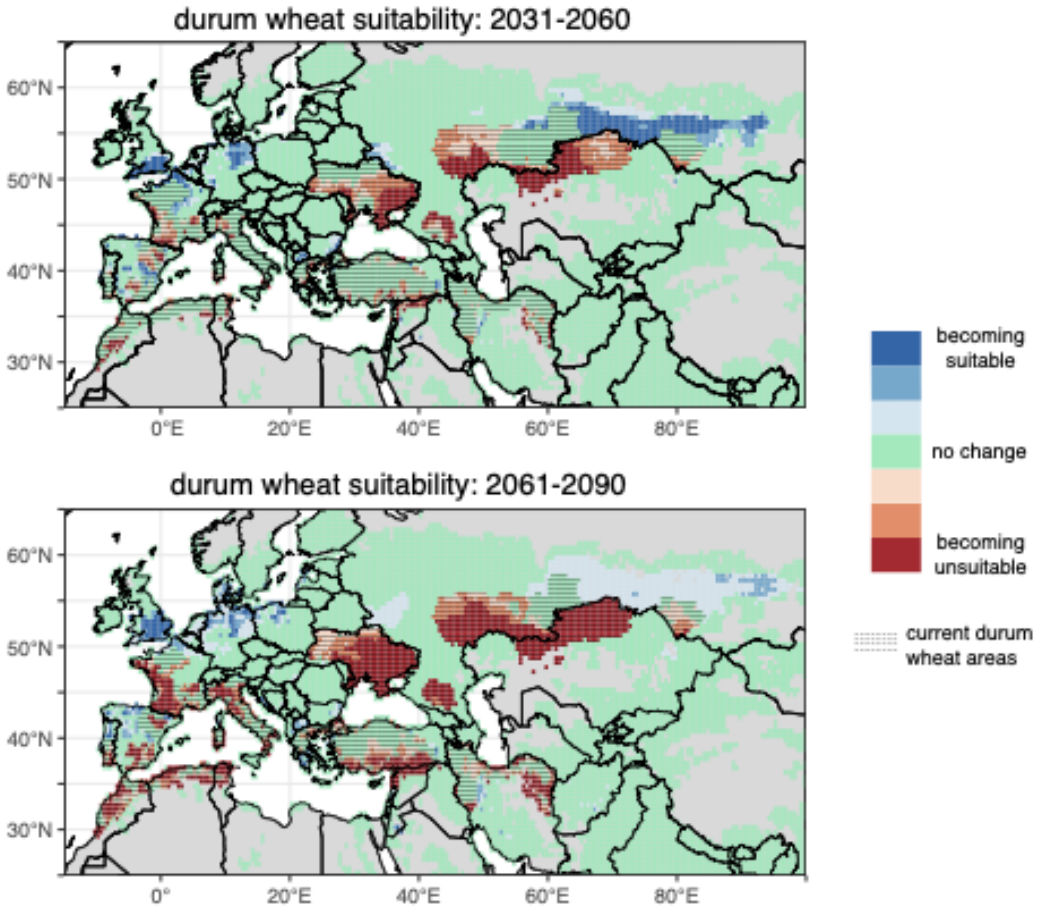


Figure 2: Impacts of projected climate change on rainfed winter-sown durum wheat suitability across Europe, the Middle East and central Asia. Blue (red) colors indicate increasing (decreasing) climate suitability in the future. Hatched areas indicate the current areal distribution of rainfed winter-sown durum wheat, while light green color indicates arable land where no change in climate suitability is simulated.

7.2 Skill and reliability assessment of seasonal forecasts on European level

The assessment of prediction skill and reliability is the first step in the development of informative agro-climate services based on seasonal predictions. Here we perform a skill assessment of the Clisagri risk indicators (RD.8) for the entire arable land across Europe. We explore the skill and the reliability of the ECMWF seasonal forecasting system SEAS5 (RD.9) in predicting agro-climate indicators relevant for European wheat farmers. A spatial analysis of seasonal forecast predictions at different stages of the wheat growing season is performed.

7.2.1 Methods

SEAS5, the ECMWF's fifth generation seasonal forecast system, is applied to derive seasonal predictions of the Clisagri agro-climate indicators. The SEAS5 seasonal forecasts were retrieved

from the Copernicus Climate Change Service (C3S, https://cds.climate.copernicus.eu/). To evaluate the SEAS5 prediction quality, we use the retrospective forecasts for the period 1993-2019. Each re-forecast ensemble consists of 25 members and reflects the uncertainty in the initial conditions of the ocean and the land state. Seasonal forecasts are bias-adjusted using the MarsMet observational database (RD.12) as a reference meteorological dataset. Quantile mapping is applied to perform this task (RD.11).

Clisagri characterizes different climate conditions and events (including extremes) relevant for wheat crop growth: drought, excessive wetness, heat stress and cold stress. Drought is defined by using the estimated hydrological balance during specific growth stages. For this purpose, the standardized precipitation evapotranspiration index (SPEI, RD.28) is used. SPEI, calculated dynamically for different growing phases (Fig. 3), can support farmers on decisions related to variety selection, sowing date, irrigation planning, application of fertilizers and crop protection.

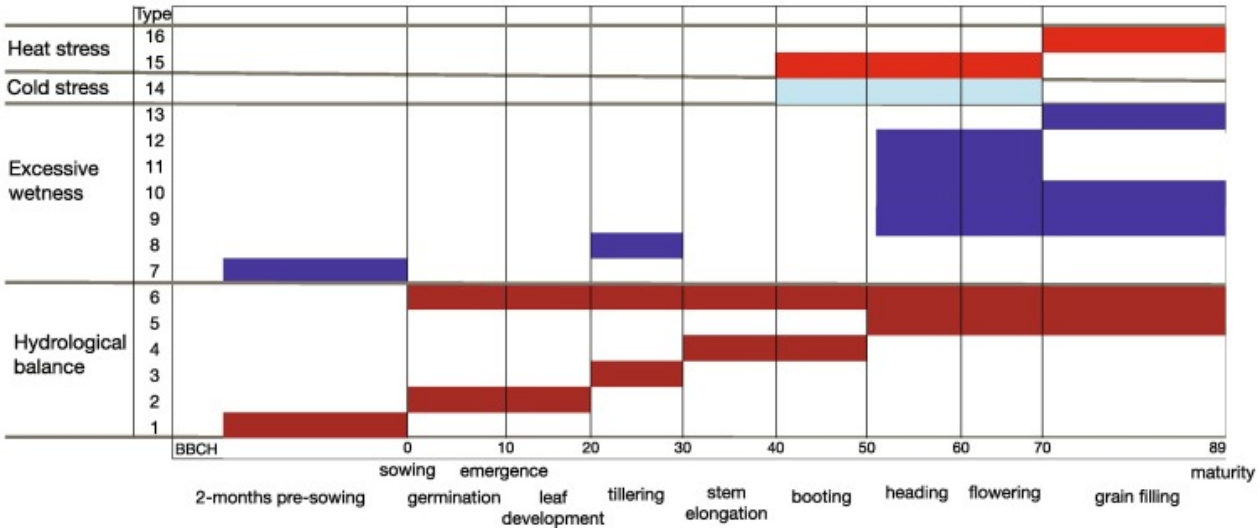


Figure 3: Different types of agro-meteorological indicators, listed in the left column, are used to fully characterize meteorological conditions during different stages of wheat growth. Four groups of indicators are chosen to characterize hydrological balance, excessive wetness, cold stress and heat stress conditions (after Ceglar et al., 2020).

The Fair Ranked Probability Skill Score (FRPSS) is used as a skill measure. FRPSS measures the squared distance between the cumulative probabilities of the categorical prediction and its corresponding observational reference. The predictions are evaluated with respect to a baseline, here the long-term climatology. The perfect forecast gets a skill score equal to 1, while forecasts that do not perform any better than the climatology get a skill score value of 0 (or lower than 0 for forecasts that are worse than the climatology).

We also estimate the forecast reliability using a reliability diagram. The reliability diagram is a diagnostic tool for probabilistic forecasts, showing for a specific event the correspondence of the predicted probabilities with the observed frequency of occurrence (RD.10). The reliability of the

system is determined according to the slope of the derived reliability line and its uncertainty range. Five categories can be defined for decision making: perfect, very useful, marginally useful, not useful and dangerously useless.

7.2.2 Results (EU countries)

We have analysed prediction skill for different seasonal forecast initializations: November, February, March, April, May and June. The prediction of the hydrological balance between sowing and leaf development is largely skillful and (at least marginally) useful across Europe; seasonal predictions over more than half of arable land show at least some level of skill (indicator 2, Fig. 4). This indicator concerns a period which largely occurs between October and December in most of Europe, thus often coinciding with the forecast initialized in November. The hydrological balance prediction for the tillering and stem elongation periods (indicators 3 and 4, Fig. 4) shows significantly lower share of arable land having some skill across Europe. These predictions are marginally useful or in some cases even dangerously useless according to the estimated forecast reliability. Predictions initialized in February and later on generally result in higher share of arable land where indicator 3 is skillful and useful. The poor reliability of the drought forecast points to issues with prediction usefulness of indicator 4 in most of Europe, except in the Iberian Peninsula, Italy, and France.

The hydrological balance between wheat heading and maturity, temporally aligned with the most sensitive period of wheat growth, can be predicted only with seasonal climate forecasts initialized in February and afterwards. Across Iberian Peninsula, Italy, south-eastern Europe, and eastern Europe seasonal predictions initialized later in the season gain skill. Even though the skillful area is increasing or remains stable, only marginal usefulness prevails over most of Europe, until the indicator is estimated with seasonal climate forecast initialized in June. The June forecast integrates partially observed climate data (period after heading, mainly occurring in May) in the index calculation. However, in most of Europe wheat still has an entire grain filling period ahead in June. The predictions are dangerously useless for the UK and Ireland for the seasonal forecasts initialized in March, April and May.

Indicator 6, which represents the hydrological balance in the entire growing season between sowing and maturity, is the most skillfully predicted indicator.. Partially, this can be attributed to persistence of hydrological balance anomalies, which are based on a combination of observed and predicted weather. The prediction of excessive wetness seems to be very challenging as no or very limited skill is estimated during the entire wheat growing season in Europe (not shown). Other approaches, for instance making use of large-scale atmospheric patterns, could be used to identify predictable signals for those harmful events (RD.26).

Figure 4: Share of arable land in the main European wheat production regions where seasonal prediction of different Clisagri hydrological balance indicators (y axis) is skillful. Symbols represent the reliability of drought (i.e. SPEI<-0.85) seasonal predictions. The hydrological balance indicators are based on SPEI and are calculated for different wheat growth stages (Fig.3) Grey areas are associated with indicators that cannot be predicted due to the too-short lead time of seasonal forecast to reach maturity (after Ceglar and Toreti, under review).

7.2.3 Results (Italy)

The main pilot area for the durum wheat services created in MED-GOLD is Italy, where many suppliers of Barilla cultivate varieties with high quality standards. The skill of ECMWF SEAS5 in predicting the CLISAGRI hydrological balance indicators has been computed systematically in order to provide the necessary background information for pilot services.

In this case, daily data from ECMWF SEAS5 have been interpolated onto the ERA5 grid in order to match the users' expectation of accessing climate information at the highest possible geographical resolution, which increases the perception of information reliability, provided that the skill is sufficient for the information itself to be usable.

As indicated in Fig. 3, the CLISAGRI hydrological balance indicators are defined over different portions of the crop cycle of different duration, from few weeks (indicator 3, hydrological balance over tillering) to the entire crop cycle (indicator 6). A key objective of the systematic analysis conducted for the CLISAGRI indicators over Italy is to gain a thorough understanding of the expected limitations in using forecasts at different starting dates for the different indicators. In particular for those indicators defined over longer time periods such as indicators 6, the input data for the indicator is prepared by integrating observed data and forecasts as described in Fig. 10.

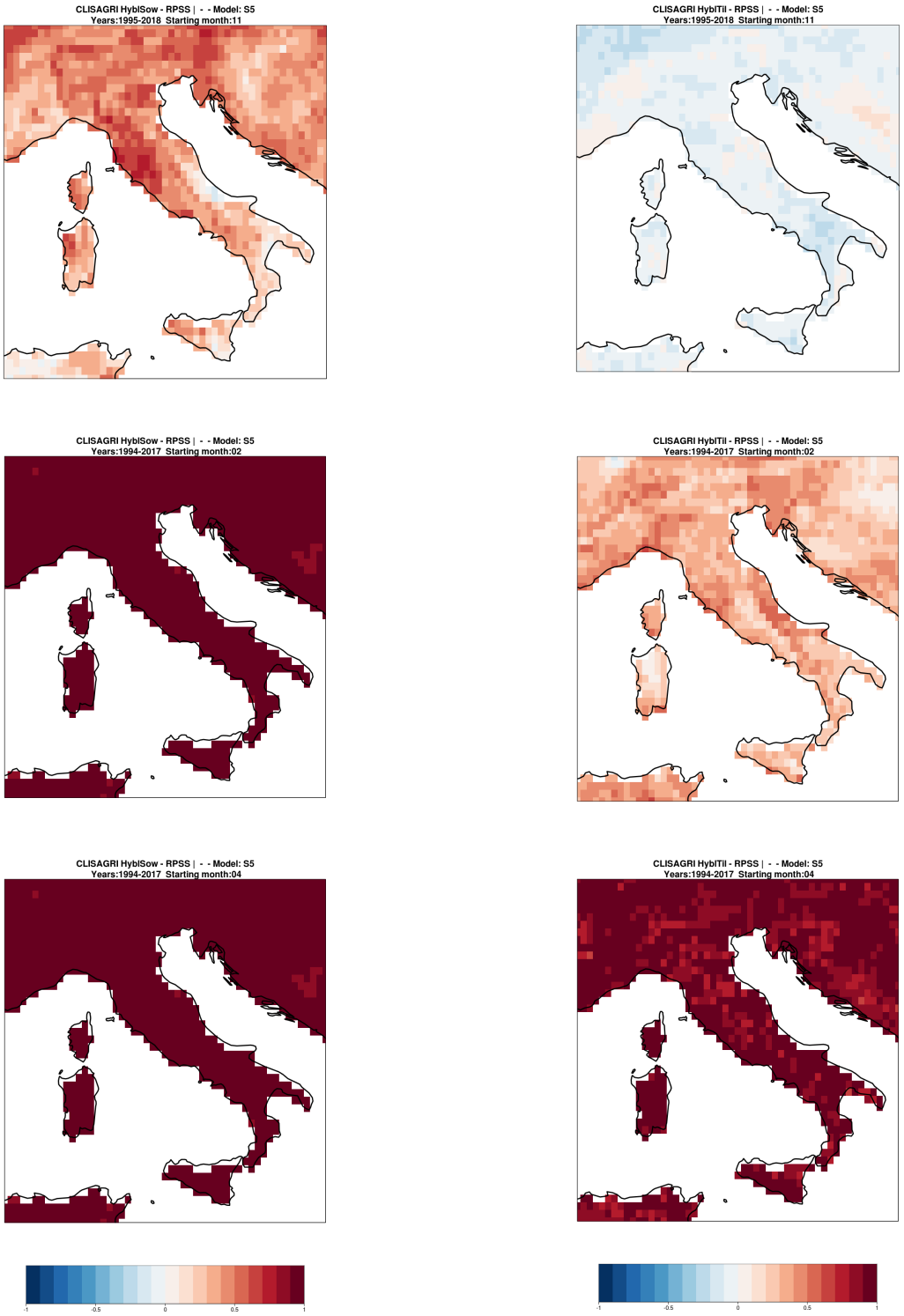


Figure 5: Fair RPSS for the CLISAGRI indicator 2 (left column) and 4 (right column) using ECMWF System5 seasonal forecasts with starting dates in November (top), February (middle), and April (bottom).

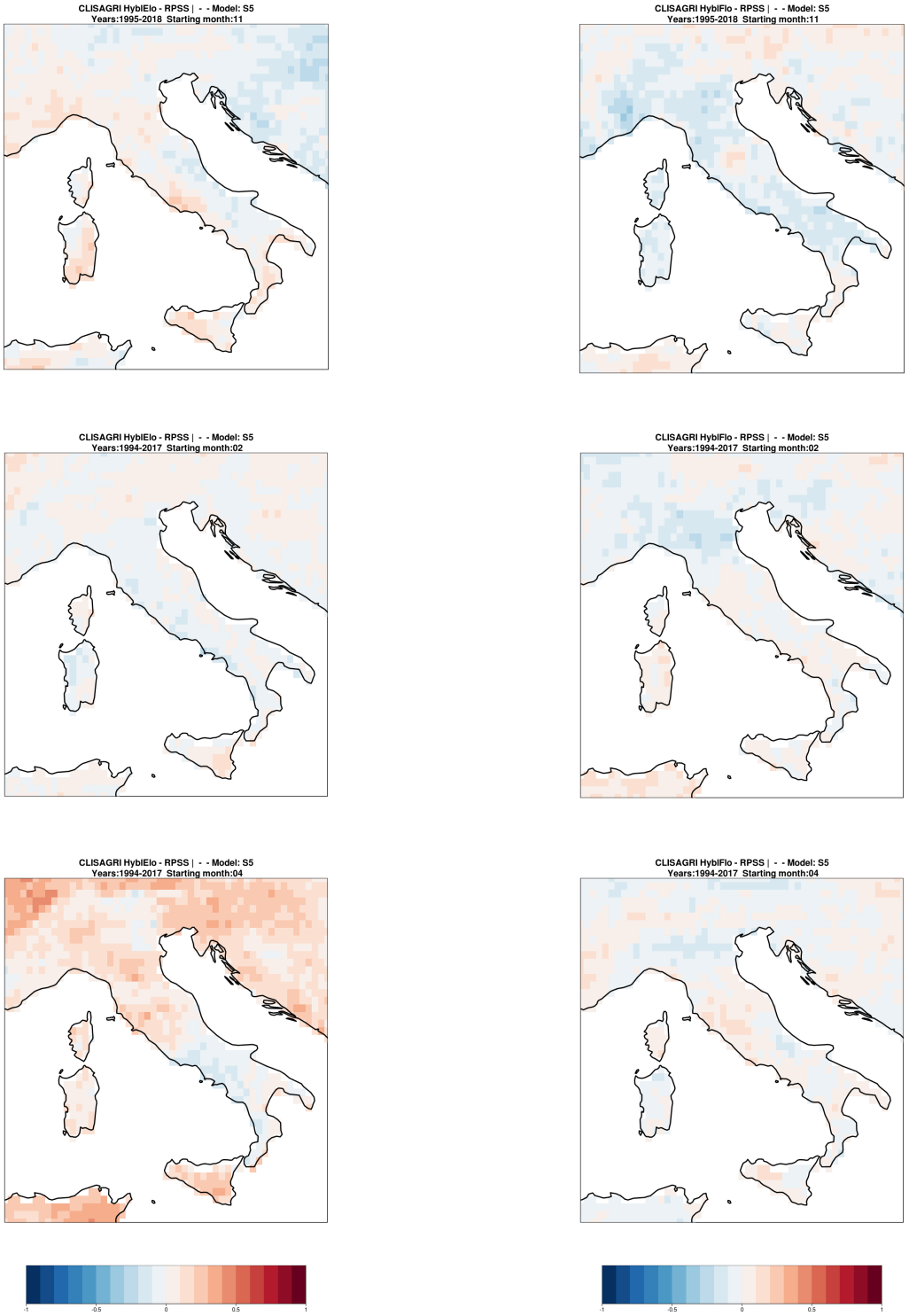


Figure 6: As figure 5 for the CLISAGRI indicators 4 and 5

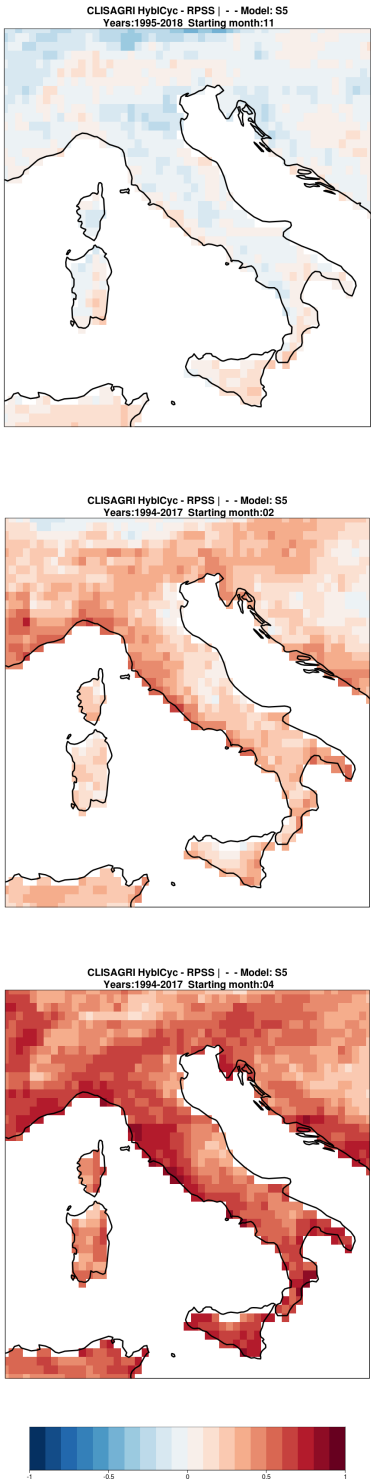


Figure 7: As figure 5 for the CLISAGRI indicator 6.

While the exact dates associated with different phenological phases change significantly over Europe, from north to south, an approximate standard crop calendar can be assumed when focusing the analysis over smaller, more homogeneous areas such as the italian peninsula. For the present analysis the following crop calendar has been assumed:

- **Sowing** -> October to November
- **Tillering** -> December to March
- **Elongation and heading** -> April to May
- **Flowering** -> May to June
- **Crop cycle** -> November to June

The corresponding skills in predicting the CLISAGRI indicators are reported in Fig. 5-7 using a limited set of standard starting dates: November, February and April.

The hydrological balance at **sowing** covers the period of October and November. Therefore, the forecast starting in November - which is merged with the observed data of October to provide input for the computation of the indicator - is already able to provide a skillful prediction of the final value of the index (Fig. 5a). The forecast issued at a later date during the crop season, clearly do not bring additional value to the computation of the indicator, and RPSS = 1 implies that all members of the integrated input of observed+forecast data are actually identical to the observed data.

The hydrological balance during **tillering** covers a longer time span, from December to March. In this case, seasonal forecasts start to provide a skilful indicator in February (Fig. 5), consistently with what already reported in Fig. 4, where the November forecast is marked as dangerously useless.

The forecast of the hydrological balance during **elongation and heading** (Fig. 6), is only marginally useful for most starting dates (see also Fig. 4), and starts to be very useful over specific areas of the italian peninsula (e.g. Tuscany and Sicily) only with the starting date of April, one the elongation phase sets in.

For the **flowering** phase, which is forecast are mostly lacking any skill until April (Fig. 6) whereas they start to be usable - RPSS > 0.6 - only at a shorter lead time.

Finally predictions of the hydrological balance over the **crop cycle** are not usable in November (Fig. 7), whereas they become skilful starting from January and February, consistently with the analysis reported in Fig. 4), especially to the west and south of the italian peninsula.

In summary, the analysis shows how the skill of seasonal forecasts in predicting the hydrological balance and the usability of the associated information changes significantly during the crop season and varies over different geographical areas, even over a relatively small region like the italian peninsula. It is therefore necessary to transparently communicate the degree of accuracy of seasonal forecasts as a fundamental component of the information provided by decision support systems such as GRANODURO.NET®, described in the following section.

7.3 GRANODURO.NET®

Granoduro.net® is an interactive web-based Decision Support System (DSS) for sustainable wheat management of durum wheat crops [see RD.14, RD.15 and RD.16]. Granoduro.net® collects crop data in real time through sensors and farmers' inputs. It organizes the data in a cloud system, interprets them via advanced modelling and big data techniques, and integrates them automatically, generating information, alarms and decision support advice, providing a comprehensive and continuous flow of updated crop related information.

Granoduro.net® has proven its added value in providing additional information to support crop farming decision-making processes. Users of granoduro.net® (farmers, technicians and agronomists in the BARILLA supply chain) have been involved in the co-development meetings, during which relevant climate information to be included in the MED-GOLD development [RD.16, RD.17] has been identified, as well as relevant indices providing useful information for durum wheat growers.

In the context of the MED-GOLD project, a new prototype functionality based on bias-corrected seasonal forecasts data has been developed. For the calculation of some indicators, ERA5 data from 1994 have been retrieved, in order to calculate standardized indices with the R package CLISAGRI (RD.8). In the new prototype functionality, models are fed with data from weather stations for past and present dates, and then with seasonal forecast data starting from the dates in which they are issued.

As reported in previous deliverables, the new prototype functionality added to granoduro.net® was co-developed with users in the durum wheat sector [RD.18, RD.19, RD.16, RD.17] and presents several tabs: one for the phenological development of durum wheat; one displaying risk indices for the main wheat diseases, one displaying climatic indices calculated by the CLISAGRI R package and finally one displaying the value of the same indices calculated using historical data. For the development of the new prototype functionality added to granoduro.net®, three locations in Italy were considered at first: Ravenna in the North of Italy, Jesi in the Center and Foggia in the South (Fig. 8). For season 2020-21 seasonal forecast data have been made available by project partners for additional cells.

Figure 8. Map showing the grids corresponding to the three locations considered for the development of the new prototype functionality added to granoduro.net®. Blue points show the cell centroid, red points show the location of the weather station from which observed data were retrieved

The wheat phenological model in granoduro.net® is based on the work of Rossi et al. [RD. 14] and has been calibrated for many different wheat varieties. The model is fed with temperature data, and simulates the crop development through the main phases: emergence, tillering, stem elongation, booting, heading, flowering and maturity. In the new prototype functionality it is being fed with seasonal forecast data, so that it can display the foreseen crop development up to six months ahead, allowing the user to have an interval of time in which the reach of a particular phenological stage is forecasted, and then allows them to better plan field interventions. The information is displayed to users as a graph (Fig. 9), as well as a table, in which the predicted dates in which phenological stages are reached are indicated.

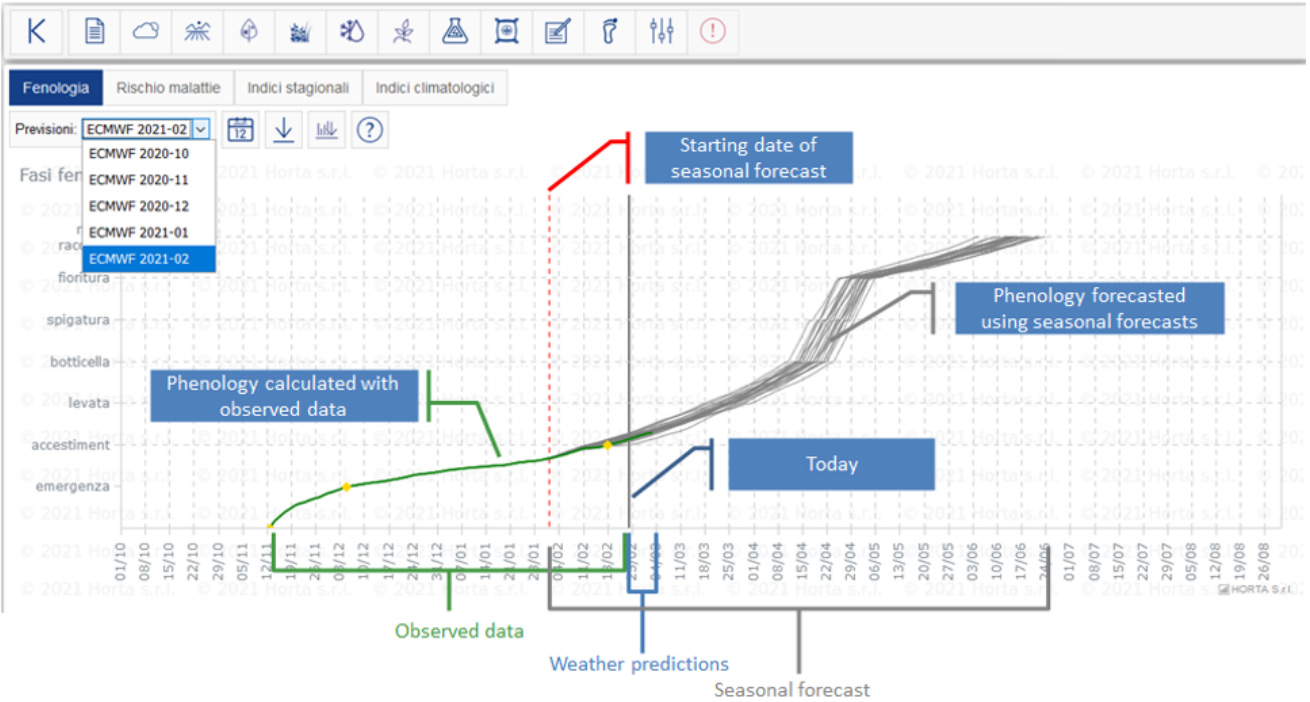


Figure 9. Illustration of the phenology tab in the new prototype functionality based on seasonal forecasts in the Decision Support System granoduro.net®.

The forecast of the main phenological stages is also used as a base for the calculation of other indices in the new prototype functionality. Main wheat diseases have been considered: stripe rust (caused by *Puccinia striiformis*), leaf rust (caused by *Puccinia triticina*), stem rust (caused by *Puccinia graminis* subs. *graminis*), powdery mildew (caused by *Erisiphe graminis* f.sp. *tritici*), Septoria blotch (caused by *Mycosphaerella graminicola* and *Leptosphaeria nodorum*) and Fusarium Head blight (caused by fungi of the genus *Fusarium*, mainly *F. graminearum* and *F. culmorum*). Phenological phases more relevant for the development of each disease have been identified, as reported in Table 2.

Table 2. Phenological periods in which disease risk is calculated for each disease considered.

Disease	From tillering to beginning of stem elongation	From stem elongation to booting	From heading to flowering	Maturity up to soft dough maturity
Stripe rust	x	x	x	x
Leaf rust		x	x	x
Stem rust		x	x	x

Powdery mildew	x	x	x	x
Septoria blotch		x	x	x
Fusarium Head Blight			x	x

The risk indices are based only on climatic information (temperature and rain data), and compute both the number of days having suitable conditions for the fungal development, and the number of disease cycles the pathogen can complete in the reference period. Using observed weather data and observed disease data (incidence or severity) collected in the pilot locations, clusters have been defined and the information provided by the two indices has then been combined using a discriminant function analysis. The risk of each disease can be predicted as three classes, to which colours were assigned according to a traffic light code going from red (high risk) to yellow (medium risk) and green (low risk). The colour of the predicted index is then displayed in the new prototype functionality as a coloured bar (Fig. 9).

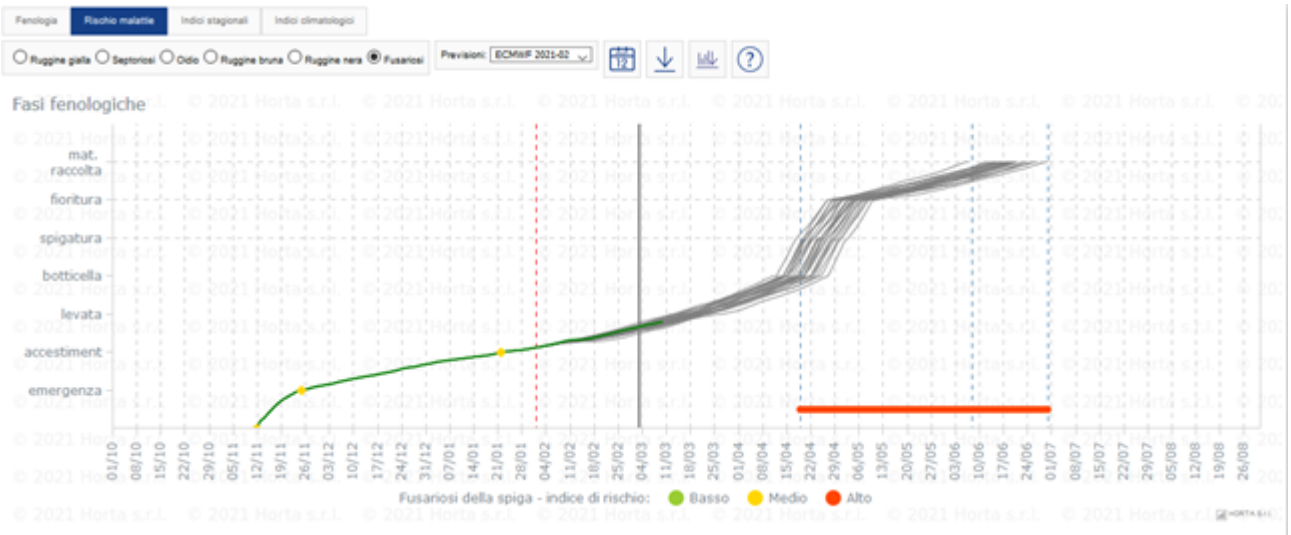


Figure 9. Wheat diseases risk tab showing forecast for Fusarium Head Blight for a crop unit in the Jesi location. The length of the coloured bar shows the relevant period for calculation, based on phenological stages. The colour of the bar shows the calculated risk using a traffic light colour code.

The tabs dedicated to climate indexes display the value of the indexes computed by means of the CLISAGRI R package, which was integrated in the system. The list of the indices calculated by CLISAGRI is displayed in RD.16. For indexes based on SPEI (Standardised Precipitation Evaporation Indexes), seven classes have been identified and associated to a colour, going from dark orange meaning 'extremely dry', decreasing colour intensity going to white meaning 'normal', then turning blue and increasing colour intensity up to dark blue meaning 'extremely wet'. For other indexes, which are based on the number of days in which particular temperature or rain conditions are forecasted, thresholds have been defined on the base of expert knowledge. This classification allows the identification of conditions which are or are not suitable for the crop, and have been assigned to a colour according to a traffic light system: green (suitable), yellow (intermediate suitability) and red (unsuitable). In order to be consistent in the several parts of the prototype functionality, the forecasted index is displayed with a coloured bar as it was for the disease risk index.

In the last tab in the new prototype functionality, the indexes present in the CLISAGRI R package are calculated on the base of historical data. The value of each index is calculated using ERA5 weather data and displayed for years since 1994, in order to give the user a reference on the value of the index assumed in the location in the past years.

7.4 DELPHI System simulation benchmarks

The Delphi model was chosen due to the recent validations of its ability to simulate crop growth, yield and product quality conducted in the same study areas [RD.22, RD.23]. The Delphi is built on a FORTRAN-based mechanistic model [RD.24] calibrated for durum wheat in Mediterranean conditions. Plant transpiration and soil evaporation, water and nitrogen soil-plant cycle are incorporated in the model. Input weather data at daily time scale are: air temperature (maximum, minimum and average), global shortwave radiation, rainfall, wind speed (average) and relative humidity (average). Input data of the main physiological parameters of the durum wheat cultivar, sowing date and number of seeds/m2, the soil hydrological profile, soil total nitrogen content profile, agronomic data on quality and quantity of nitrogen and roots growth data are also required [RD.24]. The system starts to simulate plant growth from 1st September to harvest date. In the operational version, the model runs simulations from January to June and, in forecast mode, the model uses the scenario files in a sort of ensemble forecast. The standard Delphi system uses three synthetic reference scenarios: “wet”, “dry” and “average” derived from the observed long-term conditions (1981– 2010). The wettest and driest scenarios are two extreme conditions crop reference years: the “wet” condition is made with the weather variables coming from to the months with the highest rainfall in the long-term period; the driest condition selects the weather variables related to the months with the lowest rainfall in the long-term period. Finally the average scenario is generated as the average of the whole crop years dataset. This strategy provides a sort of ensemble forecast to determine an outlook of the final yield at any stage of the growing season, with an associated uncertainty range. As soon as the availability of observed data increases during the growing season, the predictions become more accurate (but its usefulness decreases).
Rather than rely on just the present information of the growth stage, we consider forecasts that start from the same initial conditions (present information). The growth stage is determined by the actual weather conditions during the period from 1st September, while the entire development to harvest will follow the conditions of scenario data. The variation in simulated yields using different scenarios could be considered as an indication of the effect of climatic uncertainty on yield prediction for a given site. This produces a narrower distribution of grain yields. As time passes and the amount of observed data available for prediction increases, the simulated prediction becomes more accurate.

7.4.1 Crop season benchmark analises

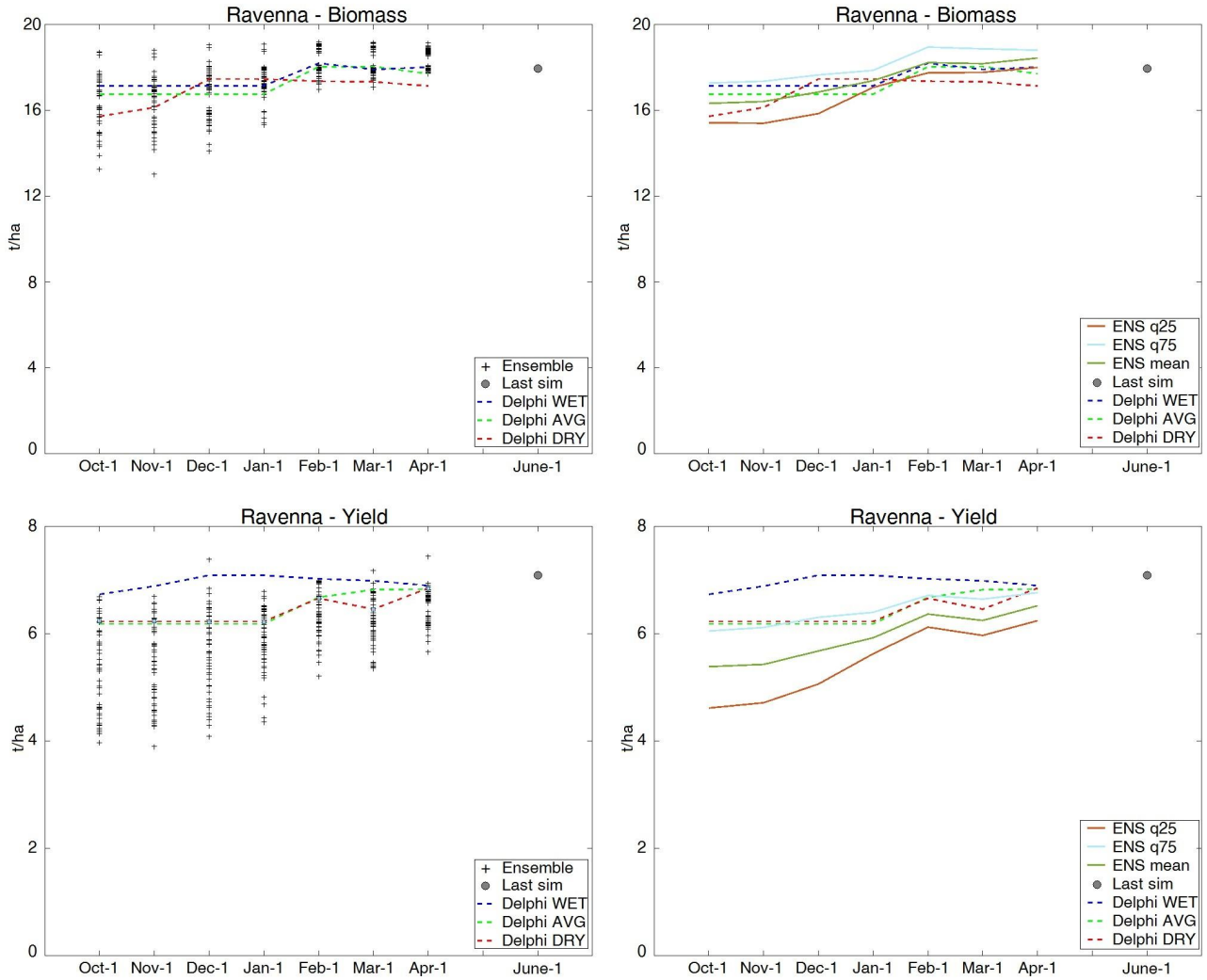
7.4.1.1 2017 - 2018 crop season analysis (biased/raw data)

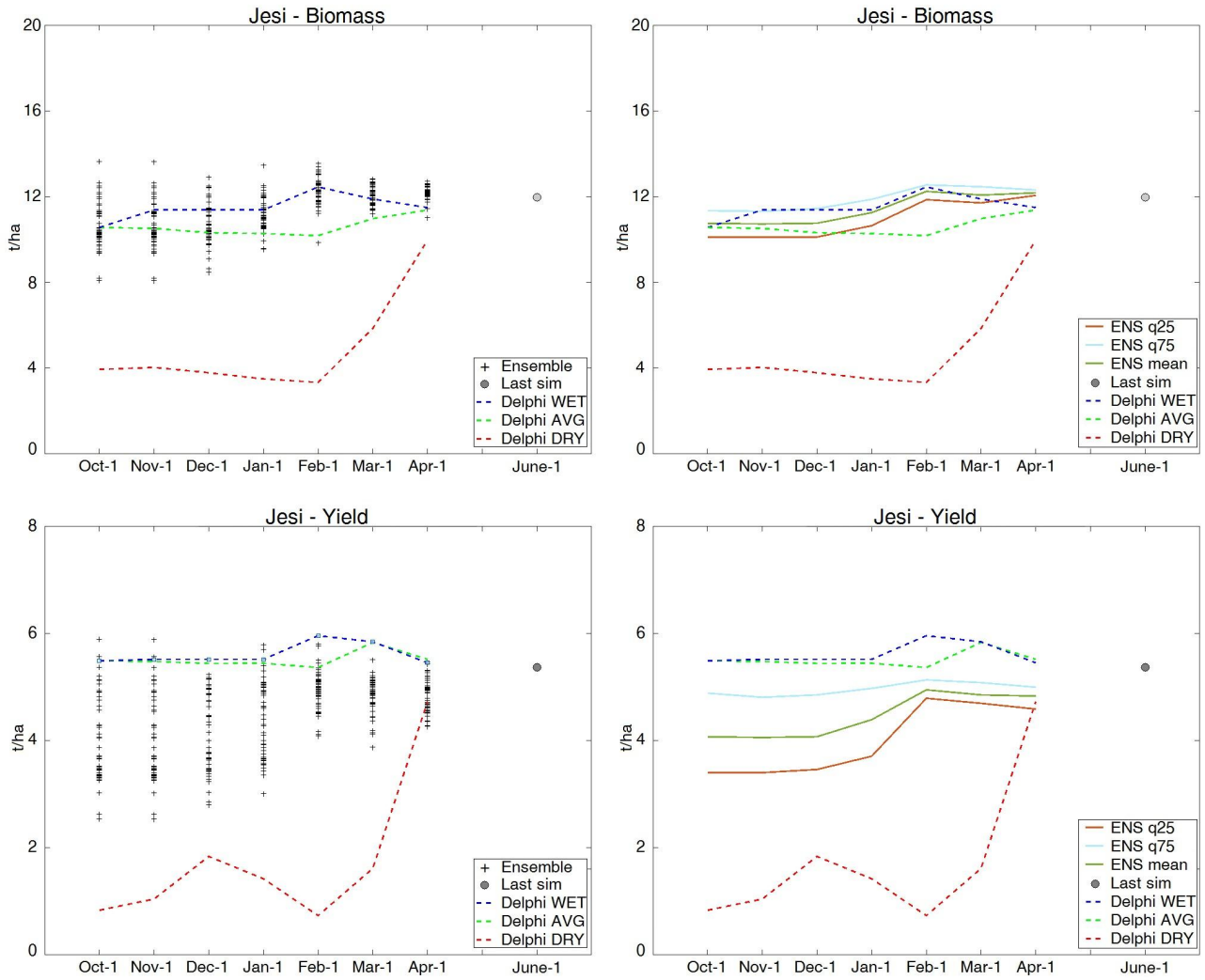
Benchmark of the DELPHI system for yield and biomass using the seasonal forecast data provided by Copernicus Data Store, SEAS5, released in October 2017 (51 member ensemble for 6 months of forecast).
Results were compared with the results of the current DELPHI System by feeding the model with synthetic weather scenarios based on historical observations (dry, average, wet scenario).

For each simulation the input weather files were built as indicated in the following scheme (Fig 10)::

Figure 10. Scheme for producing the meteorological data needed to feed the crop simulation model from the moment of estimation to the end of the growing season.

For the three case studies (Ravenna, Jesi and Foggia sites) yield and biomass predictions were calculated at a monthly time step, starting from October 1st. For each case study we report charts with all the ensemble members simulations (black cross) and the Dry-Average-Wet scenarios (colored dashed lines) results and charts with the 25th and 75th percentiles for all ensembles predictions (colored continuous lines); a gray filled circle represents the observed value.


Ravenna - Biomass
t/ha
Ensemble
Last sim
Delphi WET
Delphi AVG
Delphi DRY
Ravenna - Biomass
ENS q25
ENS q75
ENS mean
Last sim
Delphi WET
Delphi AVG
Delphi DRY
Ravenna - Yield
Ravenna - Yield
Oct-1
Nov-1
Dec-1
Jan-1
Feb-1
Mar-1
Apr-1
June-1


Jesi - Biomass
t/ha
Oct-1
Nov-1
Dec-1
Jan-1
Feb-1
Mar-1
Apr-1
June-1
Ensemble
Last sim
Delphi WET
Delphi AVG
Delphi DRY
Jesi - Biomass
ENS q25
ENS q75
ENS mean
Last sim
Delphi WET
Delphi AVG
Delphi DRY
Jesi - Yield
Ensemble
Last sim
Delphi WET
Delphi AVG
Delphi DRY
Jesi - Yield
ENS q25
ENS q75
ENS mean
Last sim
Delphi WET
Delphi AVG
Delphi DRY

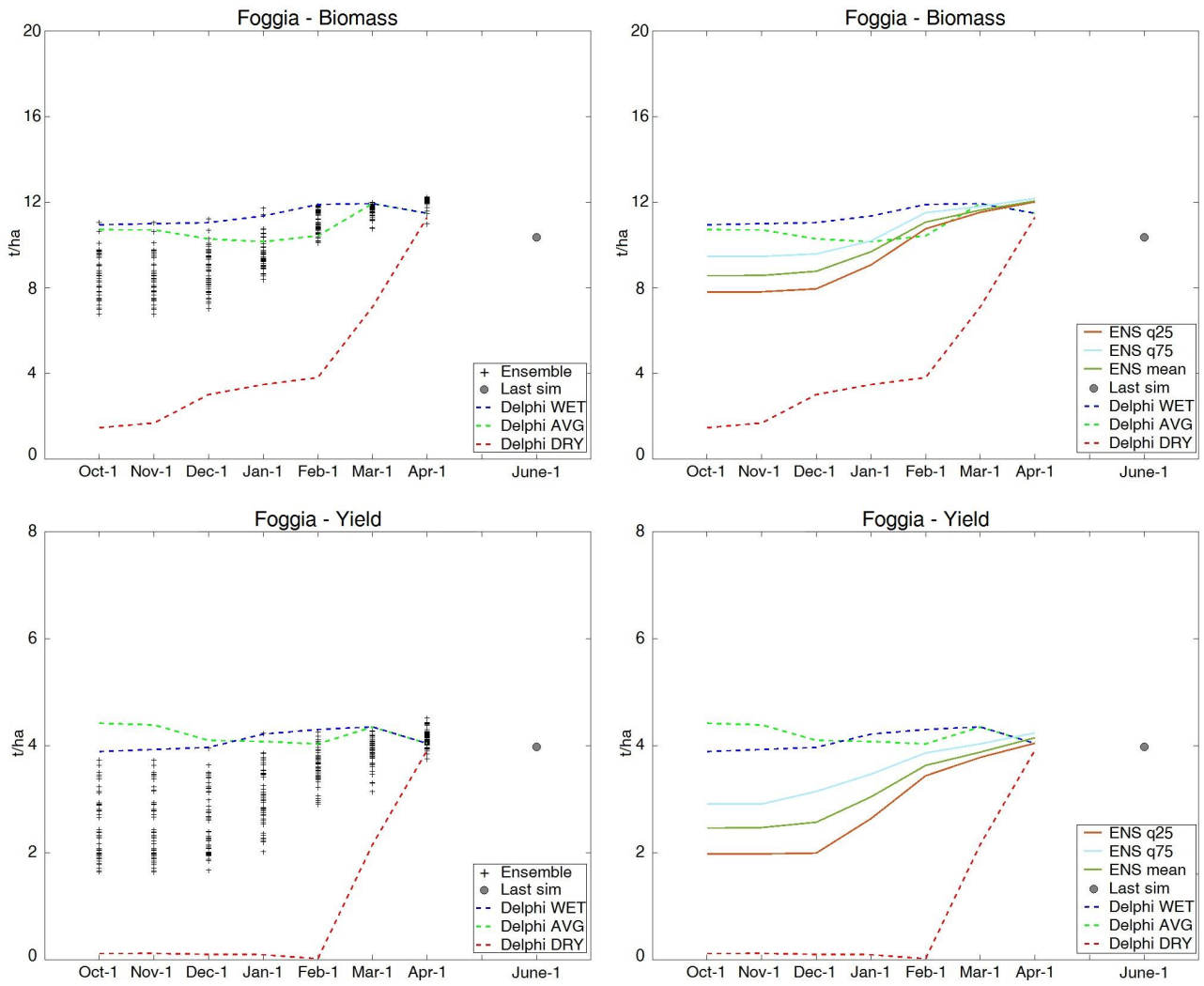


Figure 11. Biomass and yield predictions for the three test pilot cases: Ravenna, Jesi and Foggia. Ensemble members simulations (black cross) and the Dry-Average-Wet scenarios (colored dashed lines) results and charts with average percentiles 25-75 for all ensembles predictions (colored continuous lines); a gray filled circle represents the observed value.

In Ravenna site, biomass the range of biomass from the seasonal forecast scenario range is wider than that provided by the Dry-Average-Wet scenario, with a tendency to overestimate its expected final value; yield has a similar behaviour with a tendency to underestimate the expected value.

In the Jesi test-site the range of the biomass values from the seasonal forecasts is narrower than that provided by the Dry-Average-Wet scenarios. Similar behaviour is shown by the yield forecast until March 1st, with a tendency to underestimate yield value.
In Foggia site, biomass and yield forecasted values have a wider range with respect to those provided by the Dry-Average-Wet scenario, with a tendency to underestimate the expected values.

Furthermore, we tested the accumulation values of Leaf Area Index, daily biomass and yield, using the seasonal forecast provided by SEAS5 released in October 2017 (with 51 ensemble members for 6 months of forecast) and compared with results of the current DELPHI System fed with observed weather data.

For the simulation the input weather files were built as indicated in the following scheme:

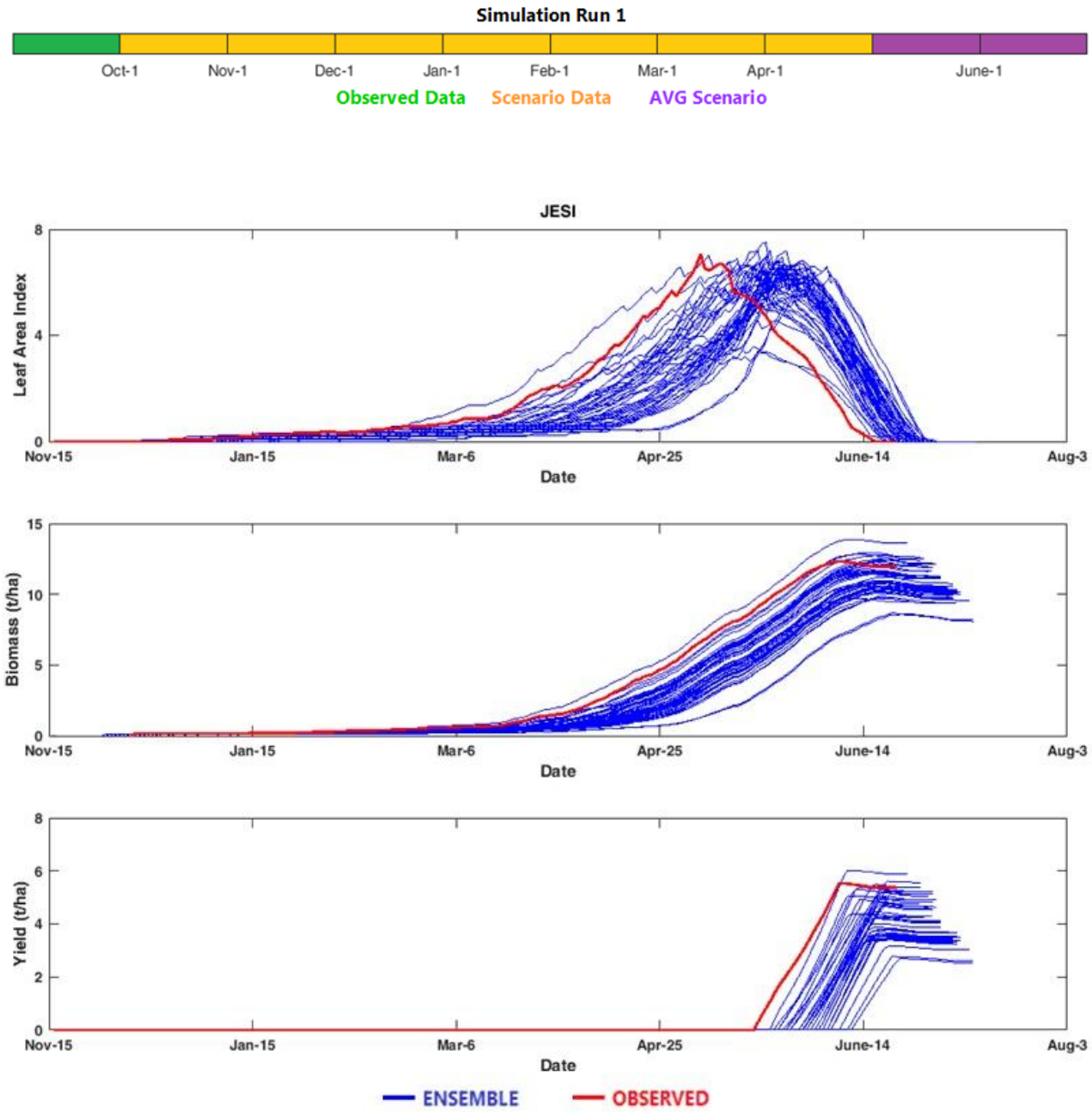


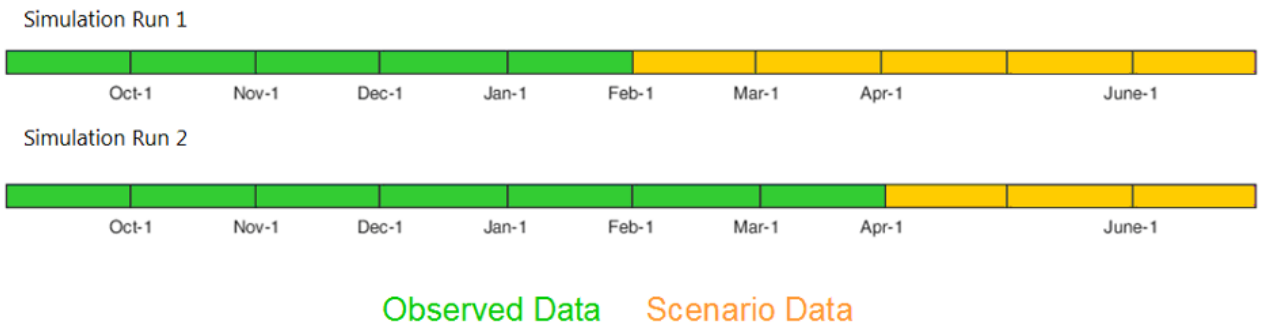
Figure 12. Daily time series example of Leaf Area Index, biomass and yield for Jesi test pilot site.

As an example we reported here the case of Jesi test-site (Fig.12). A clear tendency of a delay in the actual signal is present for all the considered accumulated variables: LAI, biomass and yield.

7.4.1.2 Biased/raw data simulation of high and low yielding crop season

In the same study areas (Ravenna, Jesi, Foggia) we tested DELPHI in crop years characterized by high and low yields (data provided by Barilla and ISTAT). The first group, called “BAD YEAR”, is populated with below average yields: 2010 for Ravenna; 2007 for Foggia and Jesi. The other group, called “GOOD YEAR”, is populated with above average yields, namely: 2012 for Ravenna; 2016 for Foggia and Jesi.

For each simulation we used the weather data provided by SEA5 system released in February and in April for each crop year based on 25 ensemble members for 6 months of forecast, with the following scheme:



Results were compared with those from the current DELPHI System by feeding the model with synthetic weather scenarios based on historical observations (dry, average, wet scenario).

Results for yield prediction on the first day of June for each crop season on the basis of three historical scenarios (red-green-blue circle) and on the basis of seasonal forecast (black square) are reported. For each year the predicted yield by feeding the model with only observed weather data is also reported (grey circle). For each year and case study we show charts with all the ensembles and the Dry-Average-Wet scenarios results and charts with percentiles 5, 25, 75, 95 for all ensembles predictions.

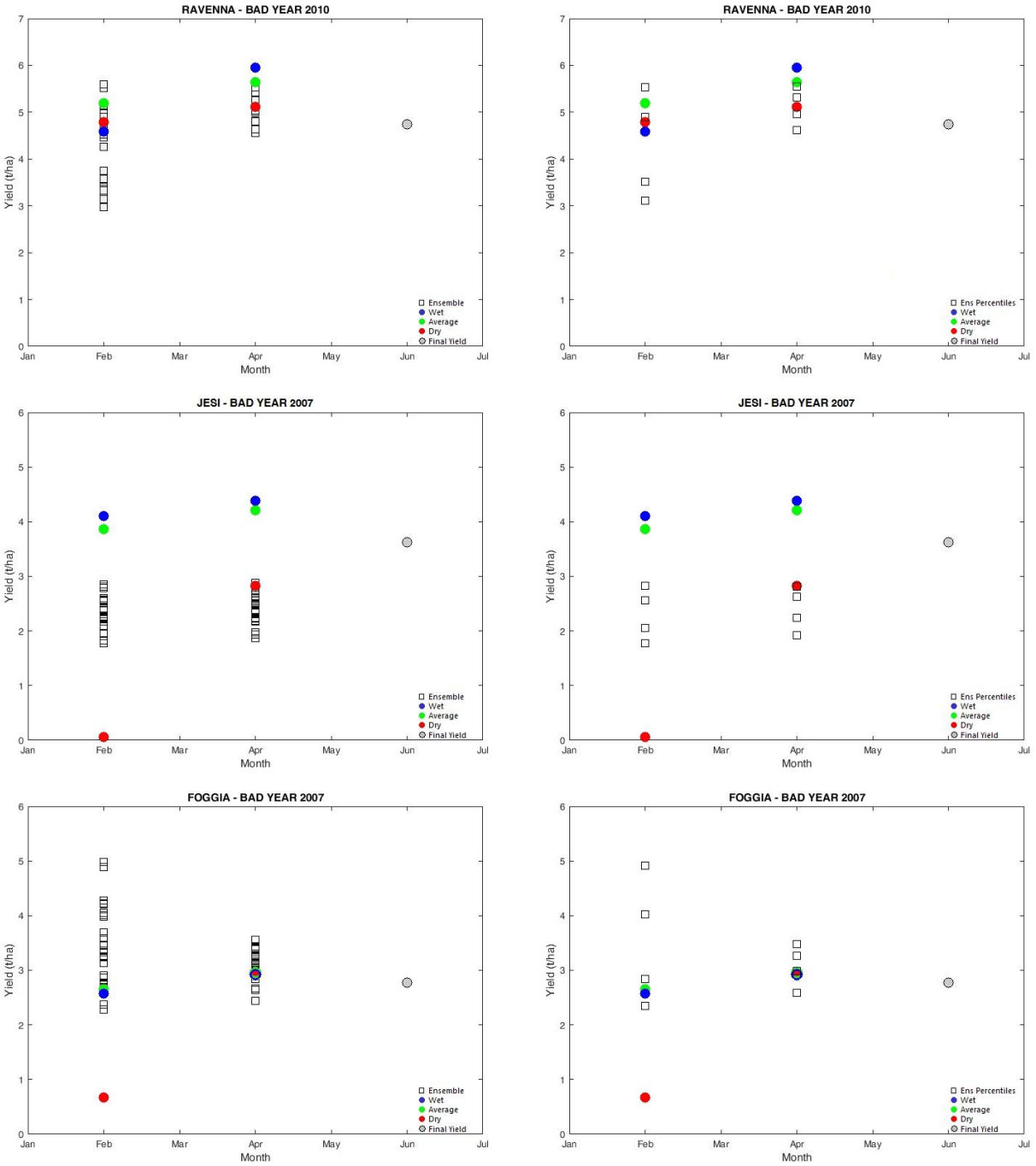


Figure 13. "BAD YEAR" group experiment results for yield prediction on the first day of June for each crop season on the basis of three historical scenarios (red-green-blue circle) and on the basis of seasonal forecast (black square) are shown. For each year the predicted yield by feeding the model with only observed weather data is also reported (grey circle). Left-hand panels show simulation results (yield) for all ensemble members, right-hand panels show four percentiles of the yield.

For “BAD YEAR” group experiments the seasonal forecast scenario range is generally wider than that provided by the Dry-Average-Wet scenario setup; with a tendency for both scenario systems to overestimate yield value (Fig.13). The range of predicted values is reduced when using simulations that started on April 1st. In this latter simulation set-up the range of predicted values have a general tendency to underestimate yield values.

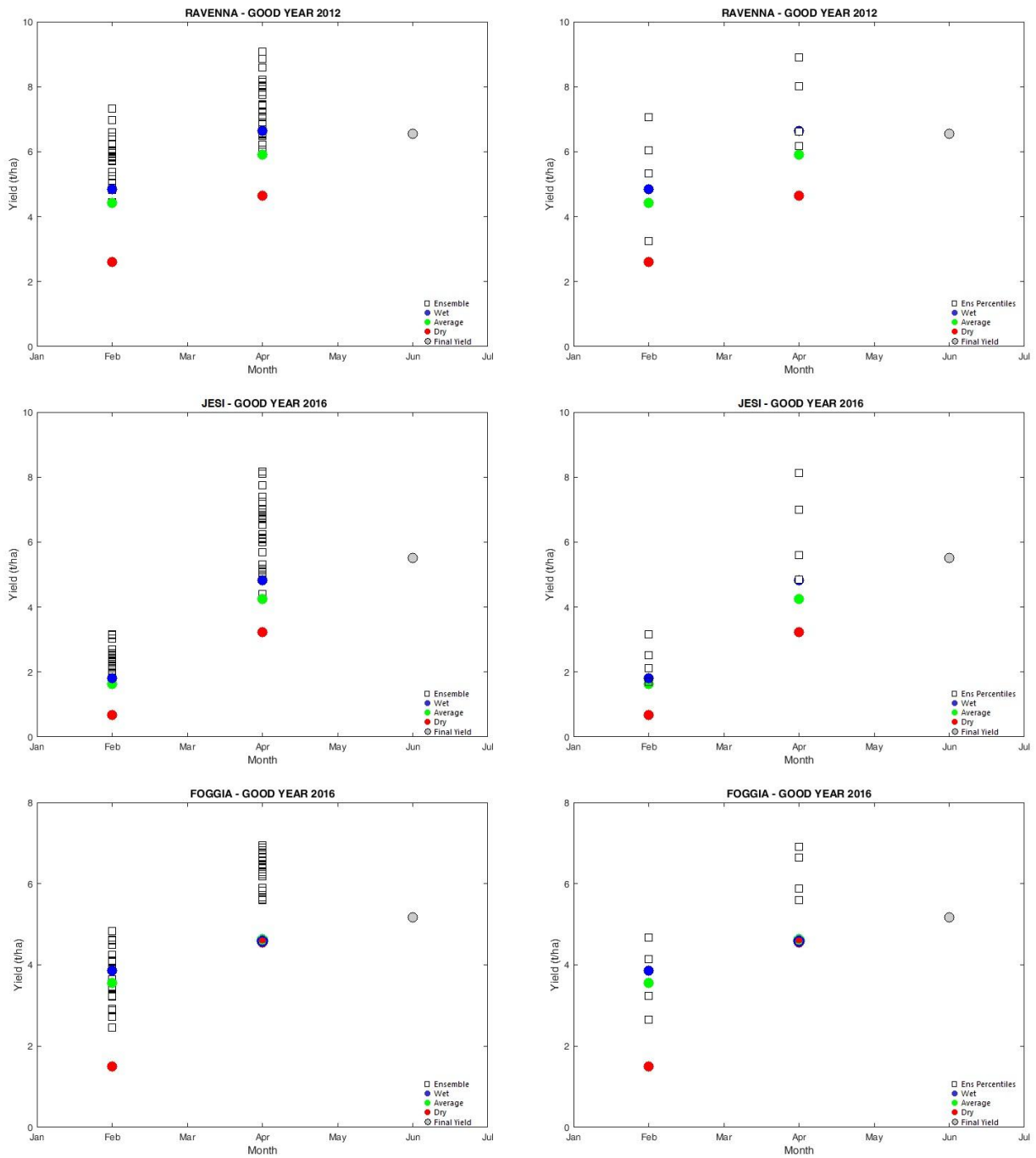
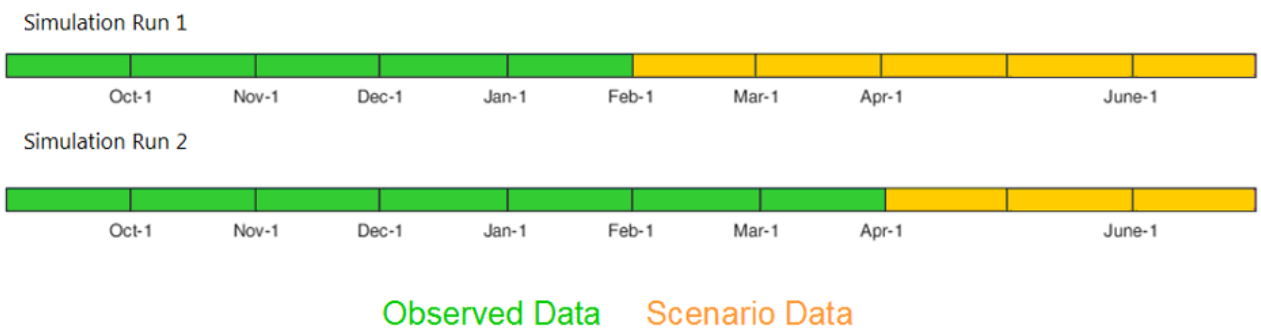


Figure 14. "GOOD YEAR" group experiment results for yield prediction on the first day of June for each crop season on the basis of three historical scenarios (red-green-blue circle) and on the basis of seasonal forecast (black square) are shown. For each year the predicted yield by feeding the model with only observed weather data is also reported (grey circle).

Seasonal forecast scenario yields' range of values for the "GOOD YEAR" group and based on the SEAS5 system is generally wider than that provided by the Dry-Average-Wet scenario (Fig.14). Furthermore the seasonal forecast scenarios have a tendency to overestimate expected yield value. This behaviour persists for those simulations started on April 1st; again there is a general tendency to overestimate expected yield value.

7.4.1.3 Unbiased simulation of high and low yielding crop season case studies: Ravenna, Jesi, Foggia

To test the gain of reliability of bias-adjusted, namely unbiased simulations, we selected several runs with the DELPHI system for crop years with a high and low performance in terms of yield (data provided by Barilla and ISTAT) for the three case studies (Ravenna, Jesi, Foggia). The first group, called "BAD YEAR", is formed from years with below average yields (Fig.13): 2010 for Ravenna; 2007 for Foggia and Jesi. The second group, called "GOOD YEAR", is formed from years with above-average yields (Fig.14): 2012 for Ravenna; 2016 for Foggia and Jesi.
For each simulation we used the ECMWF SEAS5 raw data provided by CDS platform released in February and in April for each crop year (25 ensemble members for 6 months of forecast) and bias adjusted where the same data are biased adjusted as described in DEL4.2 (par: 3.1.3, RD.20) with the *CST_calibration* method for all the weather variables. As usual, results were compared with the results of the current DELPHI System fed with synthetic weather scenarios based on historical observations (dry, average, wet scenario).
For each simulation the input weather files were built as indicated in the following scheme:



Results are shown for yield prediction on the first day of June for each crop season on the basis of three historical scenarios (red-green-blue circle) and on the basis of seasonal forecast (black square) are reported. For each year the predicted yield by feeding the model with only observed weather data is also reported (grey circle).
For each year and case study we report charts with all the ensembles and the Dry-Average-Wet scenarios results and charts with percentiles 5, 25, 75, 95 for all ensembles predictions.

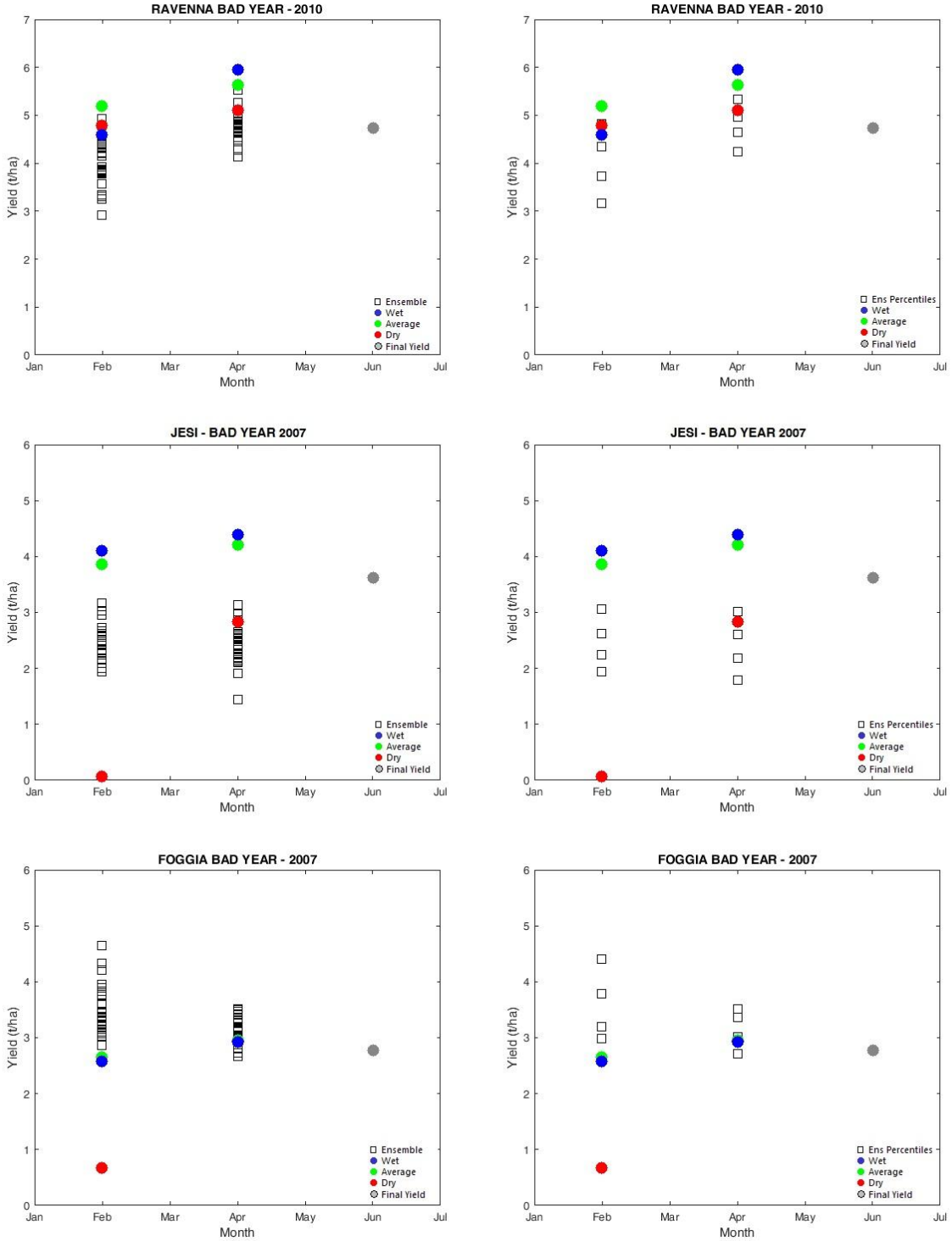


Figure 15. Unbiased "BAD YEAR" group experiment results for yield prediction on the first day of June for each crop season on the basis of three historical scenarios (red-green-blue circle) and on the basis of seasonal forecast (black square) are shown. For each year the predicted yield by feeding the model with only observed weather data is also reported (grey circle).

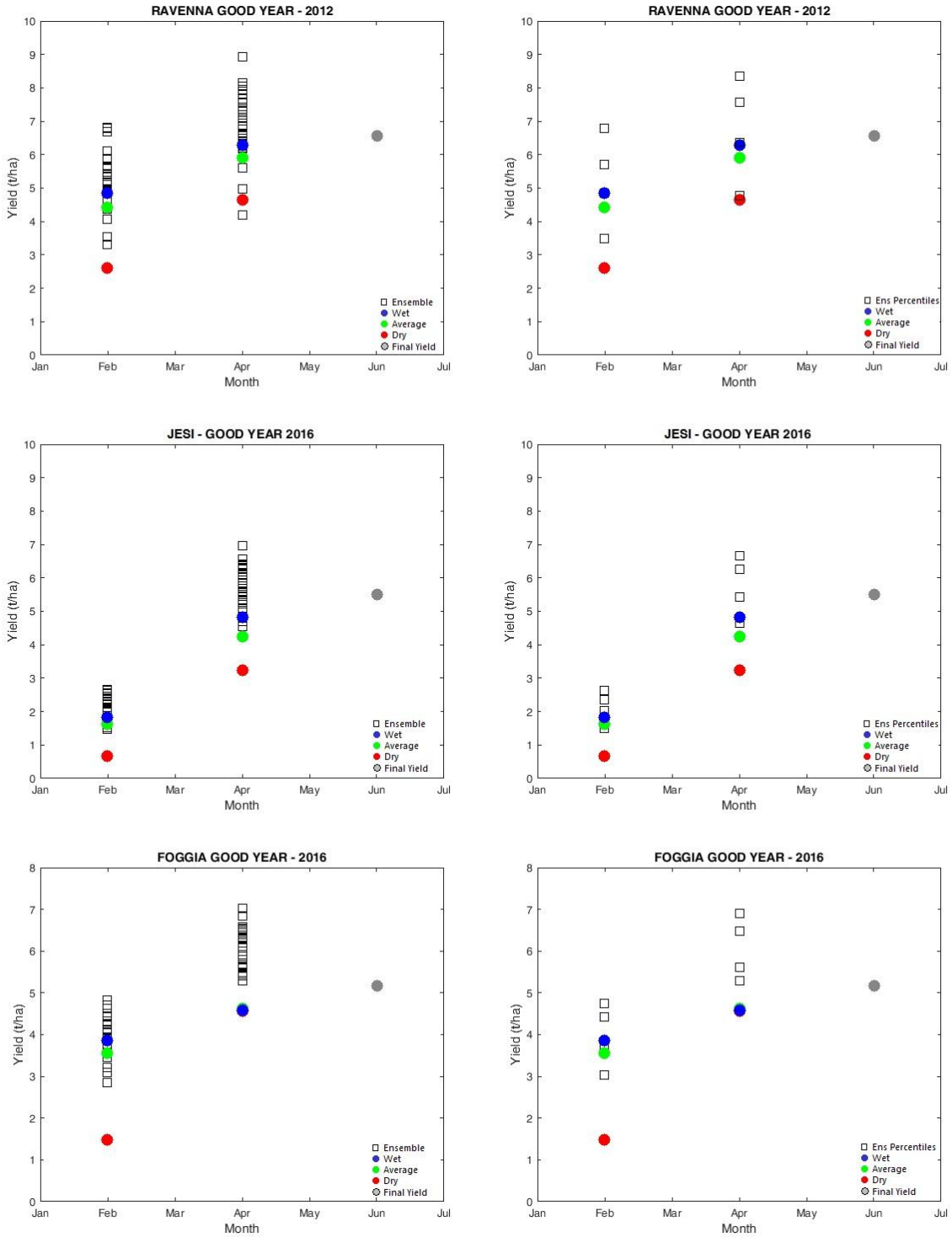


Figure 16. Unbiased "GOOD YEAR" group experiment results for yield prediction on the first day of June for each crop season on the basis of three historical scenarios (red-green-blue circle) and on the basis of seasonal forecast (black

square) are shown. For each year the predicted yield by feeding the model with only observed weather data is also reported (grey circle).

Tab 3 summarizes all the results (yield) obtained by simulating crop years with low and high yield, using both the biased and the unbiased seasonal forecast. For a complete comparison, the reference values provided by Barilla-ISTAT have also been included.

Table 3 Durum wheat yield summary table, for both biased and unbiased seasonal forecast simulations including the yield data (reference) provided by Barilla-ISTAT. Long term crop season simulations data are relative to the 1988 – 2018 period.

FEBRUARY	BIASED			UNBIASED			YIELD_REF (t/ha)
GOOD_YEAR	MIN	MAX	MEAN	MIN	MAX	MEAN	
RAVENNA	4.44	7.32	5.56	3.30	6.81	5.23	**6.55**
JESI	1.67	3.16	2.35	1.48	2.66	2.13	**5.50**
FOGGIA	2.46	4.83	3.71	2.86	4.82	4.03	**5.17**
BAD_YEAR							
RAVENNA	2.98	5.59	4.14	2.91	4.93	3.99	**4.74**
JESI	1.78	2.85	2.29	1.94	3.16	2.43	**3.62**
FOGGIA	2.28	4.98	3.45	2.86	4.64	3.52	**2.77**

APRIL	BIASED			UNBIASED			
GOOD_YEAR	MIN	MAX	MEAN	MIN	MAX	MEAN	
RAVENNA	6.08	9.07	7.35	4.19	8.92	6.85	**6.55**
JESI	4.40	8.17	6.38	4.55	6.98	5.74	**5.50**
FOGGIA	5.59	6.95	6.29	5.28	7.03	6.08	**5.17**
BAD_YEAR							
RAVENNA	4.56	5.59	5.12	4.13	5.53	4.78	**4.74**
JESI	1.87	2.87	2.43	1.44	3.13	2.41	**3.62**
FOGGIA	2.43	3.56	3.12	2.66	3.52	3.16	**2.77**

The long term simulation benchmark has been configured for the usual test-sites: Ravenna, Jesi and Foggia. The study period is 31 years long: 1988 – 2018. The reference yield values were computed using the ERA5 reanalysis dataset. The raw data (biased) simulations were initialized with the 25

ECMWF ensemble member hindcasts issued in February. The bias adjusted yield forecasts (unbiased) were computed with the ECMWF ensemble 25 members hindcast issued in February and adjusted with the *CSTool_Quantile* function for rainfall and *CST_calibration* for air temperature, relative humidity, wind speed and solar radiation (see more details on the methods in DEL4.2 par. 3.1.3).
Results were compared with those from the current DELPHI System by feeding the model with ERA5 reanalysis dataset and synthetic weather scenarios based on historical observations (dry, average, wet scenario).
For each simulation the input weather files were built as indicated below, where green shows the observed weather data and yellow the forecast weather data:

Results for yield prediction at harvesting time for each crop season on the basis of seasonal forecasts are analysed. For each crop year, the predicted yield by feeding the model with only ERA5 reanalysis data is used as reference to compute the benchmark. In particular for each analysis the average bias is calculated as the difference between simulations with adjusted seasonal forecasts and simulations with raw data. Pearson correlation coefficients were calculated using both using the biased and unbiased datasets, and comparing them with model outputs feeded with ERA5 data, chosen as reference.
To complete the test, the same analysis carried out using the synthetic weather scenarios based on historical observations (dry, average, wet scenario) are reported.

Table 4 Durum wheat yield summaries results, for both biased, unbiased and reference scenarios of seasonal forecast simulations for the 1988-2018 period. In a) Pearson correlation coefficient for the different simulation variants with respect of reference ERA5 outputs. b) Mean difference values for simulation variants. c) Correct percentage of forecast hits in successfully yield prediction of above or below its average yield value. d) Correct percentage of forecast hits in successfully prediction of interannual yield value above or below its average value.

a) Pearson Corr. Coef. for 1988-2018

	BIASED	UNBIASED	RefDRY	RefAVG	RefWET
Ravenna	*0.0003*	*-0.0064*	*0.09*	*0.34*	*0.08*
Jesi	*0.164*	*0.16*	*0.05*	*-0.1*	*0.16*
Foggia	*-0.19*	*0.46*	*0.33*	*0.16*	*0.26*

b) Mean difference for 1988-2018 [t/ha]

	BIASED	UNBIASED	RefDRY	RefAVG	RefWET
Ravenna	*0.61*	*0.64*	*-0.43*	*-0.01*	*0.22*
Jesi	*0.5*	*0.49*	*-3.93*	*-1.55*	*0.26*
Foggia	*1.11*	*0.094*	*-3.38*	*-1.5*	*-0.13*

c) Predicting yield above/below the average [%]

	BIASED	UNBIASED	RefDRY	RefAVG	RefWET
Ravenna	*38.7*	*38.7*	*61*	*67*	*42*
Jesi	*48.4*	*48.4*	*0*	*0*	*58*
Foggia	*0*	*71*	*1*	*1*	*45*

d) Predicting inter-annual yield variability [%]

	BIASED	UNBIASED	RefDRY	RefAVG	RefWET
Ravenna	*46.7*	*50*	*50*	*60*	*43*
Jesi	*73.3*	*73.3*	*53*	*57*	*63*
Foggia	*43.3*	*70*	*50*	*50*	*30*

For Ravenna and Jesi (Table 4) case study sites no improvement is reported by using unbiased data. The final performances (bias and correlation coefficients) are lower than those obtained by using historical observations with reference scenarios, dry, average and wet scenarios. The forecast for Jesi based on the wet scenario has higher skill than the forecast based on both biased and unbiased dataset. Ravenna forecasts, based on dry/average/wet scenarios, have higher skill than forecasts based both on biased and unbiased dataset. The Ravenna forecast based on the dry/wet scenarios has similar skill than forecast based both on biased and unbiased dataset. Ravenna forecast based on average scenario has higher skill than forecast based both on biased and unbiased dataset.

A further bias in the datasets for Jesi and Ravenna seems evident, which leads to a general overestimation of the yield forecast, however without affecting the ability to catch most of the interannual variability.

For the Foggia case study a significant improvement is reported in the use of unbiased data. Indeed, the final performances are higher in terms of r and lower in terms of bias than those obtained by using historical observations (dry, average, wet scenario).

The Foggia forecast based on the unbiased dataset and the Jesi forecast based both on biased and unbiased dataset have higher skill than the forecast based on dry/average/wet scenarios.

To extend the analysis of reliability to the entire Italian peninsula, a special case study has been set up for the period 1993 – 2018 with 26 complete crop years. As in the cases above, the yield reference baseline has been computed, by feeding the DELPHI model with the ERA5 reanalysis dataset. Different bias adjustment strategies have been tested. Hereafter these solutions in details:

1) Yield forecast (bias - ***BC0 code***): ECMWF ensemble members hindcast (25 members) / released in February;

2) Yield forecast (unbiased, CST_calibration for all the weather variables - ***BC1 code***) : ECMWF ensemble member hindcast (25 members) / released in February;

3) Yield forecast (unbiased, CST_calibration for air temperature, relative humidity, wind speed and solar radiation + CST_QuantileMapping for rainfall - ***BC2 code***) : ECMWF ensemble hindcast (25 members) / released in February

4) Results were compared with the results of the current Delphi System by feeding the model with ERA5 reanalysis dataset + synthetic weather scenarios based on historical observations (*dry, average, wet codes*).

For each simulation the input weather files were built as indicated below, where in green the ERA5 weather data, and in yellow the forecast weather data:

Results for yield prediction at harvesting time for each crop season on the basis of 4 different yield forecast approaches (bias/raw data; CST calibration; CST calibration + CST QuantileMapping; current system based on historical observations) are reported.

For each year the predicted yield by feeding the model with only ERA5 reanalysis data is used as reference dataset in assessing the reliability of 4 different yield forecast approaches.

The reliability has been assessed in terms of:

1) Pearson's correlation coefficient (ERA5 reference yield VS yield forecast approach), for the whole study period (Fig. 17).

2) Overall Accuracy in terms of correctly classified (forecasted and observed) crop years showing a yield above or below the average, for the whole study period (Fig.16).

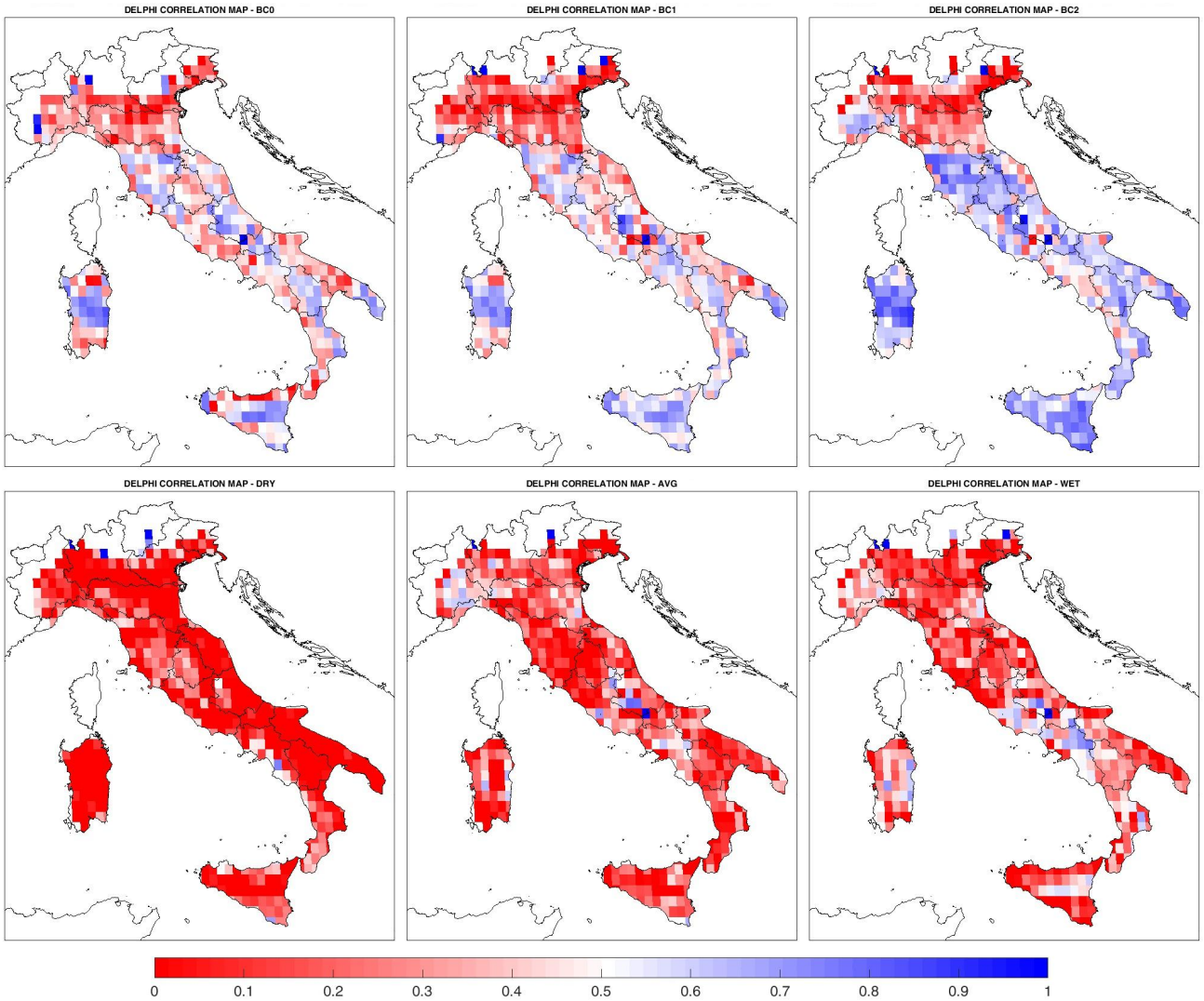


Figure 17. Pearson's correlation map as test statistics to measure the statistical relationship between ERA5 yield reference and BC0-BC1-BC2-DRY-AVG-WET yield forecast simulations.

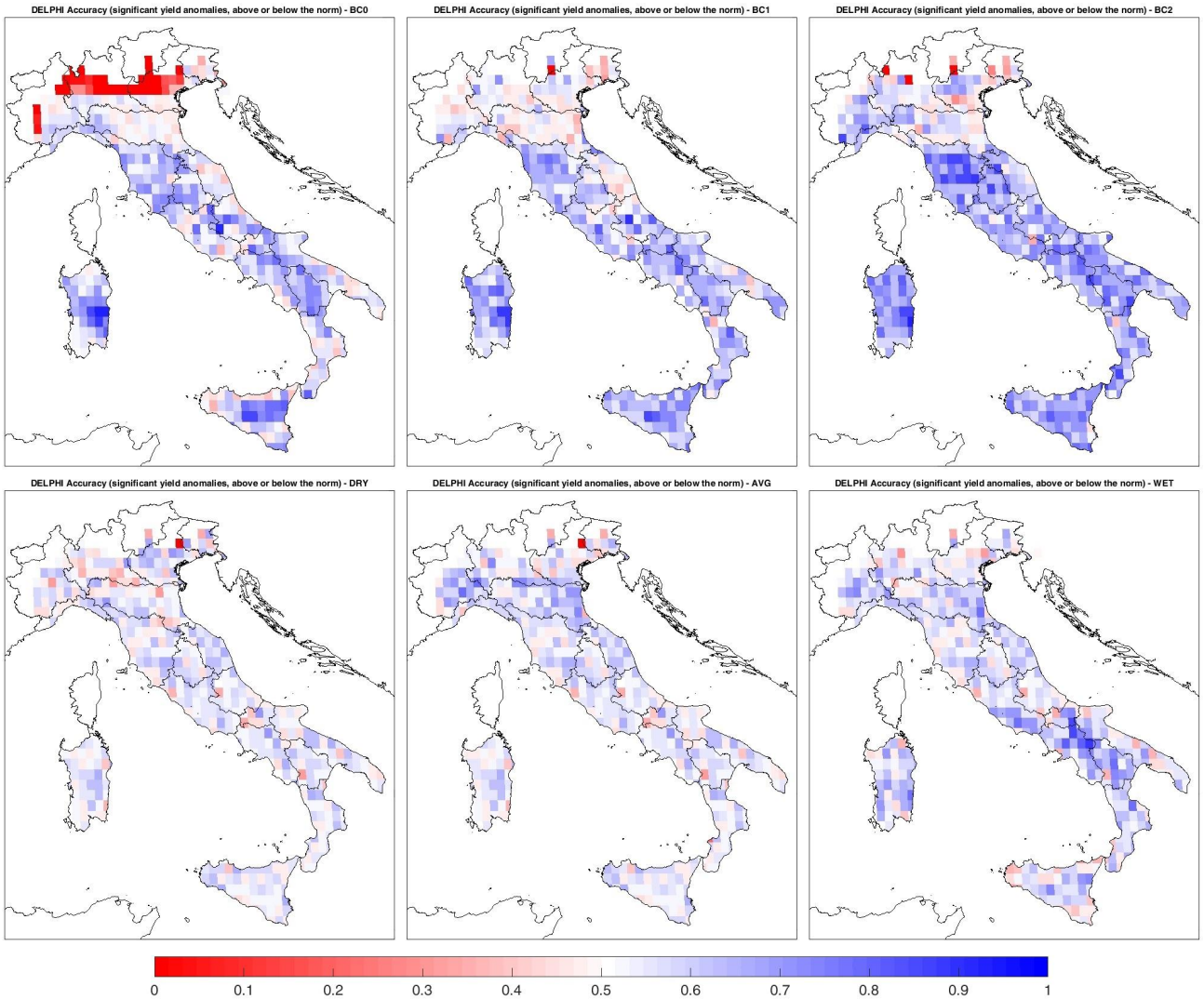


Figure 18. Overall Accuracy to evaluate the capability of the different yield forecast simulations in predicting correctly if the crop year is characterized by anomalies (yield above or below the average).

In general, the best performances are obtained from all systems for the areas of Central and South Italy. On average, the crop maturity/harvesting takes place earlier (1-20 June, ~ 4 month-forecast) than in northern Italy (20 June-15 July). This means that the seasonal forecast dataset used for North Italy is longer, affecting the reliability of yield forecast released in February (5 months-forecast).

In detail, the yield forecasts of the Delphi Model based on seasonal forecasts significantly improve the yield forecasts of the same model based on historical scenarios. The mere adoption of seasonal forecasts, without any bias correction (BC0), improves the performance of the system based on

historical scenarios (Dry-Avg-Wet) in terms of Pearson's correlation and no impact in terms of Accuracy: BC0 has Accuracy = 53% (16 std) and r = 0.42 (0.21 std) while Dry has Accuracy = 52% (8 std) and r = 0.01 (0.28 std); Avg has Accuracy = 53% (8 std) and r = 0.15 (0.25 std); Wet has Accuracy = 54% (10 std) and r = 0.17 (0.26 std).
BC1 slightly improved the performance in terms of Accuracy with an overall of 59% (11 std) and showing a correlation value similar to BC0, r = 0.43 (0.07 std).
BC2 further increases accuracy (63%, 12 std) and r = 0.52 (0.11 std), resulting as the best yield prediction system.

7.4.2 Delphi System – Update Tool (crop season 2020 - 2021)

Based on the results obtained during the benchmark activities, the Delphi System has been updated with a new tool where the previous forecasting system (historical scenario) has been replaced with ECMWF SEAS5 ensemble forecast with *CST_calibration* and CST *QuantileMapping* bias correction. From January 2021, the yield forecasts for the whole Italian area are operational and transferred to the end users. End user can choose the starting month of the forecast (from January to June, currently January and February are available), the area (Italy or any regions), the product (yield, biomass or grain protein) and the ensemble forecast aggregation in terms of percentile (5,25,50,75,95).

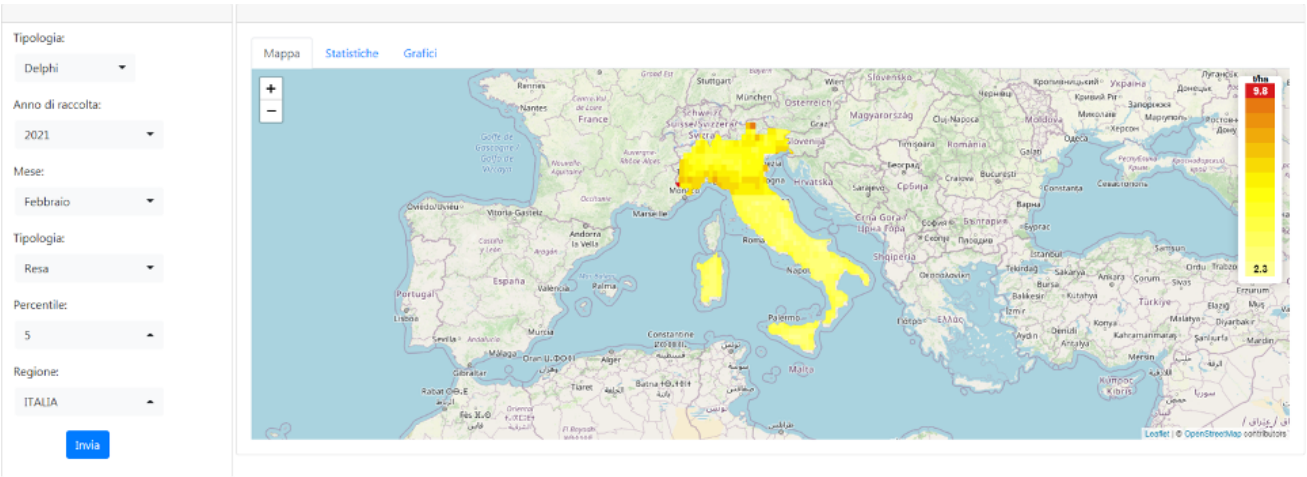


Figure 19. Yield forecast for Italy released in February, percentile 5

7.5 Providing a service for longer time scales

The last component developed addresses the longer time scales, i.e. the coming 2-3 decades. It is based on the CMIP5 Euro-Cordex climate projections under the high-end emission scenario RCP8.5 and is focused on the current durum wheat areas (identified by setting at the grid level a 1% threshold of the total grid area). The durum yield projections are obtained by forcing a crop growth model with the bias-adjusted daily output of five Regional Climate Models (RD.29). The model, ECroPS, has been recently developed by EC-JRC and it is going to be released freely under the open-source EUPL licence. ECroPS is designed for massive simulations and it is characterized by an MPI-Python architecture (RD.30). It builds on the Wofost model, and it includes a new CO2 parameterization scheme (to better account for the so-called fertilization effects) and also a new component simulating heat stress effects at anthesis. Prior to the simulations, the model was tested on selected experimental sites in Sardinia (RD.31). Furthermore, the experimental data from several sites in the Mediterranean on 18 durum wheat varieties were analysed to create a pool of representative ideotypes (the modelling correspondent of a specific plant variety). All 18 varieties were classified into three families sharing similar growing characteristics (in terms of heading requirements) and for each of them six ideotypes were identified. All projections were then run by using the 18 durum wheat varieties.
The effects of climate change have been estimated by comparing changes in mean yield and interannual variability over a period of 20 years 2021-2040 with respect to the CMIP5 baseline (1986-2005). The statistical significance has been assessed by using a 2-sample Anderson-Darling EDF test. Models' ensembles have been also derived for each of the 18 ideotypes. Moreover for each climate model, the best variety has been identified by minimising the negative impacts of climate change on mean yield and also by minimising the interannual variability.
All results are made available through a web-service prototype based on R-cran shiny (https://ec-jrc.shinyapps.io/medgold/). This web service (Fig. 19) offers a dynamic interactive approach and produces on-the-fly maps by letting users define their specific parameter combinations (e.g. crop variety, model, etc.) and/or by selecting pre-defined output (e.g. ensemble median, best variety, etc.). Some examples of the results follow.

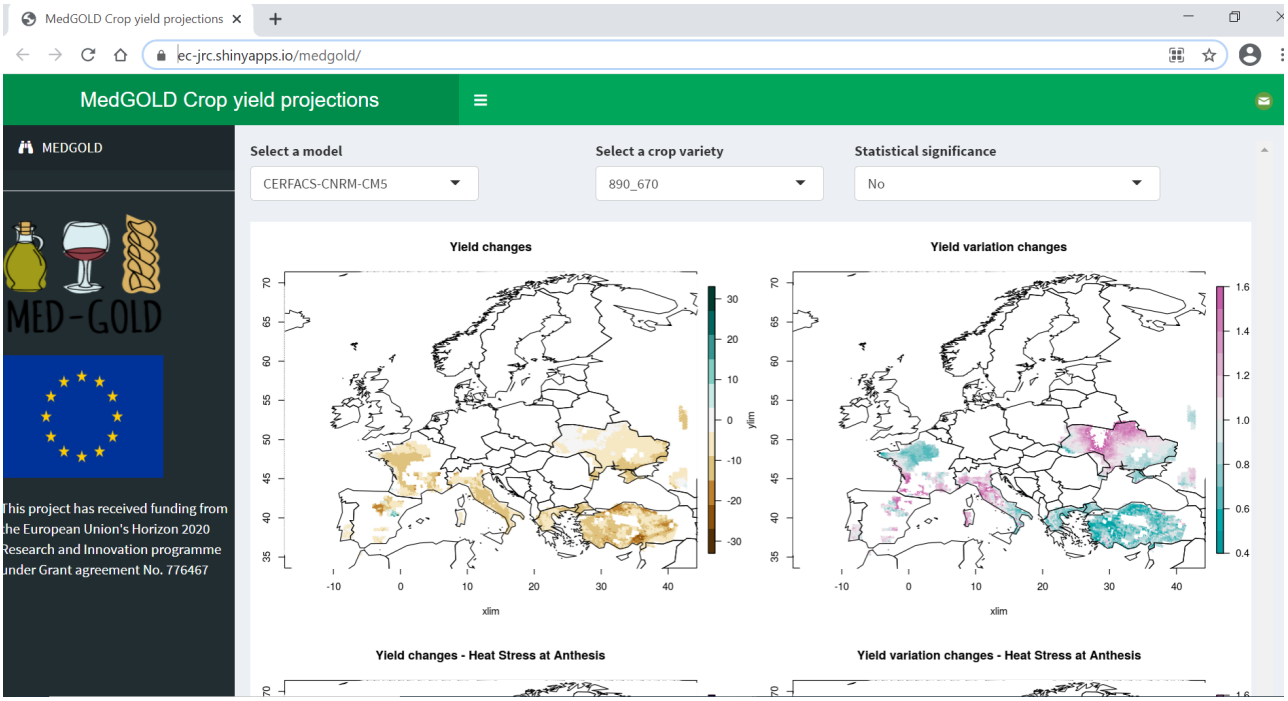


Figure 20 The MedGOLD web-service prototype for the climate projections, Accessible at https://ec-jrc.shinyapps.io/medgold/

Fig. 20 shows the changes estimated by using an early-flowering variety. Negative impacts in terms of mean yield, ranging from -10% to -5%, are clearly visible in all regions with more pronounced reductions in Italy, Greece, Turkey, and Ukraine. More pronounced impacts affect a late-flowering variety as shown in Figure 21, with mean yield reductions in the eastern Mediterranean regions mostly from -15% to -10%. In terms of best variety with respect to reduced impacts of climate change under projections simulated by the IPSL-CM5 model, Fig. 22 highlights important regional differences pointing to the need of developing and adopting targeted adaptation strategies and agro-management choices. This clearly confirms once more the key needs of sectoral climate services.

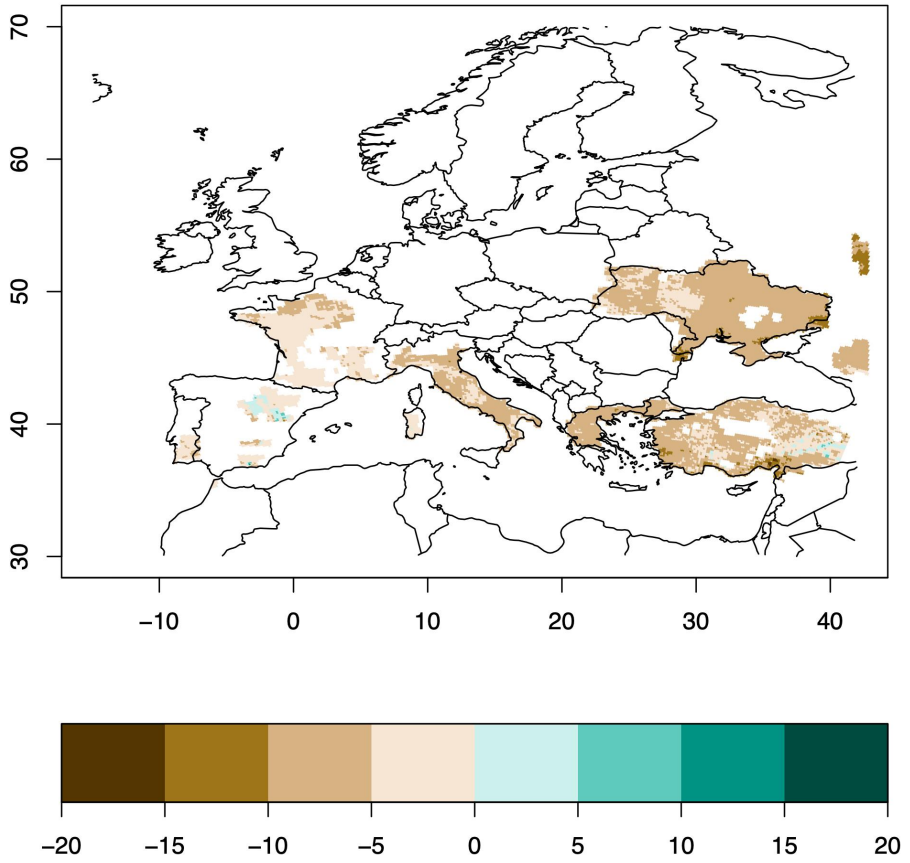


Figure 21. Ensemble median changes (% w.r.t. the baseline period) of mean yield projected for 2021-2040 by using an early-flowering durum-wheat variety.

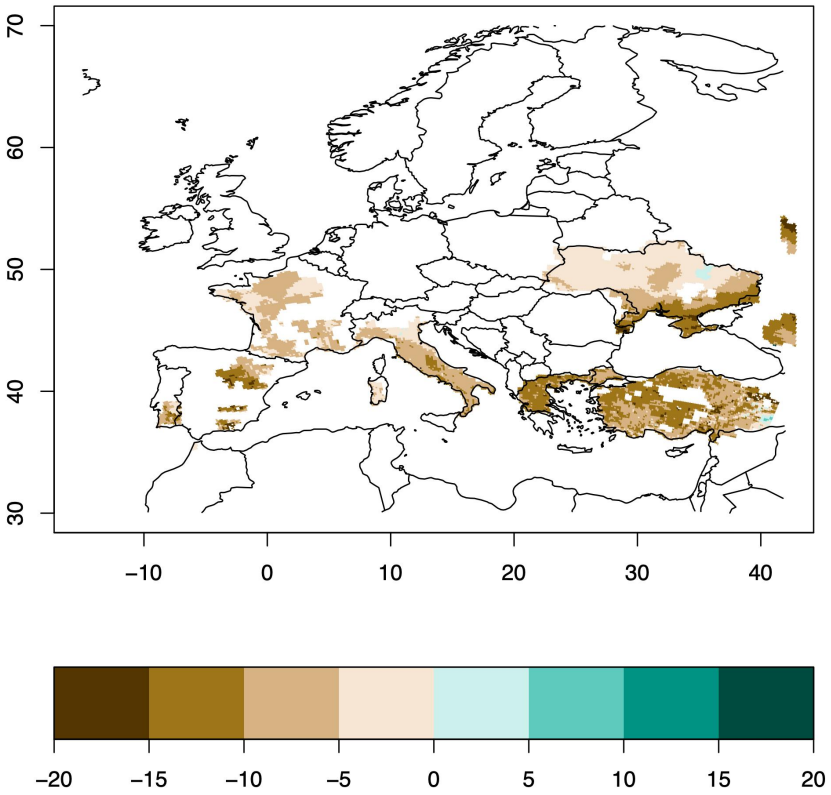


Figure 22 Ensemble median changes (% w.r.t. the baseline period) of mean yield projected for 2021-2040 by using a late-flowering durum-wheat variety.

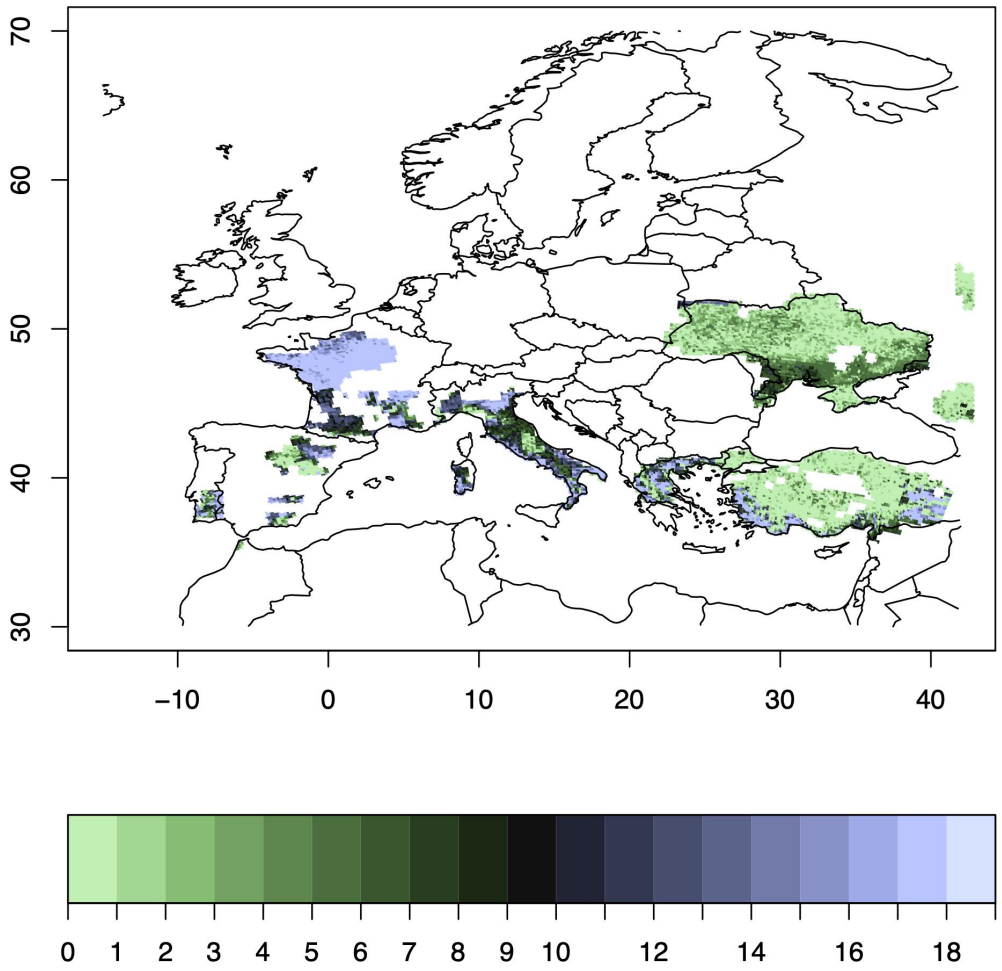


Figure 23 Best variety estimated in terms of reduced negative impacts of climate change as projected in the period 2021-2040 by the IPSL-CM5 model. Each color is associated with one of the 18 durum wheat varieties which are ranked according to their flowering timing (from the earliest to the latest).

8 EXPLOITATION OF RESULTS

Different ways of exploitation of these results are possible:

- the results shown in this report are part of ongoing and already planned scientific publications;
- the reported materials represent a framework of developing and delivering a robust and salient pilot climate service for the agro-food sector;
- there is an ongoing dissemination activity, based on regular meetings with users and stakeholders of the durum wheat, to provide climate outlook and climate change information;
- Demonstration of materials and results will pave the way of commercial expansion of the active commercial and non-commercial services among new users and stakeholders.

Several strategies for further development of the present climate service pilot are underway. Among others, there is an extensive action of upscaling tailored information dissemination: several climate related information will be included in the MED-GOLD DASHBOARD. Thus some of the used co-developed durum wheat information, designed originally for Italy, wil be available to a larger community in other countries in the Mediterranean basin.

Recently MED-GOLD project was flagged as one of the important R&I contributions in shaping the new EU Climate Adaptation Strategy in a recent EU factsheet.

END OF DOCUMENT