SPECIAL FOCUS[i] – May 2021

Poor yield outlook for winter cereals in Algeria

The winter cereal season is ongoing in Algeria and has been marked by **above-average temperatures** (Figure 1) and a **large rainfall deficit** (Figure 2). At the end of April, the dominant red pattern in Figure 3 indicates that crops and rangelands have not received sufficient rainfall to fulfill their water requirements. The combined effects of poor rainfall and above-average temperatures **negatively impacted crops and rangelands** in the western and central parts of the country. The hot and dry conditions had a negative impact for cereals during flowering and grain-filling, particularly by accelerating the grain filling on the expense of biomass accumulation. This is reflected by the cumulative Normalised Difference Vegetation Index (NDVI) anomaly map (Figure 4), where this biomass proxy shows negative anomalies in various provinces. In contrast, crop conditions appear generally better in the northeast. As a result of the persistent dry conditions that hampered crop growth in central and western provinces, there is a **prospect of below-average national yield** and production of winter cereals and **low vegetation** and **water availability in pastoral areas**.

According to the JRC MARS bulletin of April, yield for wheat and barley at the national level is forecasted 20% and 15%, respectively, below the 5-year average. The MARS bulletin for May with updated national yield forecasts will be released on 25 May, and most likely will be corrected downwards based on the latest information on rainfall and vegetation conditions.

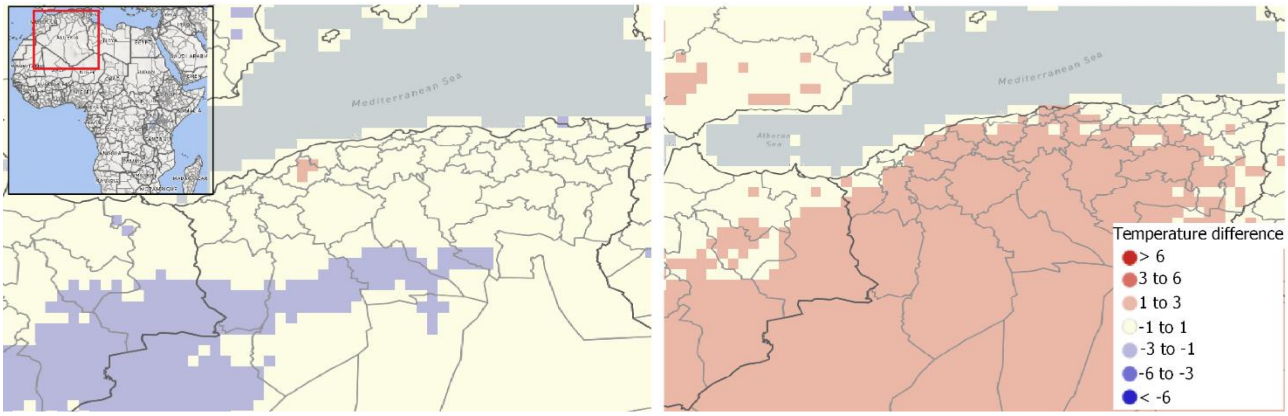

Figure 1. Difference of cumulative mean air temperature with historical average for March (left) and April (right) in °C.

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.

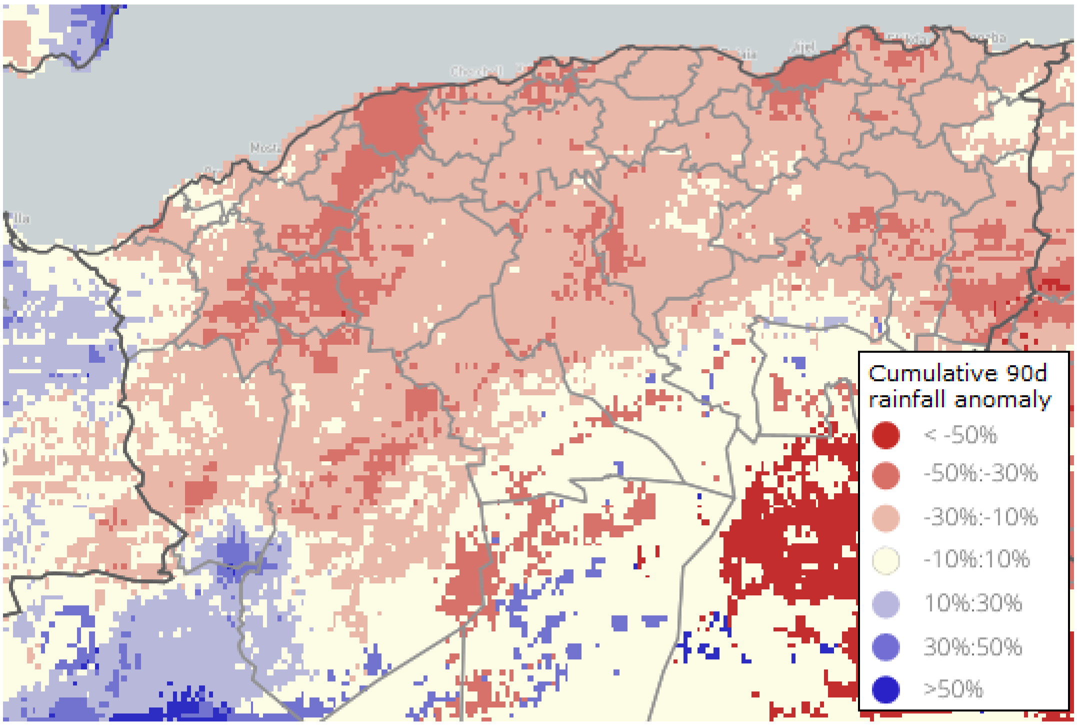

Figure 2. Cumulative rainfall anomaly for February/March/April in %, showing significant seasonal rainfall deficits for the affecting the northern part of Algeria.

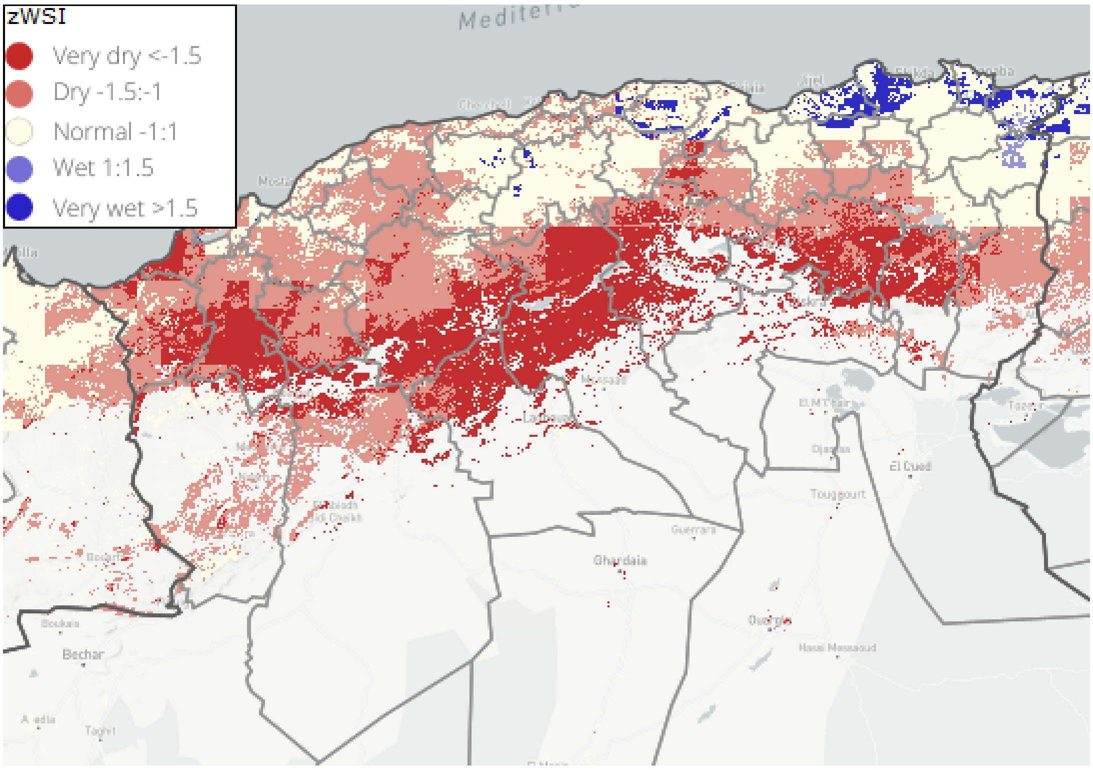

Figure 3. Spatial distribution of anomalies in the Water Satisfaction Index for crops from the start of the growing season until the end of April 2021.

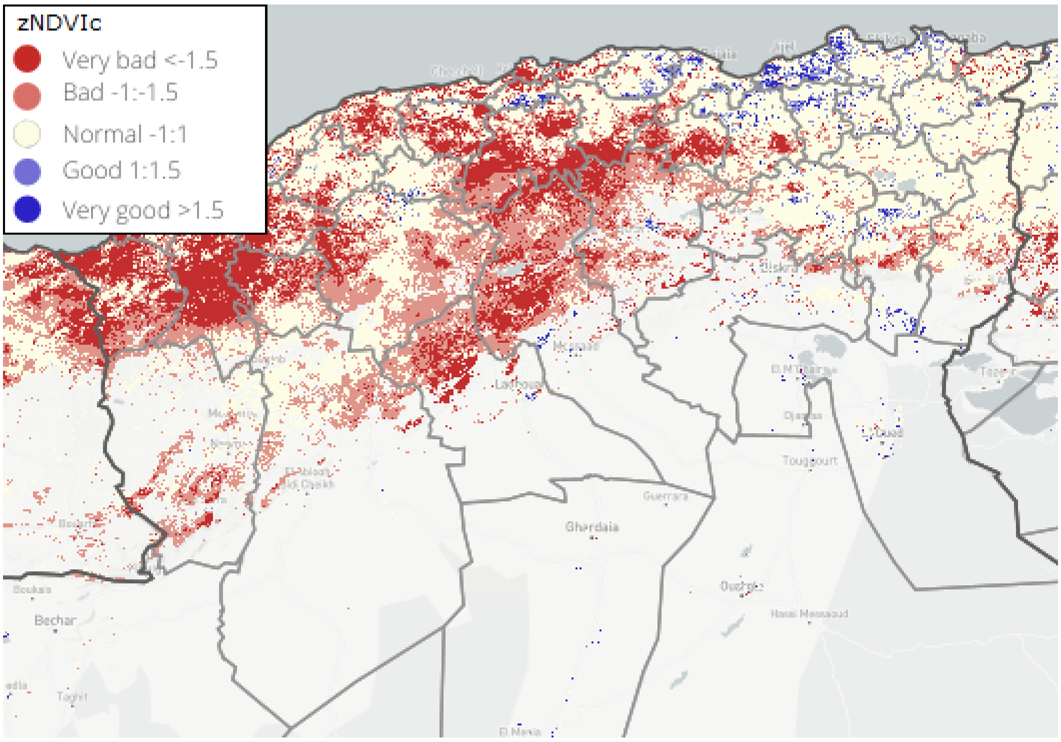

Figure 4. Standardized anomalies in cumulative NDVI from the start of the growing season until the end of April 2021.

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.

In order to obtain **quantitative yield forecasts for the main Algerian cereals** (durum and soft wheat, and barley) and the most important provinces, we deployed **a new 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 ASAP NDVI, temperature, precipitation, and incident radiation data with machine-learning algorithms. The resulting yield forecasts computed at the end of April are shown per province and crop in Figures 5, 7, and 9. In Figures 6, 8, and 10, it is also mapped per province and per crop the percent difference of forecasted yield with the average.

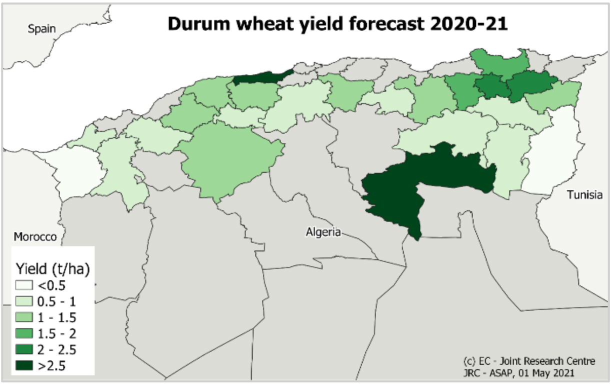

Figure 5. Durum wheat 2020-21 yield forecast at the provincial level. Forecasts cover the major producing provinces that contribute to the 90% of the national mean crop production, thus excluding marginal production provinces.

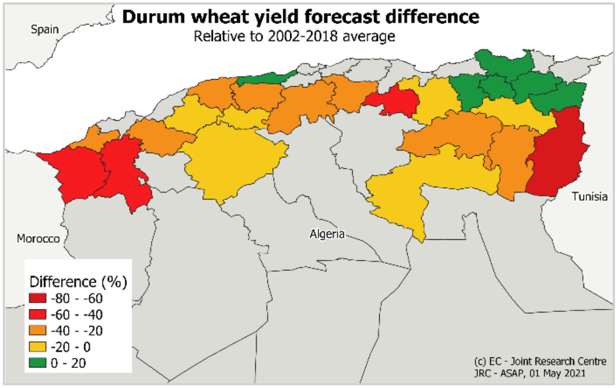

Figure 6. Durum wheat 2020-21 yield forecast difference (in %) with 2002-2018 average yield at the provincial level.

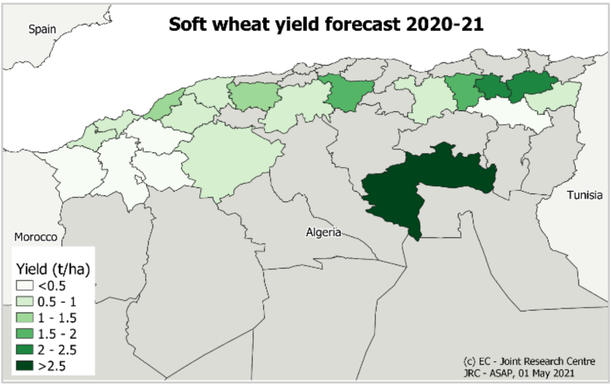

Figure 7. Soft wheat 2020-21 yield forecast at the provincial level. Forecasts cover the major producing provinces that contribute to the 90% of the national mean crop production, thus excluding marginal production provinces.

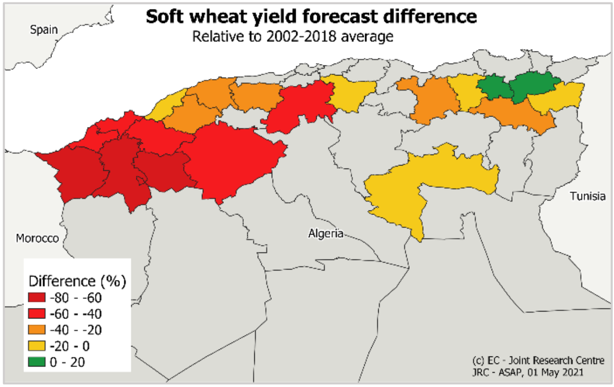

Figure 8. Soft wheat 2020-21 yield forecast difference (in %) with 2002-2018 average yield at the provincial level.

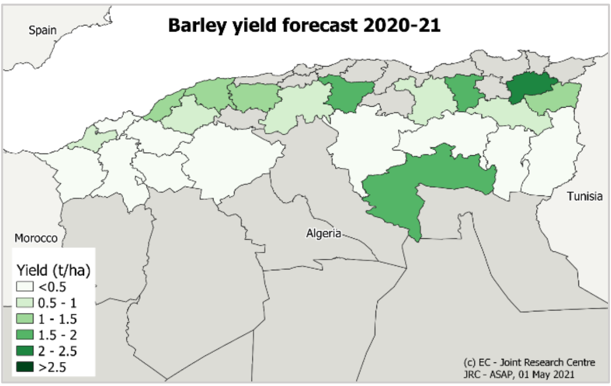

Figure 9. Barley 2020-21 yield forecast at the provincial level. Forecasts cover the major producing provinces that contribute to the 90% of the national mean crop production, thus excluding marginal production provinces.

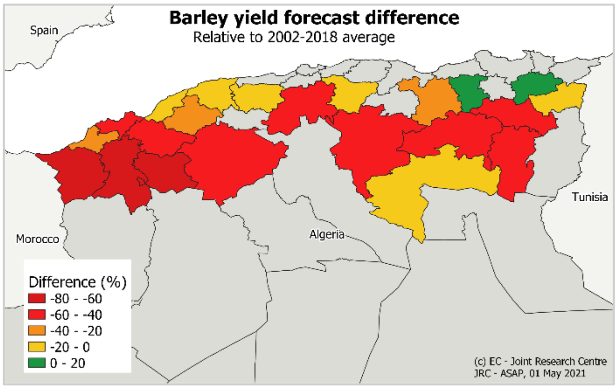

Figure 10. Barley 2020-21 yield forecast difference (in %) with 2002-2018 average yield at the provincial level.

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.

Forecasts of **national production** are reported in Table 1. It is evident that the **worst yield prospect is for barely and soft wheat** (ca. 40% and 30% below-average, respectively), while the most important one, for **durum wheat, is less impacted**.

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.

Crop	Forecasted Yield (t/ha)	Yield difference with average (%)	Forecasted production (tons)	Percentile
Barley	0.59	-41.76	597993	0.14
Durum wheat	1.09	-14.91	1386255	0.18
Soft wheat	0.77	-32.64	452464	0.14

If the final actual yield will reflect our negative forecasts, not all the sown area might be actually harvested. In this case, it is expected that harvesting would not take place in the most affected areas (i.e. the areas with the poorest yields), resulting in final yield statistical figures larger than the forecasted ones.

More information can be found here:

- Meroni, M., Waldner, F., Seguini, L., Kerdiles, H., Rembold, F. (2021). *Yield forecasting with machine learning and small data: what gains for grains?* (arXiv:2104.13246)
- JRC MARS bulletin (April 2021): https://ec.europa.eu/jrc/sites/jrcsh/files/jrc-mars-bulletin-vol29-no4.pdf
- Schauberger, B., Jägermeyr, J., Gornott, C., 2020. A systematic review of local to regional yield forecasting approaches and frequently used data resources. Eur. J. Agron. 120, 126153. 588 https://doi.org/10.1016/j.eja.2020.126153
- Atzberger, C., Vuolo, F., Klisch, A., Rembold, F., Meroni, M., Marcio Pupin, M., Formaggio, A., 2016. Agriculture, in: Thenkabail, P.S. (Ed.), Remote Sensing Handbook. CRC Press, pp. 71–103.
- Rembold, F., Atzberger, C., Savin, I., Rojas, O., 2013. Using Low Resolution Satellite Imagery for Yield 576 Prediction and Yield Anomaly Detection. Remote Sens. 5, 1704–1733. 577 https://doi.org/10.3390/rs5041704
- Waldner, F., Horan, H., Chen, Y., Hochman, Z., 2019. High temporal resolution of leaf area data improves empirical estimation of grain yield. Sci. Rep. 9, 1–14. https://doi.org/10.1038/s41598-019-51715-7
- Rouse, J.W., Haas, R.H., Schell, J.A., Deering, D.W., Harlan, J.C., 1974. Monitoring the vernal advancements and retro gradation of natural vegetation. Greenbelt, MD.
- Becker-Reshef, I., Vermote, E., Lindeman, M., Justice, C., 2010. A generalized regression-based model for forecasting winter wheat yields in Kansas and Ukraine using MODIS data. Remote Sens. Environ. 114, 1312–1323. https://doi.org/10.1016/j.rse.2010.01.010
- Franch, B., Vermote, E.F., Becker-Reshef, I., Claverie, M., Huang, J., Zhang, J., Justice, C., Sobrino, J.A., 2015. Improving the timeliness of winter wheat production forecast in the United States of America, Ukraine and China using MODIS data and NCAR Growing Degree Day information. Remote Sens. Environ. 161, 131–148. https://doi.org/10.1016/j.rse.2015.02.014
- López-lozano, R., Duveiller, G., Seguini, L., Meroni, M., García-condado, S., Hooker, J., Leo, O., Baruth, B., 2015. Agricultural and Forest Meteorology Towards regional grain yield forecasting with 1 km- resolution EO biophysical products : Strengths and limitations at pan-European level. Agric. For. Meteorol. 206, 12–32. https://doi.org/10.1016/j.agrformet.2015.02.021
- Meroni, M., Marinho, E., Sghaier, N., Verstrate, M.M., Leo, O., 2013. Remote sensing based yield estimation in a stochastic framework - Case study of durum wheat in Tunisia. Remote Sens. 5. https://doi.org/10.3390/rs5020539
- Cai, Y., Guan, K., Lobell, D., Potgieter, A.B., Wang, S., Peng, J., Xu, T., Asseng, S., Zhang, Y., You, L., Peng, B., 2019a. Integrating satellite and climate data to predict wheat yield in Australia using machine learning approaches. Agric. For. Meteorol. 274, 144–159. https://doi.org/10.1016/j.agrformet.2019.03.010
- Cai, Y., Guan, K., Lobell, D., Potgieter, A.B., Wang, S., Peng, J., Xu, T., Asseng, S., Zhang, Y., You, L., Peng, B., 2019b. Integrating satellite and climate data to predict wheat yield in Australia using machine learning approaches. Agric. For. Meteorol. 274, 144–159. https://doi.org/10.1016/j.agrformet.2019.03.010
- Johnson, M.D., Hsieh, W.W., Cannon, A.J., Davidson, A., 2016. Crop yield forecasting on the Canadian Prairies by remotely sensed vegetation indices and machine learning methods. Agric. For. Meteorol. 219, 74–84. https://doi.org/10.1016/j.agrformet.2015.11.003
- Mateo-Sanchis, A., Piles, M., Muñoz-Marí, J., Adsuara, J.E., Pérez-Suay, A., Camps-Valls, G., 2019. Synergistic integration of optical and microwave satellite data for crop yield estimation. Remote Sens. Environ. 234, 111460. https://doi.org/10.1016/j.rse.2019.111460
- Wolanin, A., Mateo-Garciá, G., Camps-Valls, G., Gómez-Chova, L., Meroni, M., Duveiller, G., Liangzhi, Y., Guanter, L., 2020. Estimating and understanding crop yields with explainable deep learning in the Indian Wheat Belt. Environ. Res. Lett. 15. https://doi.org/10.1088/1748-9326/ab68ac
- Zhang, L., Zhang, Z., Luo, Y., Cao, J., Tao, F., 2020. Combining optical, fluorescence, thermal satellite, and environmental data to predict county-level maize yield in China using machine learning approaches. Remote Sens. 12. https://doi.org/10.3390/RS12010021

- 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.

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

JRC ASAP team

Jrc-asap@ec.europa.eu

Acknowledgements

Special thanks for reviewing the report to Giacinto Manfron and Bettina Baruth.

---

[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/)

