Algeria's third consecutive winter drought leads to low cereal yield and production expectations

The 2022-2023 winter cereal season has been marked by a **prolonged rainfall deficit** lasting from November to December (Figure 1) and with less than 50% of seasonal rainfall peaks. March and April's rainfall has been below-average throughout the country's northern part, followed by irregular and below-average rainfall in the early parts of the season. As a result, winter wheat and barley growth have been delayed since the start of the season, and cereals biomass is well below average in most regions (except for some areas along the north/eastern coastal part).

At the end of April, the dominant red pattern in Figure 2 indicates that crops and rangelands in most northern parts of the country have not received sufficient rainfall to fulfil their water requirements. Above-average temperatures in October-December and then again in March-April, have further deteriorated crop conditions. The dry conditions harmed 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.

As a result of the persistent dry conditions that hampered crop growth in northern parts of the country, there is a **prospect of below to well below-average national yield and production** for winter cereals and **low vegetation** and **water availability for pastoral areas**. The 2023 below-average forecast follows the below-average yield for barley and soft wheat that affected the country in 2022 (Special Focus - May 2022) and 2021 (Special Focus – May 2021).

The national level forecasts (Table 1) are in line with those of the second MARS North Africa bulletin of May 2023, where total wheat and barley yield is forecasted to be 24% and 14%, respectively, below the last 5-year average.

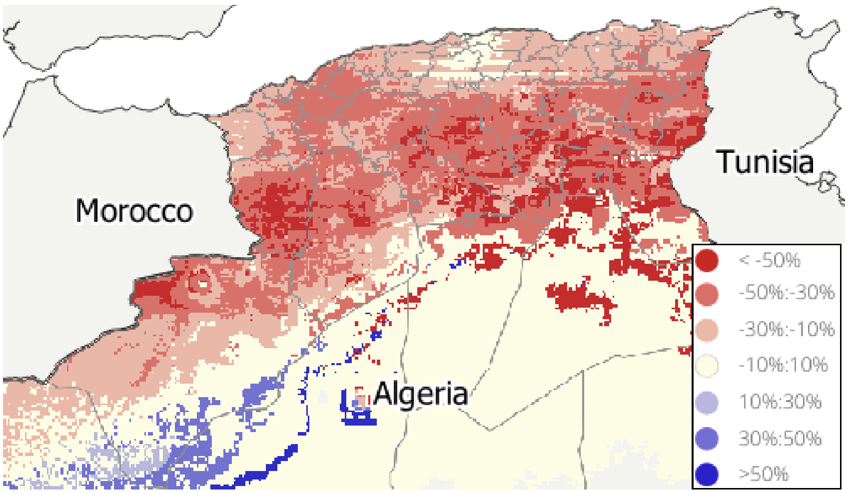

*Figure 1. Cumulative rainfall anomaly for November / December / January in % (*relative difference with the historical average*), showing significant seasonal rainfall deficits that affected the northern part of Algeria.*

INFO BOX 1 - WATER SATISFACTION INDEX
The Water Satisfaction Index (WSI) is an indicator of crop (or rangeland) performance. 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]().

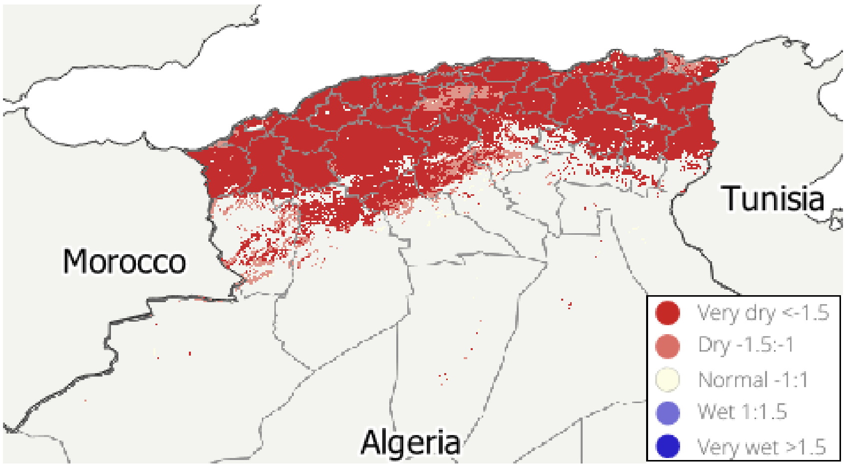

Figure 2. Spatial distribution of anomalies in the Water Satisfaction Index for crops from the start of the growing season until the end of April 2023.

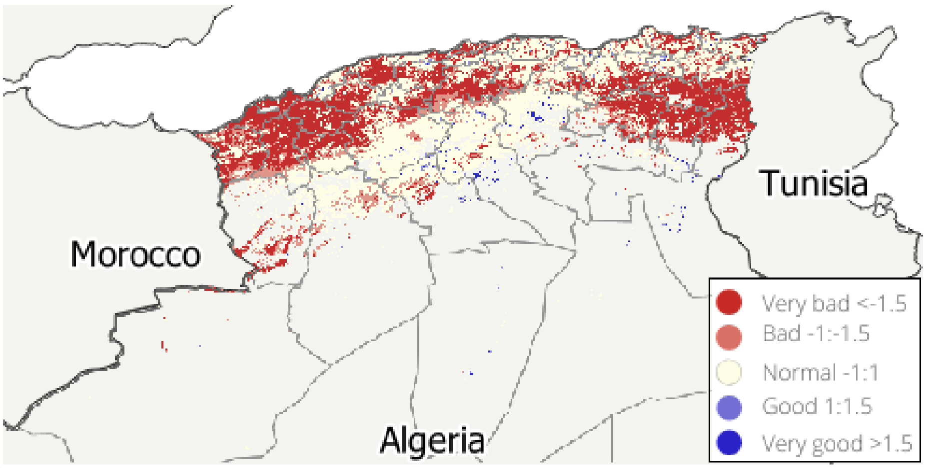

Figure 3. Standardized anomalies in cumulative NDVI from the start of the growing season until the end of April 2023.

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. For more on NDVI and NDVI anomalies, see here: [ASAP warning classification scheme]()

Quantitative 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 2023 (available input data until the end of April) are shown per province and crop in Figures 5, 7, and 9. In Figures 6, 8, and 10 the percent difference of forecasted yield with the 2002-2018 average is also mapped per province and crop. For a better understanding of the yield maps, the location of croplands is presented in Figure 4.

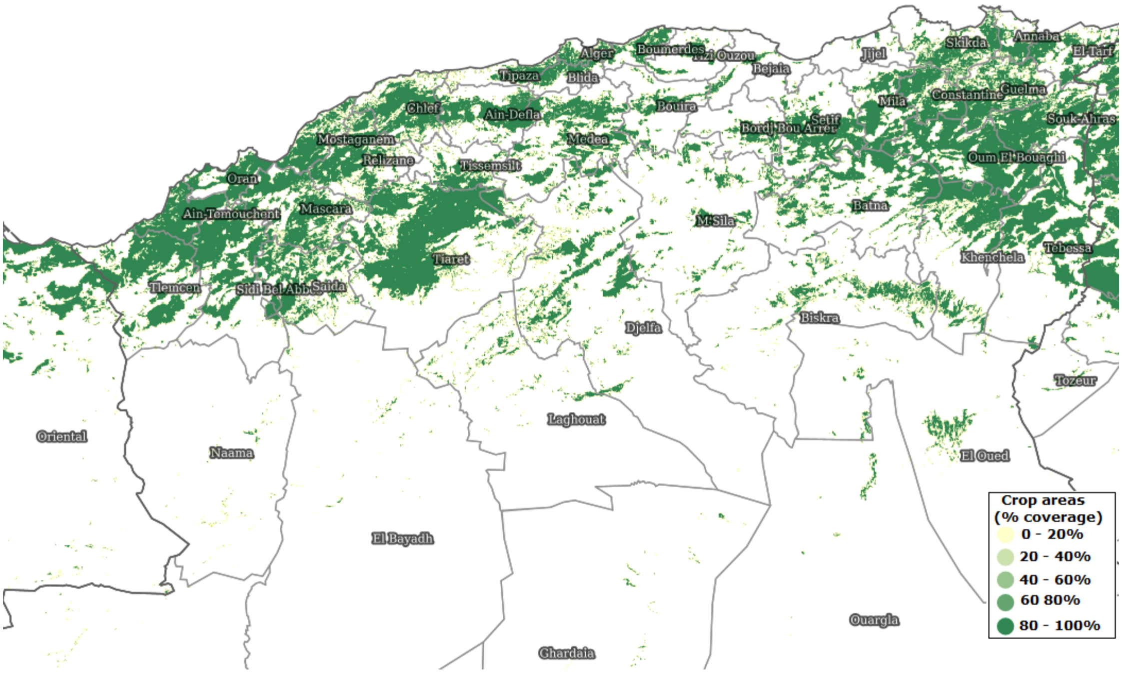

Figure 4. Crop map for Algeria (source: [EC-JRC ASAP Warning Explorer](#)).

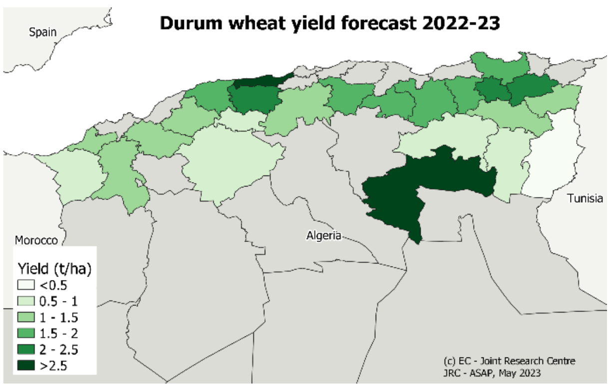

Figure 5. Durum wheat 2022-23 yield forecast at the provincial level. Forecasts cover the major producing provinces that contribute to 90% of the national mean crop production, thus excluding marginal production provinces.

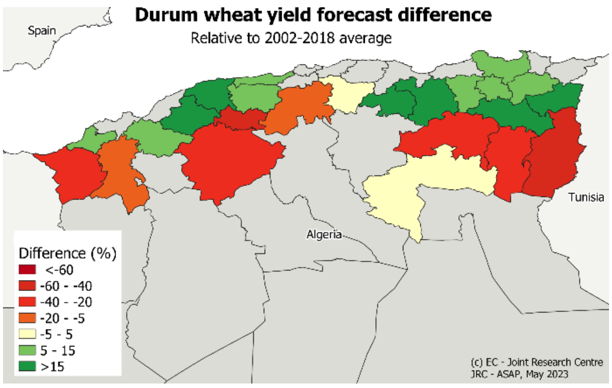

Figure 6. Durum wheat 2022-23 yield forecast difference (in %) with 2002-2018 average yield at the provincial level.

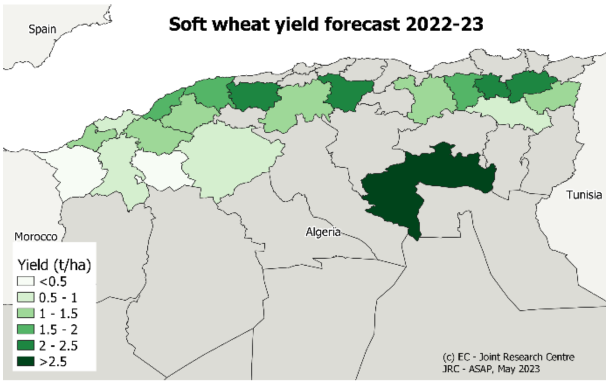

Figure 7. Soft wheat 2022-23 yield forecast at the provincial level. Forecasts cover the major producing provinces that contribute to 90% of the national mean crop production, thus excluding marginal production provinces.

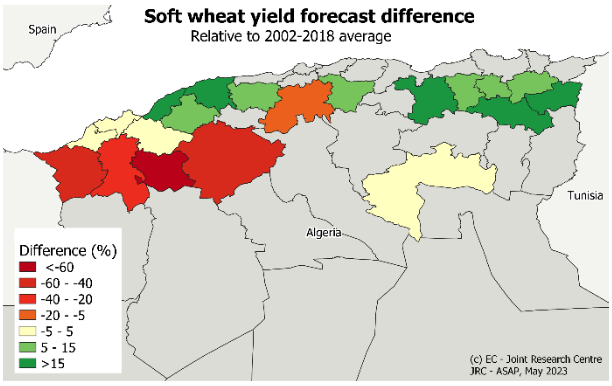

Figure 8. Soft wheat 2022-23 yield forecast difference (in %) with 2002-2018 average yield at the provincial level.

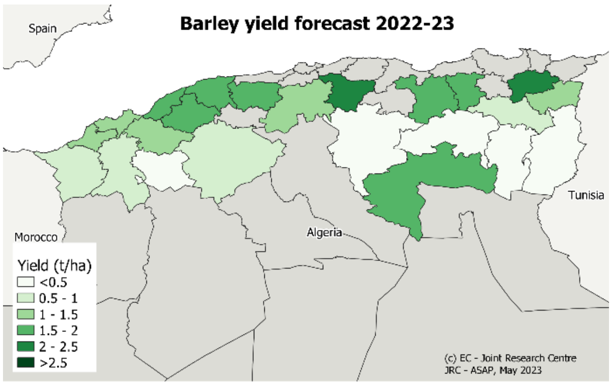

Figure 9. Barley 2022-23 yield forecast at the provincial level. Forecasts cover the major producing provinces that contribute to 90% of the national mean crop production, thus excluding marginal production provinces.

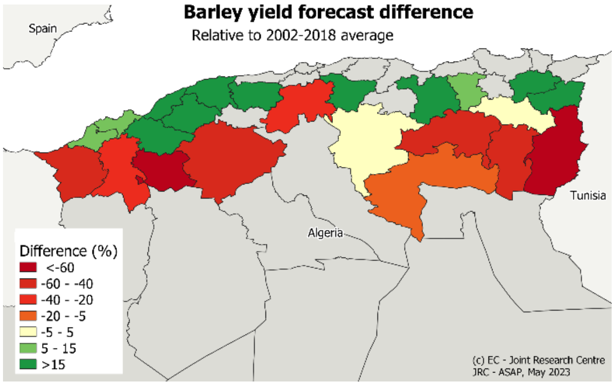

Figure 10. Barley 2022-23 yield forecast difference (in %) with 2002-2018 average yield at the provincial level.

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.

The production forecasts are also shown per province and crop in Figures 11-13.

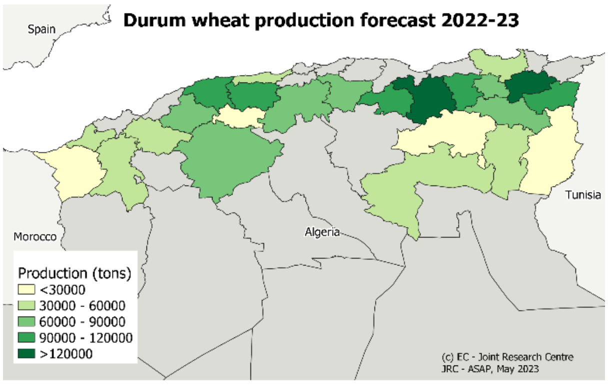

Figure 11. Durum wheat 2022-23 production forecast at the provincial level. Forecasts cover the major producing provinces that contribute to 90% of the national mean crop production, thus excluding marginal production provinces.

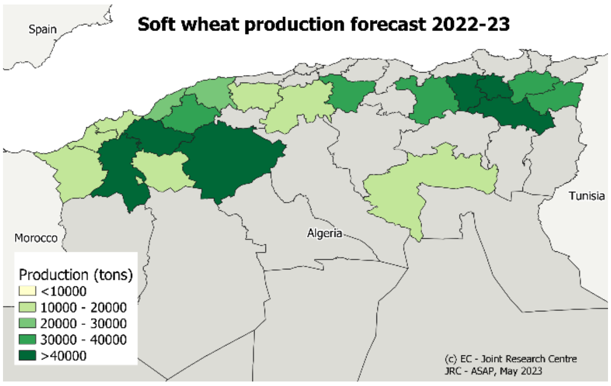

Figure 12. Soft wheat 2022-23 production forecast at the provincial level. Forecasts cover the major producing provinces that contribute to 90% of the national mean crop production, thus excluding marginal production provinces.

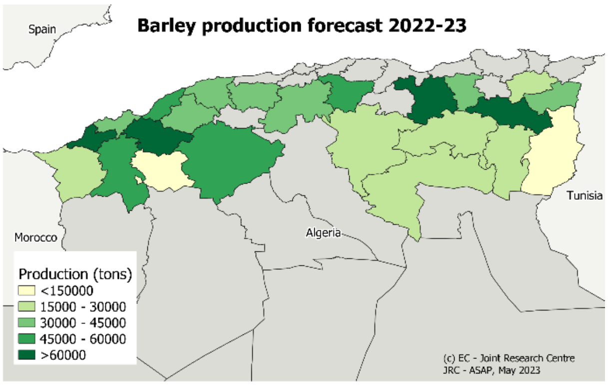

Figure 13. Barley 2022-23 production forecast at the provincial level. Forecasts cover the major producing provinces that contribute to 90% of the national mean crop production, thus excluding marginal production provinces.

Forecasts of **national production** are reported in Table 1. It is evident that the yield forecast for barley and soft wheat is well below the 5-year average (ca. 22% and 28% below-average, respectively). Yield expectations for the most important cereal, **durum wheat, is also below the 5-year average, but less severely impacted** (ca. 15% below). This can be explained by the fact that the northeaster part, where a significant cropping area exists (Figure 4), is slightly less drought-affected (Figure 3, 6 and 11).

Table 1. National production forecasts. The average crop area is used to estimate production from forecasted yield.

	May forecast*		
Crop	Forecasted Yield (t/ha)	Yield difference with 5-year average (%)***	Forecasted production (tons)
Barley	0.90 (1.06 MARS) **	-21.81	911,182
Durum wheat	1.32 (1.32 MARS)	-14.47	1,670,079
Soft wheat	1.05 (1.10 MARS) **	-27.96	615,455

** Issued on the 5th of May*
*** The discrepancy is attributed to the slightly different statistical data used for the calculations.*
**** 2014-2018*

More information on the methodology can be found here:

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

Feedback can also be posted on Twitter by including the hashtag: #asapEU

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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/)

