Challenges In Reanalysis Products To Assess Extreme Weather Impacts On Yield Underestimate Drought

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Abstract

The incidence of dry or wet day sequences has a great influence on crops management and development. The lack of spatialized observed data with appropriate temporal resolution to investigate the changes that has occurred during the last century regarding the length and frequencies of those sequences has led to reliance on reanalysis products. However, the question can be raised about the suitability of those products when evaluating such climate indices and their impacts on crop production. Different products are here investigated to evaluate the way that succession of dry and wet days are depicted. We showed clearly that the frequency and intensity of dry and wet spells returned can differ widely between products. For instance, number of dry spell events can range from 1 to 11 over the same decade for two different products. This divergence in representation of spells could generate substantial differences in impact analysis of crop yields in agricultural modeling.

Introduction

Variations in crop yield at global and European scale have been shown to be strongly influenced by climate variability¹⁻³, and the frequency of extreme weather events, such as heatwaves, droughts and floods, is increasing⁴⁻⁶. This raises urgent food security concerns about crop yields and food production at local and global scale. A major challenge in research assessing weather impacts on crop yields is to use of spatially distributed datasets covering long periods, because local processes are influenced by short-duration weather conditions⁷. For instance, agricultural water management need to be conducted on a daily basis and cannot be driven by seasonal parameters for effective mitigation of dry or wet spells for optimal crop production. In recent decades perceptions in Northern Europe have shifted from agriculture being likely to experience overall positive effects of climate change, with wetter and warmer weather promoting crop growth⁸, to extreme weather damaging crop production⁹. With overall wetter weather appearing increasingly likely in the Nordic region¹⁰, the impacts on agriculture may be complex¹¹. Precipitation increases mainly outside the cropping season and altered rainfall frequency-intensity pattern within the cropping season are expected to increase the incidence of water deficits¹² and excess saturation, negatively affecting crop production⁹. Investigating the links between climate variability, extreme weather, and crop production locally is limited by poor availability of long-term meteorological datasets with high temporal resolution, as few synoptic weather stations offer the necessary > 30 years of continuous daily data¹³. In Sweden, for example, the automatic network providing such data (> 90% continuous) has only operated since 1995¹⁴. Lack of observed data with appropriate temporal resolution has led to heavy reliance on reanalysis products (RPs), such as ERA5¹⁵ in Europe or MERRA¹⁶ in the US, in research on historical occurrence and impacts of extreme weather. However, questions can be raised about the suitability of RPs when evaluating climate impacts on crop yield, since these evaluations are conducted on annual to monthly basis or concerning isolated daily extreme events¹⁵⁻¹⁸. However, dry and wet spells during the growing season are as important as daily extreme or monthly indicators for crop yields. The incidence of dry and wet days influences the quantity and quality

of the harvested crop¹⁹, and the irrigation/drainage strategy needed to mitigate weather effects. Choice of RP may therefore influence the representation of events known to impact crop production at local scale.

Methods

Five gridded reanalysis products were compared: MESAN²³ (5-km resolution, availability 1979–2013), NASApower (0.5°-resolution, availability 1990-present, derived from MERRA-2¹⁶), Ag-ERA5 (0.1°-resolution, availability 1979–2018, derived from ERA5¹⁵), and UERRA-HARMONIE¹⁸ (11-km resolution, availability 1961–2018). NASApower was downloaded from the dedicated web platform (<https://power.larc.nasa.gov/>), Ag-ERA5 was downloaded from the Copernicus Climate data store (<https://cds.climate.copernicus.eu/>), and MESAN was provided by the Swedish Hydrological and Meteorological Institute (SMHI) (<https://www.smhi.se/data/oppna-data/meteorologiska-data/analysmodell-mesan-1.30445>). All three datasets were used in their native format. The UERRA project produces daily precipitation data (06.00–18.00 h). To adjust to agro-hydrological standard and for comparison with the other RPs, the version of UERRA-HARMONIE used was a reprocessed dataset with daily precipitation summed from 00.00–24.00h kindly provided by SMHI, which manages the UERRA project. Data from each dataset were extracted using the CDO package of the Max Planck Institute²⁴. The overlapping grid cell from each dataset was compared with observed data from the SMHI meteorological station at Ultuna (SMHI-97490, 59.8139N; 17.6469E), downloaded from www.smhi.se/data/ in January 2021. The period of comparison (1990–2000) was chosen as a 10-year period with no missing data in any dataset. The evaluation was based on data for the period April 1–September 30, which corresponds to the typical cropping season in Sweden. The analysis of dry and wet spells was based on the widely used definition as a period of at least five consecutive days with precipitation lower and higher than 1 mm, respectively²⁵. Data manipulation, comparison, statistics, and diagram were produced using R studio. Lin's concordance correlation coefficient²⁶ was used to compare observed data and RP values calculated using the `epi.ccc` R function.

Results And Discussion

We used a simple local example in a preliminary attempt to assess the challenge of discrepancies between RPs. We compared four RPs against observations from a weather station near a long-term agricultural trial in Uppsala, Sweden. Analysis of daily and monthly absolute error for rainfall and temperature showed that the four RPs provided a fair representation of local climate relative to observations (Figs. 1 to 3). Monthly precipitation amount (Fig. 1) was depicted accurately, with concordance correlation coefficient (CCC) ranging from 0.79 to 0.97. Daily precipitation values showed weaker agreement with observations, but were acceptable ($\text{CCC} \geq 0.6$). Observed and RP-derived minimum ($T_{\min}$) and maximum ($T_{\max}$) temperature showed stronger correlations, with $\text{CCC} > 0.95$ for monthly error and > 0.90 for daily error. The slightly lower agreement seen for precipitation is consistent with the inherent characteristics of precipitation as a more stochastic parameter, with higher variation in

time and space than temperature. This preliminary analysis showed good representativeness of RPs in depicting the general climate at the local field site.

Our next task was to capture the incidence, distribution, and accumulated duration of wet and dry days during the cropping period to assess the potential impact on yield. The four RPs were used to depict the number of rainy days (> 1 mm) in 10 cropping seasons at the study site (Fig. 2). All RPs consistently overestimated the number of rainy days, by 10–35% compared with observed data. MESAN showed best agreement ($CCC = 0.71$) with observed patterns, but agreement decreased substantially for the other RPs ($CCC = 0.19$ – 0.25).

Another important criterion is how RPs distribute wet and dry days over the growing season, and generate wet and dry spells. Based on the temporal distribution and relationship between number and length of spells for the four RPs, all underestimated dry spells and overestimated wet spells (Fig. 3). For instance, of 25 observed dry spells lasting 10–14 days, MESAN captured 22, NASApower and AgERA5 15, and HARMONIE 14. Of 18 extreme dry spells lasting > 15 days, MESAN, NASApower, AgERA5, and HARMONIE captured 15, 6, 8, and 6, respectively. On the other hand, only five wet spells lasting 5–9 days were observed, but MESAN, NASApower, AgERA5, and HARMONIE returned 13, 42, 29, and 37 respectively. This overestimation of wet spells is consistent with the excess number of rainy days identified in Fig. 2.

The data in Figs. 2 and 3 represent only one grid cell of each RP, but this local agro-climatic approach is necessary to investigate climate impacts on crop yield (quantity and quality). Our final task was to estimate, at larger scale, the difference induced by choice of RP. Scaling up the analysis to territory level using classical weather station is generally impossible, as lack of spatialized observed data is the reason for using RPs. We assessed the difference between RPs by comparing them for the study region, i.e., the agriculture-dominated region of southern Sweden. HARMONIE and MESAN, which diverged most strongly in the dry/wet spell analysis in Fig. 3, were compared (Fig. 4).

For southern Sweden 1990–2000, a difference between the two RPs of less than five events were observed in 38% of cells for dry spells lasting 5–9 days. This increased to 58% of cells for dry spells lasting 10–14 days, but declined to 32% for spells > 15 days. At some locations, HARMONIE returned only one dry spell > 15 days over the decade, while MESAN returned 11 (Fig. 4).

Reanalysis products offer a useful solution to the problem of lack of observed weather data and are very often used in crop modeling studies^{1,3,9,20}. However, we showed clearly that the frequency and intensity of dry and wet spells returned can differ widely between RPs. When RP data are used in agricultural models, this divergence in representation of dry and wet spells can generate substantial differences in impact analysis of crop yields and quality. There are also implications for strategies and investments in agricultural water management (drainage and irrigation), as system design, precision, and cost-benefit must be conducted at high spatial and temporal resolution in order to be meaningful for local farmers and beneficiaries.

The bias of dry and wet day sequences highlighted in this manuscript is coherent with the main objective of RPs which is primarily to characterize the climate at large scale. Typical approaches used to validate them are usually considering the spatial and temporal large scale factors^{15–18}. Their usage for agricultural modeling is then adapted to evaluate the interaction between crop production and climate variable at national or regional scale if related to temperature (e.g. 21,22). However, as illustrated here, those products should be carefully used for assessing climate impacts – especially those linked to precipitation – on more reduced scale.

A noteworthy finding here was for instance the underestimation of long dry spells (> 10 days), i.e., of the risk of drought, and resulting yield and food security implications at local or even regional level. Representation of meteorological events resulting in dry and wet spells, which is not generally considered when evaluating RP quality, is a future challenge for agro-climatic research.

Of the four RPs investigated, MESAN (available until 2013) best depicted dry and wet days and spells. MESAN was developed over a more limited area (northern Europe) than the other RPs (European or global scale), which could explain its better representation of agro-climatic parameters at the Swedish field site. Our findings indicate that agro-hydrologists and agro-meteorologists need to exercise caution when choosing climate RPs for agricultural research. The scientific community should work to improve representations of important agro-climatic features, in particular the distribution of wet and dry spells, in evaluations of soil moisture and yield responses in agro-climatic investigations.

This comparison of RPs was conducted in a region with a dense observation data network, on which the RPs are based. Divergence between available RPs may be even stronger in poorly monitored regions, such as sub-Saharan Africa. The issue of accurate representation of dry and wet spells may also arise in results generated by climate models, which are widely used to project food production over the next century.

Declarations

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Figures

Figure 1

Error between observations and reanalysis product values for cropping season (April-September) 1990-2000 at Ultuna. Left Panel: error based on daily data and right panel: error based on monthly data. Agreement given as concordance correlation coefficient (Conc.Corr.Coeff).

Figure 2

Number of rainy days (>1 mm) in the cropping season, 1990-2000, based on observations and different reanalysis products, with agreement given as concordance correlation coefficient (CCC).

Figure 3

Distribution, number, and length of dry and wet spells per cropping season, 1990-2000, for each reanalysis product. Left-hand panels show the distribution April-September of spells exceeding five

consecutive days, right-hand panels show spell length and total number of spells.

Figure 4

Difference in number of dry spells (top row) and corresponding percentage difference (lower row) between the MESAN and HARMONIE reanalysis products for southern Sweden, 1990-2000.

Supplementary Files

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