SPECIAL FOCUS[i] – May 2022

Below-average yield prospects for barley and soft wheat in Algeria

The winter cereal season is finalizing in Algeria and has been marked by a **large rainfall deficit** lasting from 10-December to 30-February (Figure 1). Although rainfall improved in March and April, it was too late to trigger a crop recovery in the main western cereal producing regions.

At mid-April, the dominant negative 90 days rainfall anomaly (red pattern in Figure 2) indicates that crops and rangelands in the western and eastern part of the country, have not received sufficient rainfall to fulfill their water requirements. The dry conditions had a negative impact for cereals during critical crop development stages. This is reflected by the cumulative Normalised Difference Vegetation Index (NDVI) anomaly map (Figure 3), a biomass proxy, showing negative anomalies in various provinces at the end of April. On the contrary, the improved rainfall in March and April, supported partial crop conditions recovery in some of the central and eastern wilayas.

As a result of the persistent dry conditions that hampered crop growth in western and inland parts of the country, there is a **prospect of below-average national yield and production** for winter cereals, and **low vegetation** and **water availability for pastoral areas**. According to the JRC MARS bulletin of April, yield for total wheat and barley at the national level is forecasted 45% and 27%, respectively, below the last 5-year average. The MARS bulletin for May with updated national yield forecasts accounting for the 1-April to 15-May period will be publicly released on 23 May.

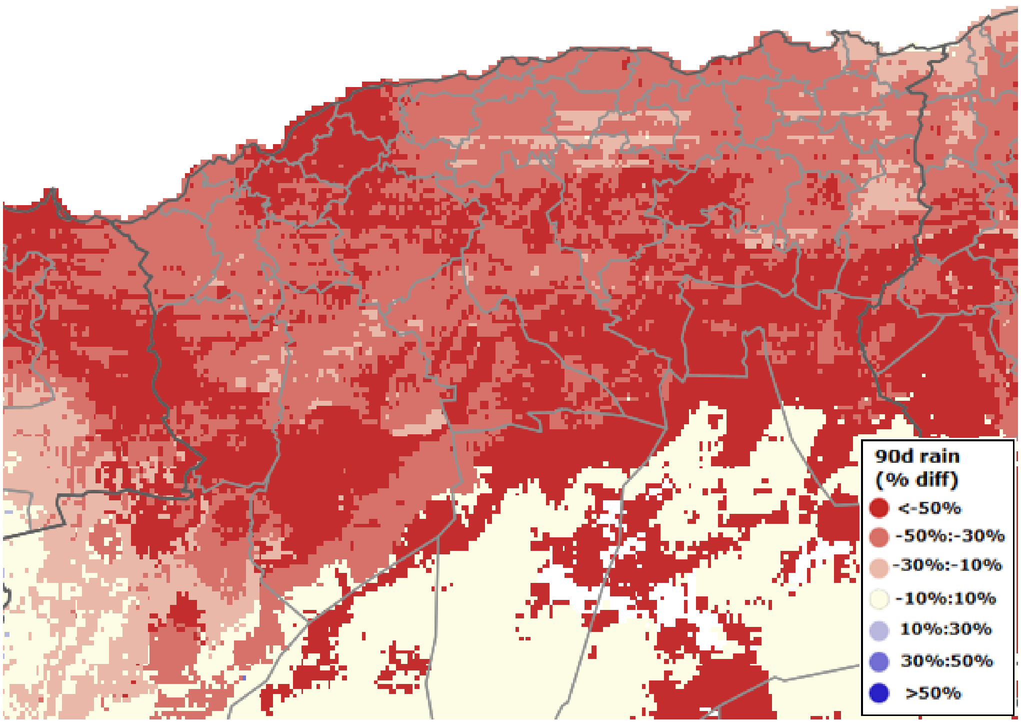

*Figure 1. Cumulative rainfall anomaly for December / January /February in % (*relative difference with the historical average*), showing significant seasonal rainfall deficits that affected the northern part of Algeria.*

INFO BOX 1 - WATER SATISFACTION INDEX

The Water Satisfaction Index (WSI) is an indicator of crop (or rangeland) performances. It expresses the percentage at which the crop water requirements have been met and thus indicates possible water stress. It is based on a water balance scheme comparing the crop (or rangeland) water demand to the actual water availability.
See more in ASAP WSI documentation.

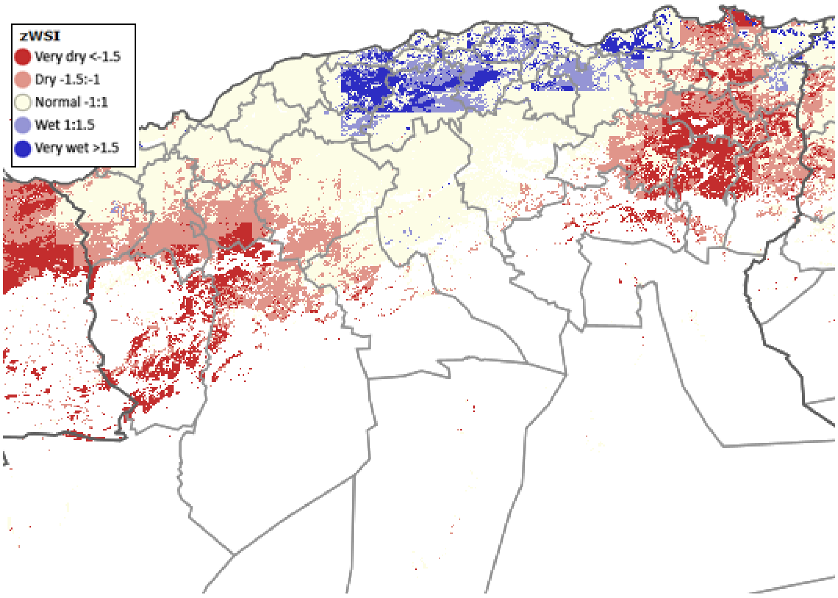

Figure 2. Spatial distribution of anomalies in the Water Satisfaction Index for crops from the start of the growing season until end of April 2022.

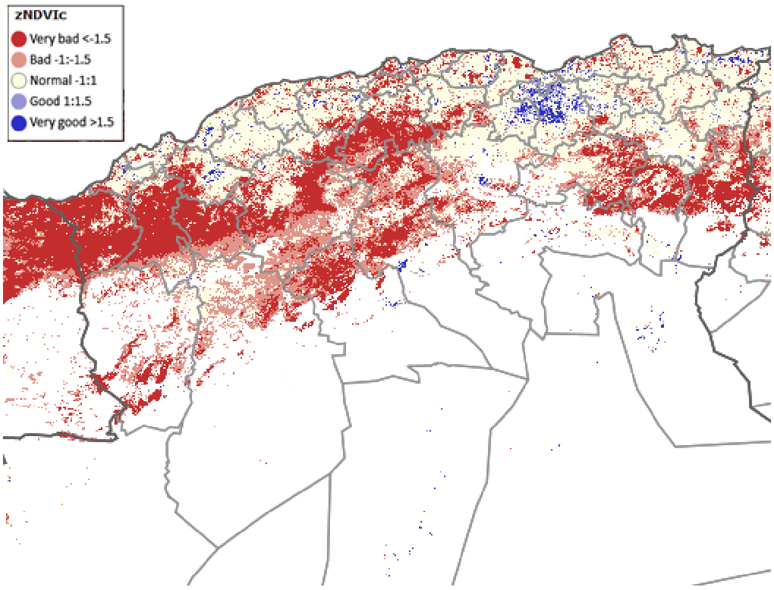

Figure 3. Standardized anomalies in cumulative NDVI from the start of the growing season until end of April 2022.

INFO BOX 2 - NORMALISED DIFFERENCE VEGETATION INDEX (NDVI)
The NDVI (Normalised Difference Vegetation Index) is used as an indicator of vegetation health. It is a combination of the red and near-infrared bands registered by satellites.

Q**uantitative yield forecasts for the main Algerian winter cereals** (durum and soft wheat, and barley) in the main producing provinces, have been computed based on **the machine learning workflow** proposed by Meroni et al. (2021), which was shown to predict historical national yields with an accuracy of 0.16-0.2 t/ha (13-14 % of mean yield) within the season. This robust and automated workflow processes automatically different combinations of yield proxies such as NDVI, temperature, precipitation, and incident radiation data, taken from the ASAP platform, with machine-learning algorithms. The resulting yield forecasts computed at the beginning of May 2022 are shown per province and crop in Figures 4, 6, and 8. In Figures 5, 7, and 9. The percent difference of forecasted yield with the average is also mapped per province and per crop.

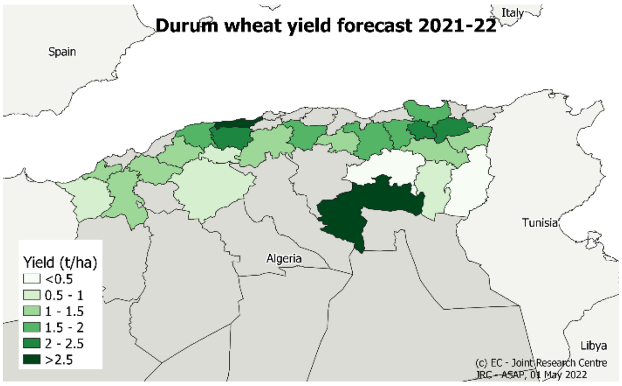

Figure 4. Durum wheat 2021-22 yield forecast at the provincial level. Forecasts cover the major producing provinces that contribute to the 90% of the national mean crop production, thus excluding marginal production provinces.

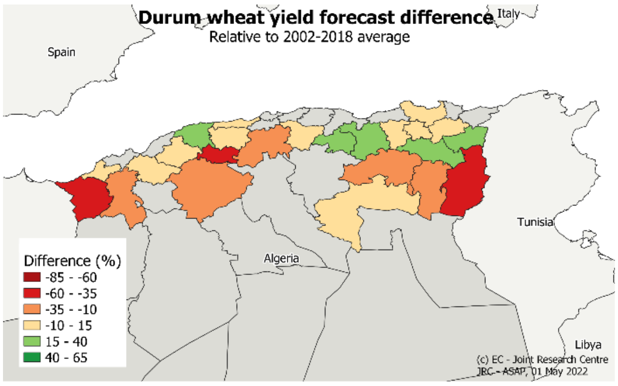

Figure 5. Durum wheat 2021-22 yield forecast difference (in %) with 2002-2018 average yield at the provincial level.

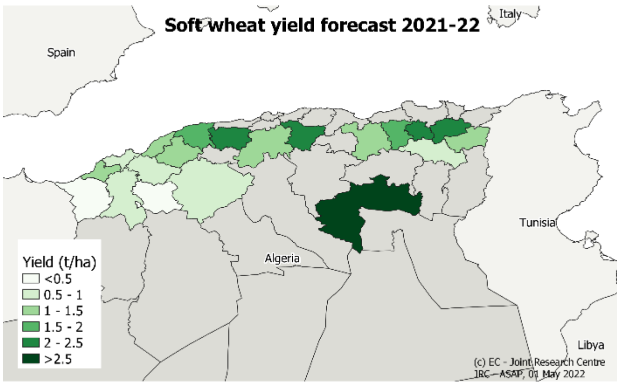

Figure 6. Soft wheat 2021-22 yield forecast at the provincial level. Forecasts cover the major producing provinces that contribute to the 90% of the national mean crop production, thus excluding marginal production provinces.

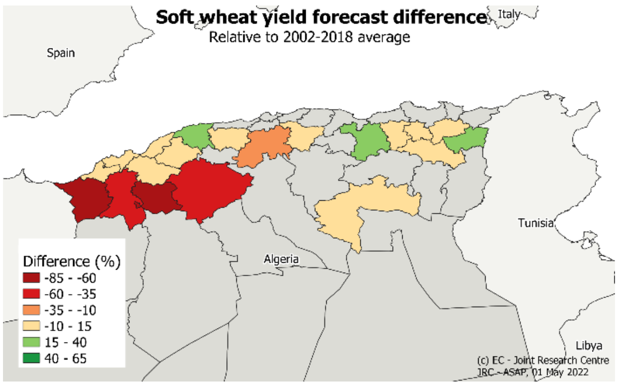

Figure 7. Soft wheat 2021-22 yield forecast difference (in %) with 2002-2018 average yield at the provincial level.

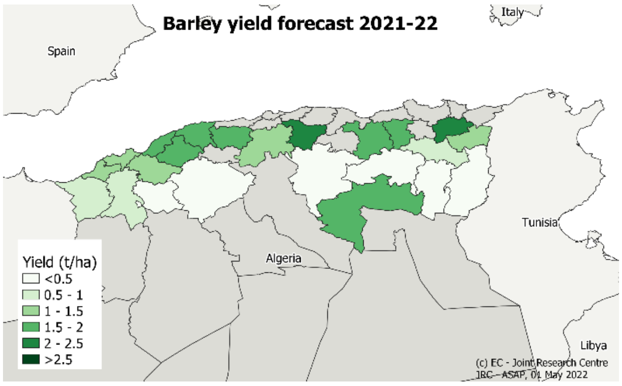

Figure 8. Barley 2021-22 yield forecast at the provincial level. Forecasts cover the major producing provinces that contribute to the 90% of the national mean crop production, thus excluding marginal production provinces.

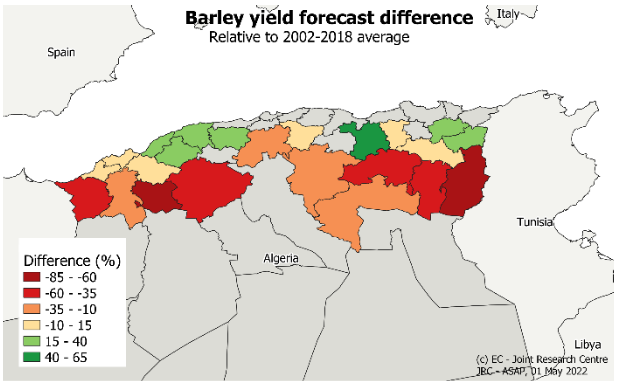

Figure 9. Barley 2021-22 yield forecast difference (in %) with 2002-2018 average yield at the provincial level.

INFO BOX 3 – IN SEASON YIELD FORECASTS WITH SATELLITE DATA

Operational yield forecasting approaches are often based on empirical regression models linking historical yields and administrative units-averages of seasonal satellite and climate data for cultivated areas (Schauberger et al., 2020). In operations, the model is then fed with data observed for the current growing season to forecast the final yield. Satellite instruments providing frequent, coarse resolution satellite image time series, such as AVHRR (Advanced Very High Resolution Radiometer), SPOT-VGT (SPOT-VEGETATION), or MODIS (Moderate Resolution Imaging Spectroradiometer), have been extensively used for yield estimation at regional scales (Atzberger et al., 2016; Rembold et al., 2013). Typically, yields are estimated by regressing either vegetation indices or crop biophysical variables at specific dates, which are proxies for green biomass, or features characterizing the dynamics of a vegetation index over time such as the senescence or the green-up rate (Waldner et al., 2019). Popular linear regression approaches use the Normalised Difference Vegetation Index (NDVI; Rouse et al., 1974) either at its peak (e.g., Becker-Reshef et al., 2010; Franch et al., 2015) or its cumulative value over the growing season (e.g., López-lozano et al., 2015; Meroni et al., 2013).

Whereas linear regressions may fail to capture the complex interactions between environmental conditions and yield, machine learning (ML) models have demonstrated powerful performance in various data-driven applications, including yield estimation (Cai et al., 2019; Johnson et al., 2016; Kamir et al., 2020; Mateo-Sanchis et al., 2019; Wolanin et al., 2020; Zhang et al., 2020).

In this report we use the approach of Meroni et al. (2021), a generic and robust machine learning workflow to forecast crop yields with small, public, and easily accessible climate and satellite time series.

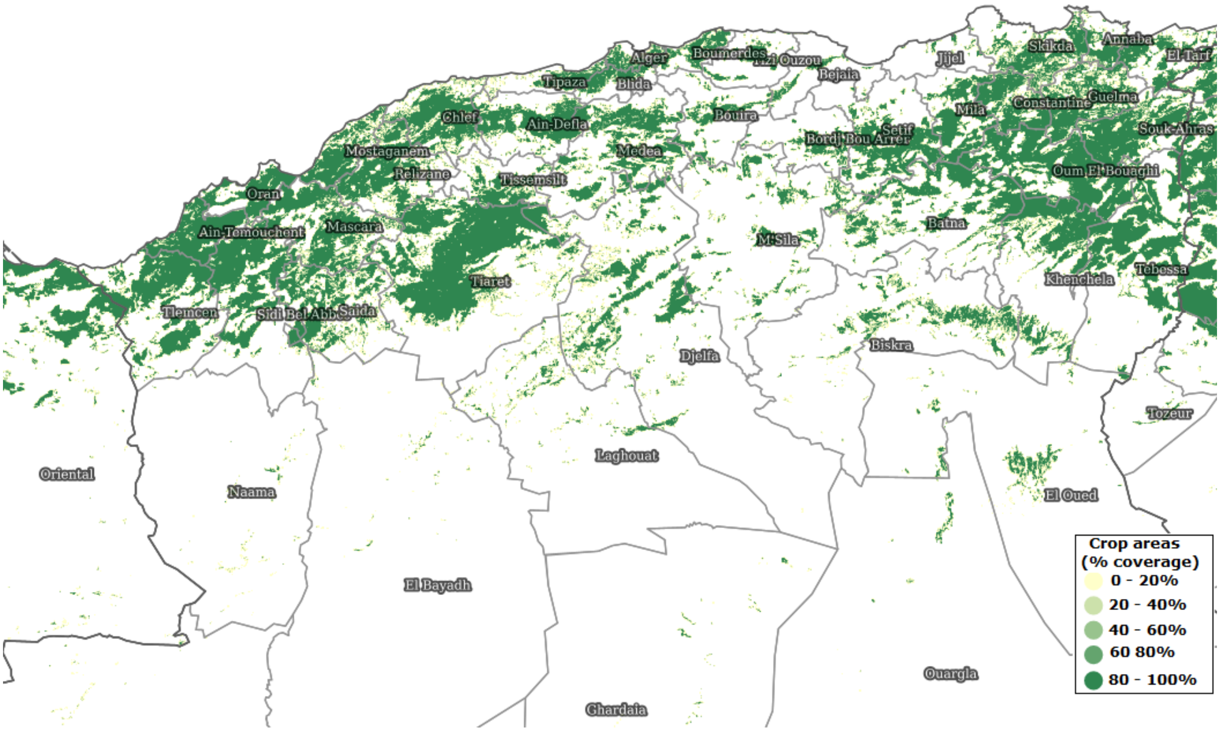

Figure 10. Crop map for Algeria (source: EC-JRC ASAP Warning Explorer).

Forecasts of **national production** are reported in Table 1. It is evident that **below-average yield is forecast for barely and soft wheat** (ca. 14% and 11% below-average, respectively), while the most important one, **durum wheat, is close to average**. The close to average yield for durum wheat can be explained by the fact that the northeast part, where a significant cropping area exists (Figure 10), is less impacted. Additionally, yield forecasts for all three crops show a clear improvement as compared with previous in season forecasts.

Table 1. National production forecasts. Average crop area is used to estimate production from forecasted yield. The percentile places the current forecast in the historical distribution of production, i.e., it refers to the fraction of observed production in 2002-2018 that is lower than the current one.

	April forecast				**May forecast**			
Crop	Forecasted Yield (t/ha)	Yield difference with average (%)	Forecasted production (tons)	Percentile	Forecasted Yield (t/ha)	Yield difference with average (%)	Forecasted production (tons)	Percentile
Barley	0.74	-27.24	747072	0.17	0.88	-13.40	889169	0.33
Durum wheat	1.11	-13.93	1402168	0.19	1.31	1.70	1656860	0.41
Soft wheat	0.90	-21.79	525323	0.23	1.02	-10.90	598505	0.38

Note: For Durum wheat, the small positive difference with average corresponds to a percentile lower than the median because the mean and the median are markedly different. In practice, both numbers indicate close to average yield.

More information can be found here:

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- JRC MARS bulletin (April 2021): https://ec.europa.eu/jrc/sites/jrcsh/files/jrc-mars-bulletin-vol29-no4.pdf
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- Kamir, E., Waldner, F., Hochman, Z., Estimating wheat yields in Australia using climate records, satellite image time series and machine learning methods, ISPRS Journal of Photogrammetry and Remote Sensing, Volume 160, 2020, p. 124-135, https://doi.org/10.1016/j.isprsjprs.2019.11.008

For any feedback and questions please write to the address below.

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[i] (Special focus reports add information based mainly on the analysis of satellite imagery and links to other sources, to the monthly ASAP global overview that can be found at the website: https://mars.jrc.ec.europa.eu/asap/)

