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Uncertainty in future irrigation water demand and risk of crop failure for maize in Europe

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Abstract

While crop models are widely used to assess the change in crop productivity with climate change, their skill in assessing irrigation water demand or the risk of crop failure in large area impact assessments is relatively unknown. The objective of this study is to investigate which aspects of modeling crop water use (reference crop evapotranspiration (ET_0), soil water extraction, soil evaporation, soil water balance and root growth) contributes most to the variability in estimates of maize crop water use and the risk of crop failure, and demonstrate the resulting uncertainty in a climate change impact study for Europe. The SIMPLACE crop modeling framework was used to couple the LINTUL5 crop model in factorial combinations of 2–3 different approaches for simulating the 5 aspects of crop water use, resulting in 51 modeling approaches. Using experiments in France and New Zealand, analysis of total sensitivity revealed that ET_0 explained the most variability in both irrigated maize water use and rainfed grain yield levels, with soil evaporation also important in the French experiment. In the European impact study, net irrigation requirement differed by 36% between the Penman and Hargreaves ET_0 methods in the baseline period. Average EU grain yields were similar between models, but differences approached 1–2 tonnes in parts of France and Southern Europe. EU wide estimates of crop failure in the historical period ranged between 5.4 years for Priestley–Taylor to every 7.9 years for the Penman ET_0 methods. While the uncertainty in absolute values between models was significant, estimates of relative changes were similar between models, confirming the utility of crop models in assessing climate change impacts. If ET_0 estimates in crop models can be improved, through the use of appropriate methods, uncertainty in irrigation water demand as well as in yield estimates under drought can be reduced.

Introduction

Large investments in irrigation project development or appropriate income support such as insurance mechanisms require sound estimates of crop water demand and the risk of crop failure due to drought, respectively. A high level of uncertainty exists in these estimates due to climate models and scenarios used, future land use changes and the choice of crop model

[1, 2], among others. This uncertainty can serve as a barrier to making timely investments as the likelihood and cost of maladaptation are high [3]. While crop models are widely used to assess the change in average productivity levels with future climate change, their skill in assessing water use, whether it be to determine drought risk in rainfed systems or irrigation water demand in large area impact assessments [4] is relatively unknown.

Recent studies have demonstrated the uncertainty in future irrigation water demand. Elliott *et al* [5] found that the relative change in global potential irrigation demand to 2050 differed from median values of +15% increase to –5% decrease for global hydrology and gridded crop models, though these models employ many different approaches for various aspects of crop water use. The diversity of ways to model crop water use may be argued as an approach to capture scientific uncertainty in crop water use across environments, as little data is available for testing at a global scale. However, taking reference crop evapotranspiration (ET_0) as an example, there appears to be greater variety in modeling approaches used in crop models (see SI appendix, table S1) than is justified from the current level of scientific understanding. Comprehensive studies confirm that there is wide variation between methods to estimate ET_0 [6–10]. While some perform well in specific environments, it is recommended to use either the ASCE or FAO–Penman–Monteith methods when applied across environments [8, 11]. The Penman–Monteith combination equations were found to give the best agreement with measured crop water use in a series of lysimeter experiments across environments [8].

In most crop modeling impact assessments, including those considering water limiting conditions, crop models are typically calibrated only on yield and growth variables [12], as data on crop water use or soil water data is usually not available. Crop modeling studies have investigated how the approach to simulate soil water balance affects estimates of simulated soil water or crop evapotranspiration [13–16]. However, there are few examples of systematic studies that look at how the soil water related models (e.g. ET_0 , ET partitioning and soil water balance) affect simulated crop grain yields under water limiting conditions (see exceptions by [14–17]), though many only investigate one aspect of water use or present unsystematic comparisons in which many aspects differ between models [18]. In some comparisons using the same crop model, different simulated biomass values were reported for non-water limiting conditions, making interpretation of the study results difficult [18]. The ability of crop models to capture the yield response to different levels of soil water deficit may be a result of calibration of water stress related parameters and not necessarily by capturing the correct process response [19] to limited soil water availability. This is here hypothesized to limit their utility in climate change impact assessments across environments where the factors driving ET_0 differ between regions and possibly under future climate conditions [20].

In this context, this study had two objectives. The first was to systematically assess using sensitivity indices which aspects of modeling crop water use (reference crop evapotranspiration (ET_0), soil water extraction, soil evaporation, soil water balance and root growth) contribute the greatest level of

uncertainty to (i) crop water demand under irrigation and (ii) yield levels under water limited conditions when coupled to the LINTUL5 crop growth model. As the choice of ET_0 method emerged from the study of the first objective as the aspect contributing the most uncertainty to estimates of irrigation water demand and rainfed crop yields, the second objective was to demonstrate the resulting uncertainty in estimates of European [1] irrigation water demand and [2] rainfed yield levels that arises from using different ET_0 methods coupled with the LINTUL5 crop growth model.

Materials and methods

Uncertainty analysis

For the first objective, maize development, growth, and water use were simulated with the SIMPLACE modeling framework [4, 21] using the LINTUL5 crop growth model [22] together in 51 models combinations, each with different crop water related models. In LINTUL5, growth and development are simulated on a daily basis in response to daily weather inputs. Plant biomass growth is determined as a function of the photosynthetically active radiation intercepted and the radiation use efficiency, which varies with development stage and average temperature; biomass is partitioned to roots, stems, leaves and grain based on the crop development stage. For temperate maize, crop development depends on the daily average temperature sums to reach flowering and maturity and is assumed independent of photoperiod effects. Nitrogen was considered non-limiting in the current study. Water limitation, quantified as the ratio of actual transpiration to potential transpiration, reduces leaf area and biomass growth, while increasing partitioning of biomass to roots. Aspects related to water use are discussed in the following section.

To assess which aspect of modeling crop water use causes the most variability in water use and grain yield, a sensitivity analysis (SA) was conducted. Rather than vary parameters as typically done in SA, we varied a particular method used to estimate one aspect of crop water use. To do so, water use was first conceptually divided into 5 components (ET_0 , soil water extraction, soil water evaporation, soil water balance and root growth) that are typically considered by crop models, see tables 1 and 2. Next, 2 to 3 methods (see SI appendix), implemented as individual submodules, of differing levels of model complexity were selected for each component (table 1, SA 1). As it is not possible to combine a very simple water balance model, typical of regional applications [4, 21], with models of soil water extraction, soil water evaporation, and root growth models, a second SA was conducted considering only 2 components (ET_0 and soil water balance) (table 2, SA 2). The third step was to construct factorial combination of the various submodules and link, within the SIMPLACE framework, the resulting water related

Table 1. Modeling components considered for different aspects of crop water use (and factor levels) in the first sensitivity analysis.

Soil water retention and flux	ET ₀ ^a	Crop extraction	Soil water evaporation	Root model
1. SLIM1 (1 layer—average soil horizon) [23]	1. Penman (1948) [24] (LINTUL5 default)	1. FAO-56 based approach [25]	1. SLIM2 default [23]	1. LINTUL5 [22]
1. SLIM2 (multiple horizons layers) [23]	1. FAO-56 Penman–Monteith [11] 1. Hargreaves [25]	1. Feddes [26]	1. FAO-56 [25]	1. SlimRoots [23]

^a The Penman (1948) method is actually a method used to estimate crop evapotranspiration (ET_c).

Table 2. Modeling components considered for different aspects of crop water use (and factor levels used) in the second sensitivity analysis.

Soil water retention and flux ^a	ET ₀
1. SLIM1 (multilayer layer—aggregate soil horizon) [23]	1. Penman ^a (1948) (Lintul5 default) [24]
1. SLIM2 (multiple layer—multi horizons) [23]	1. FAO-56 Penman–Monteith [11]
1. LINTUL5 ^a (1 layer—aggregate soil horizon) [22]	1. Hargreaves [25]

submodules together with the LINTUL5 above ground crop model.

The 51 models were calibrated (SI appendix and figure S1), and evaluated using two experimental maize data sets. Irrigated maize was considered in Lusignan, France and in Lincoln, New Zealand data with a rainout shelter and full irrigation were available. After calibration, 5 sets of simulations for each site were conducted for each of the 51 models (full irrigation, no irrigation, and with 25%, 50% and 75% of irrigation water volumes). To determine the contribution of various model components to the total variability in crop water use and final grain yield estimates, total sensitivity indices (TS) were calculated for each simulation according to Monod *et al* [27] as:

$$TS_i = 1 - \frac{\text{var}(E[Y|X_{-i}])}{\text{var}(Y)}. \quad (1)$$

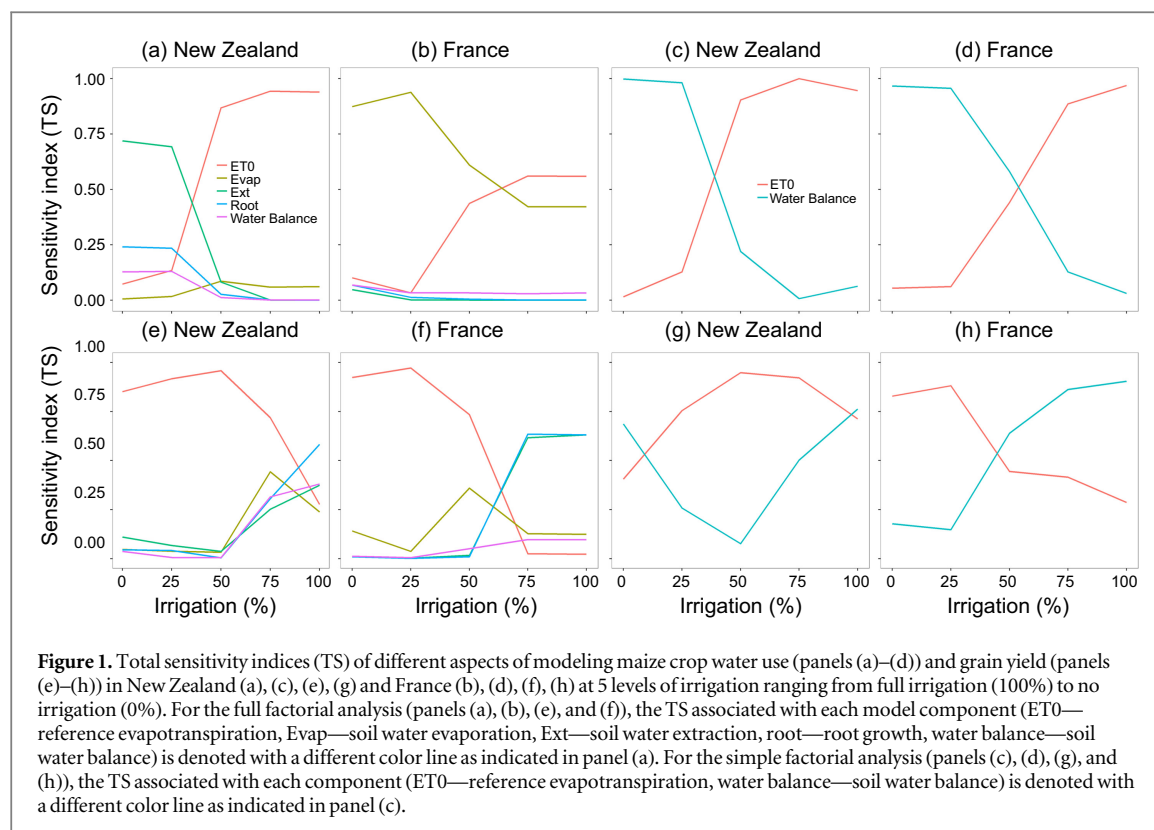
European impact assessment

Based on the results of the SA, LINTUL5 was used with one of four ET₀ models (or ET_c in the case of the Penman method): Priestley–Taylor (1972), Penman (1948), Hargreaves and Samini (1985) and the FAO-56 Penman–Monteith (1998). Priestley–Taylor was not considered in the SA, as three submodules covering a range complexity were selected. After ET₀ emerged as a critical modeled component, Priestley–Taylor was additionally considered because it is used in many crop models (see table S2). In the resulting four model

combinations, the respective ET₀ model was combined with the LINTUL5 above ground crop model and SLIM1 (multilayer layer—aggregate soil horizon) together with the SLIMRoots, FAO-56 [11] based soil water extraction method and the FAO-56 [11] soil water evaporation method. Differences in water use under full irrigation, as well as grain yields and crop failure under rainfed conditions, were evaluated in both a historical period as well as in two scenario periods with climate change. The LINTUL crop models have been previously applied in climate change studies (e.g. [28, 29]) and with the SIMPLACE framework at local [30], national [31] and continental scales [4, 21, 31]. Simulations were conducted with climate and soil input data at 25 km resolution.

Historical, 25 km resolution, gridded climate data from the JRC were used for a baseline period from 1984 to 2013. This data was used to define the simulation unit of the models, with all other available data either aggregated or disaggregated to match the spatial resolution and extent of the historical climate data. The delta method was used to estimate two climate scenarios for a future period of 2036–2065 (nominally referred to as 2050) with two representative concentration pathways (RCP): RCP4.5 and RCP8.5, by adding deltas to the historical climate data (see SI appendix). Soils coinciding with agricultural land on the Corine Land Cover 2006 raster data v17 were selected from the gridded derived soil layers at a 1 km spatial resolution from the European soil database [32, 33] (see SI appendix). The spatial distribution of the ratio of the area with irrigated maize to the total area in maize production was available at the NUTSIII level [34]. Anthesis dates were calibrated for each simulation unit using phenology observations from the JRC MARS database and assuming maize was photoperiod insensitive. Phenology was re-adjusted for each scenario period and RCP combination to match the sowing and maturity dates in the baseline period (autonomous adaptation).

Output variables assessed in this study include crop water use (ET_c) under full irrigation. For the Priestley–Taylor, Penman–Monteith and Hargreaves methods, ET_c is estimated by multiplying ET₀ by a



crop coefficient to relate the crop ET to that of the reference surface, k_{cb} and K_e , for transpiration and evaporation respectively, as well as account for stresses such as water deficit or salinity, k_s . See SI for more discussion of methods implemented in this study (SI appendix). The Penman (1948) method estimates directly crop evapotranspiration (ET_c). NIR is determined from an approximate soil water balance considering ET_c , growing season precipitation (P), runoff (RO) and drainage (D), all during the growing season:

$$NIR = ET_c - P + RO + D. \quad (2)$$

For rainfed conditions, average grain yield and the frequency of crop failure are evaluated. In both cases, the evaluation is conducted in the historical period as well as in a future periods for two scenarios. Crop grain yields were considered to have failed when yield levels fell below 70% of simulated mean yield for a particular scenario period, region and ET₀ model. The frequency with which grain yields fell beneath this model specific threshold was quantified as the average interval between successive failures, here estimated by dividing the length of the simulation period (30 years) by the number of failures counted in the 30 year simulation period.

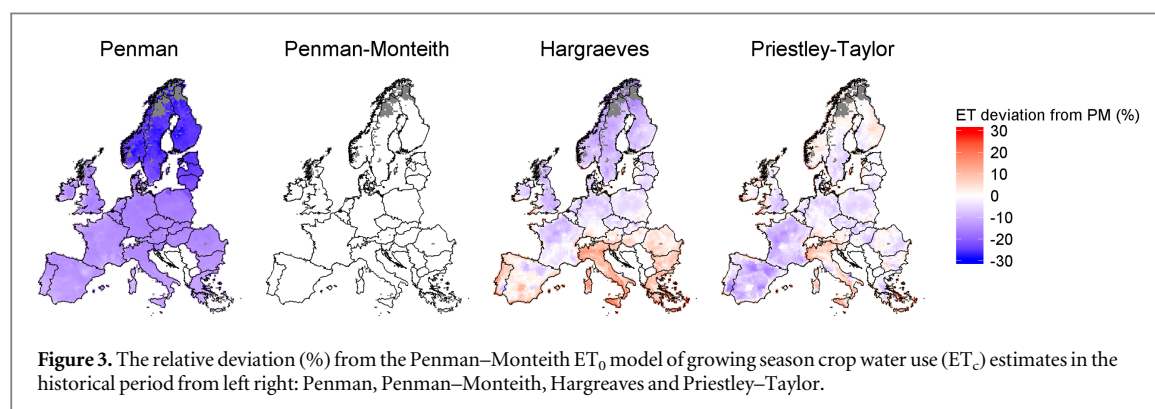
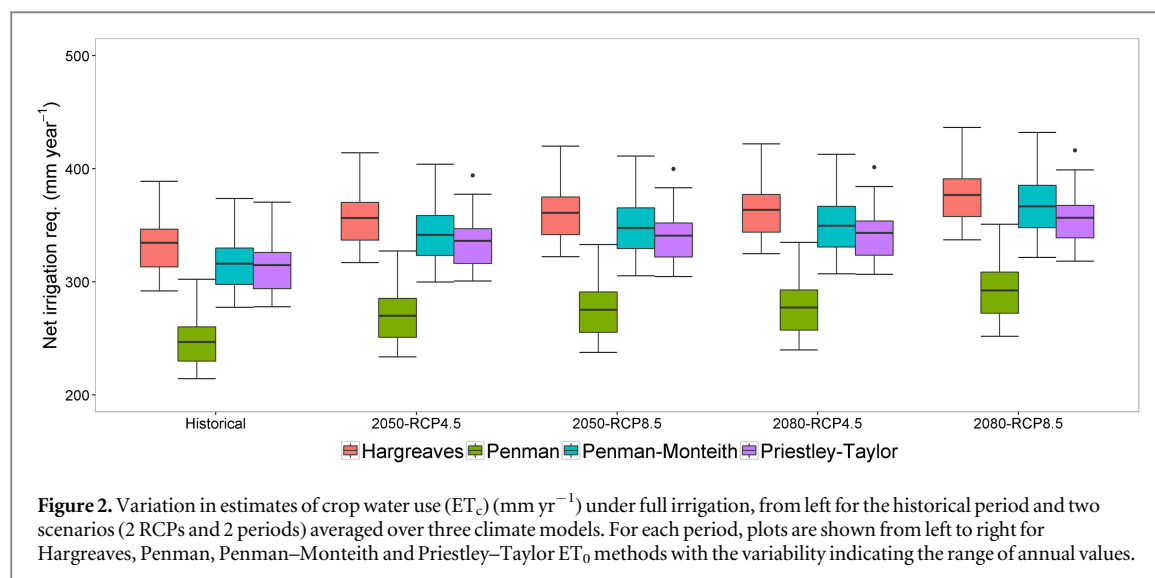
Results

Uncertainty analysis

Under fully or near fully irrigated conditions (figure 1, irrigation percentages 100% or 75%), most variability in ET_c was explained by the method used to estimate

ET₀. Under irrigated conditions, the ET₀ method described 60% and 100% of the variability in ET_c estimates in France and New Zealand, respectively. This was confirmed in the second analysis in which 3 water balance models were coupled with 3 ET₀ models in which the ET₀ method explained close to 100% of the variability in ET_c for both the experiments in France and New Zealand (SI appendix, figure S1). Under water limiting conditions, many components contribute to the variability in ET_c and this appears to vary between the two locations with soil water evaporation dominating in France whereas the soil water extraction method explains the largest amount of variability in the New Zealand experiment. In both of these cases, the respective factor has an interaction with the ET₀ method that explains at least 10% of the variability in ET_c for one of the dry treatments (0%, 25% or 50% irrigation). Further, the root model explained a large amount of variability in the New Zealand experiment under dry soil conditions.

Likewise, the factors explaining the greatest levels of variability in yield levels differed depending on the level of water limitation experienced. Under rainfed and water limiting conditions (0% to 50% irrigation), the ET₀ method explained at least 80% of the variability in grain yields for both the experiments in New Zealand and France (figure 1). This result was confirmed, particularly for the French dataset, when only water balance and ET₀ method were considered as factors in the SA (SI appendix, figure S1). Under high irrigation amounts, it appears that many of the factors contribute to the variability in grain yields. In reality,



all model achieved close to potential yield for both locations, and little variability was found in these estimates (SI appendix, figures S2 and S3).

European net irrigation and crop water demand under irrigated conditions

Across Europe, median NIR in the historical period ranged between 247 and 335 mm yr^{-1} for the Penman and Hargreaves methods, respectively. The Priestley–Taylor and Penman–Monteith estimates were very close to that of Hargreaves (figure 2). This 36% difference between the highest and lowest estimates among ET_0 methods decreased to 31% and 30% in 2050 and 2080, respectively, averaged across all GCMs. The Hargreaves NIR estimate was always greatest and the Penman always least. The uncertainty in NIR estimates arising from the ET_0 method is approximately the same size as the uncertainty stemming from the choice of GCM, which contributes to uncertainty in both the calculation of ET_0 , as well as differences in future precipitation amounts across climate models. The average relative changes in NIR with climate change to 2050 were 6.5%–9.4% and 8.7%–12.3% to 2080 for RCP4.5 across ET_0 methods. These relative changes increased to 7.9%–11.6% (2050) and 12.6%–18.4% (2080) for RCP8.5. In all cases, the smallest relative changes were estimated by the Hargreaves

model whereas the highest relative changes were from the Penman model. All four ET_0 models simulated increasing ET_c under irrigation under climate change reflecting evaporative demand from warmer temperatures (SI appendix, figure S2). The Penman method has lower estimated ET_c across Europe, with deviation expressed relative to the Penman–Monteith (figure 3).

Grain yields under rainfed conditions

EU average rainfed maize yield levels varied as expected across Europe (figure 4(a)). The EU average water-limited yield was 4.8 t ha^{-1} in the historical period, with the Priestley–Taylor model (similar to Hargreaves and Penman–Monteith) giving the lowest estimate of 4.5 t ha^{-1} while the Penman model produced the highest estimate at 5.6 t ha^{-1} , 19% higher than that of Priestley–Taylor. Average yield levels increased for the climate scenarios considered to 2050 and 2080 (figure 5), as a result of maintaining the current growing season with generally higher precipitation. Averaged for scenarios, the EU average relative changes in grain yield with climate change to 2050 and 2080 were 8.5%–10.9% and 9.6%–13.4%, respectively. When spatial patterns across Europe are considered, the differences in average yield levels stemming from the ET_0 models is minimal in

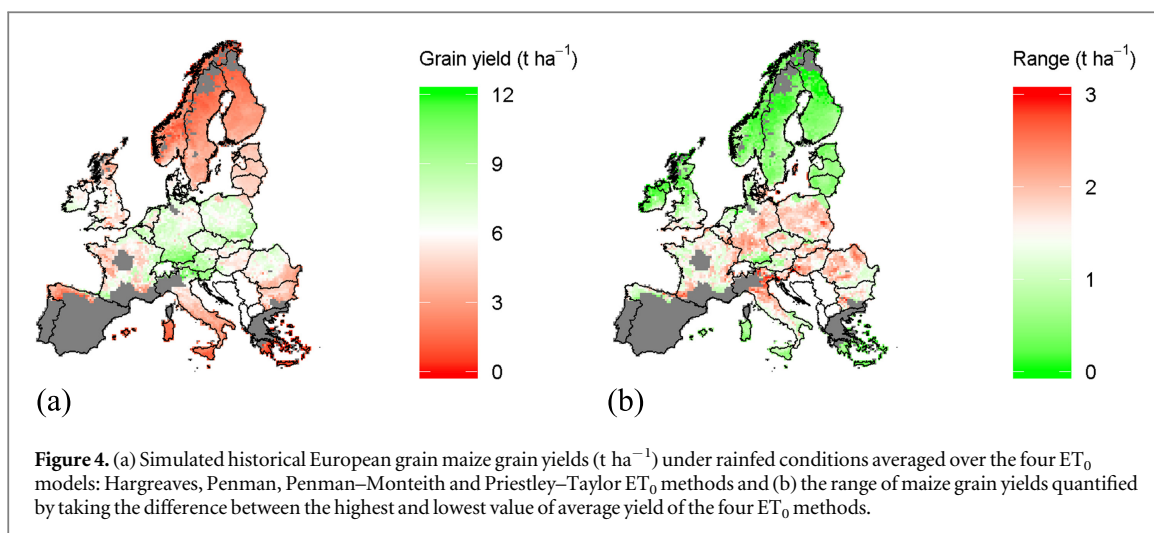


Figure 4. (a) Simulated historical European grain maize grain yields (t ha⁻¹) under rainfed conditions averaged over the four ET₀ models: Hargreaves, Penman, Penman–Monteith and Priestley–Taylor ET₀ methods and (b) the range of maize grain yields quantified by taking the difference between the highest and lowest value of average yield of the four ET₀ methods.

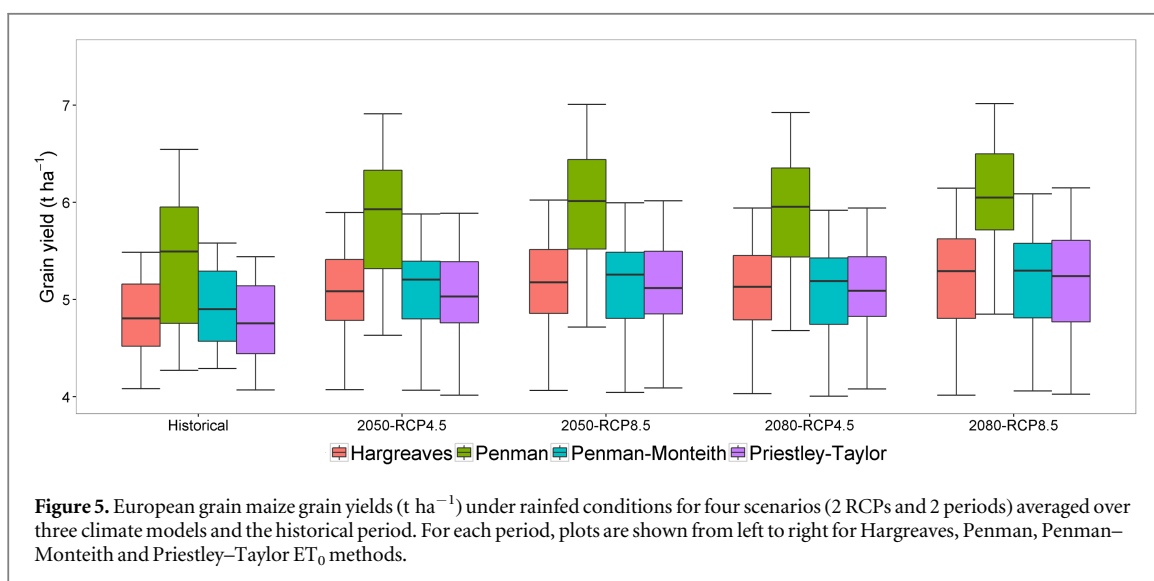


Figure 5. European grain maize grain yields (t ha⁻¹) under rainfed conditions for four scenarios (2 RCPs and 2 periods) averaged over three climate models and the historical period. For each period, plots are shown from left to right for Hargreaves, Penman, Penman–Monteith and Priestley–Taylor ET₀ methods.

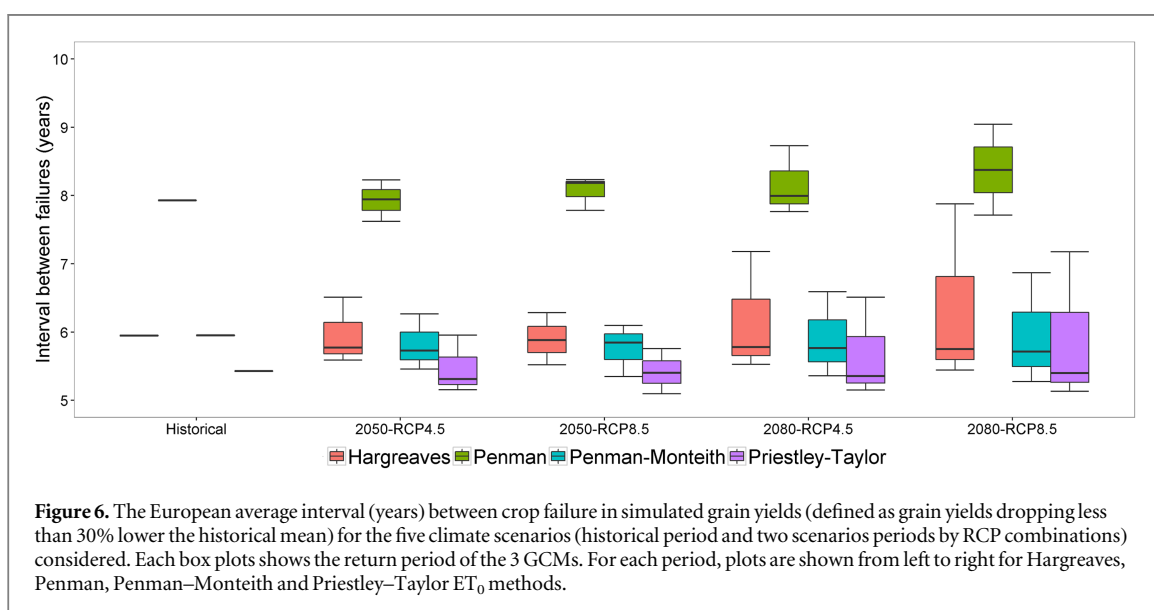


Figure 6. The European average interval (years) between crop failure in simulated grain yields (defined as grain yields dropping less than 30% lower the historical mean) for the five climate scenarios (historical period and two scenarios periods by RCP combinations) considered. Each box plots shows the return period of the 3 GCMs. For each period, plots are shown from left to right for Hargreaves, Penman, Penman–Monteith and Priestley–Taylor ET₀ methods.

Northern Europe but approaches 1–2 tonnes in much of France and up to 3 tonnes in part of Eastern Europe (figure 4(b)). This range is large part explained

by the Penman model having up to 50% higher average rainfed yield levels than the other models (SI appendix, figure S4).

Crop failure for rainfed grain maize

At the European level, crop failure in the historical period ranged between every 5.4 years for Priestley–Taylor to 7.9 years for the Penman model, 32% less frequent (figure 6), with spatial patterns in figure S6. The time between successive crop failures tends to increase with climate change. By 2080, as much uncertainty in the average time between successive crop failures results from the choice of GCM as from the ET_0 model selected.

Discussion

Assessing agricultural water use is critical given the large share of freshwater used in agriculture, future increase in demand for food and the uncertainty in water supply due to climate change. While crop models are better suited to assess the dynamics of crop water use and irrigation demand than hydrological models [5], many sources of uncertainty surround the use of crop models related to model structure [1, 2, 35], study methodologies and assumptions about irrigation [4], nitrogen [21] and other technological developments [36], among others. While the uncertainty in crop model simulations has been demonstrated in a number of crop model intercomparisons such as those cited above, there has been little emphasis on comparing models on their estimates of water use. A further limitation of model comparisons is the difficulty in generalize their findings to lead to model improvement as the models differ in many aspects [37]. As far as we are aware, this study is one of the first to systematically investigate crop water use (see also [15]), to offer insights into which components explain the most variability in simulated yield and water use. Our findings indicate that the sensitivity to model components differed with the intensity of resource use (irrigated versus rainfed conditions), and also with the impact variable considered (yield versus water use). These findings are also reported in a study investigating methods to simulate crop rotations [38].

However, our study contains some limitations which should be considered in the interpretation of our results. We have only coupled our modeling approaches for crop water use to one crop model and the results may be different with other models. This suggests a role for cross model comparison [1, 39] of the sensitivity of crop models to various components of modeling crop water use. The AgMIP project is now undertaking a comprehensive maize model comparison for estimates of crop ET involving more than 20 crop models and various experts in modeling crop water use. Secondly, our modeling approaches did not consider the impact of extreme events, either by explicitly considering heat stress effects in our model or by including changed climate variability in the climate scenario data, which are expected to increase [40]. However, due to the influence of soil water status and

crop water use on heat stress effects through canopy temperature [37, 41], the differences in simulated grain yields are expected to be greater than estimated here. A further limitation of the study is in the sowing and harvest dates used for simulating irrigated production in regions that are predominantly rainfed, as our observational dataset includes only dates for the dominant production system. Therefore, if the growing season was shifted with the use of other sowing and harvest dates, the climate effects may have had a different effect. Likewise, due to possible mismatches in sowing dates and varieties, we only simulated rainfed grain yields in areas that currently have at least 50% rainfed production. As a result, we have not analyzed rainfed production in mainly irrigated regions, despite the fact that these regions are likely to experience water limited conditions and high risk of crop failure.

European crop water demand under irrigated conditions

A number of studies have compared ET_0 methods across environments, relating differences in ET_0 estimates to the underlying sensitivity of the methods to climate variables. In a comparison of different land surface and global hydrology models, models that used the Priestley–Taylor formula were found to produce lower estimates of ET_0 than those using the Penman–Monteith equation in dry areas, whereas there was little difference between methods in humid areas [42]. Results from Kingston *et al* [9] confirm the result that Priestley–Taylor ET_0 estimates are lower than those of Penman–Monteith in arid and semi-arid areas. However, in a global comparison of different ET_0 methods, Weiß and Menzel [10] determined that the Priestley–Taylor gave much greater estimates than the Penman–Monteith in semi-arid and arid conditions. In our study, differences between ET_0 methods in estimates of absolute crop water demand were on the order of 20%. A number of reasons explain the differences, many of which are difficult to generalize due to the nonlinear relationship between key variables. For example, neither Priestley–Taylor nor Hargreaves contain windspeed terms, which can largely explain why they exhibit lower coefficients of variation and deviate from FAO-56 Penman–Monteith in regions with high wind speeds, moderated by degree of aridity. A case of bias is found in the method used to estimate net radiation in Penman (1948), which creates a bias of underestimation in net radiation as compared to the FAO-56 Penman–Monteith method. Nonetheless, the purpose of our study is not to explain the differences which are well explained in other studies, but rather to investigate the implications across production conditions and impact variables in a large scale impact study. Finally, other authors have found that any of the ET_0 methods that assume neutral stability conditions, such as the four methods tested here, lead to underestimation in dry arid areas [43, 44], whereas iterative

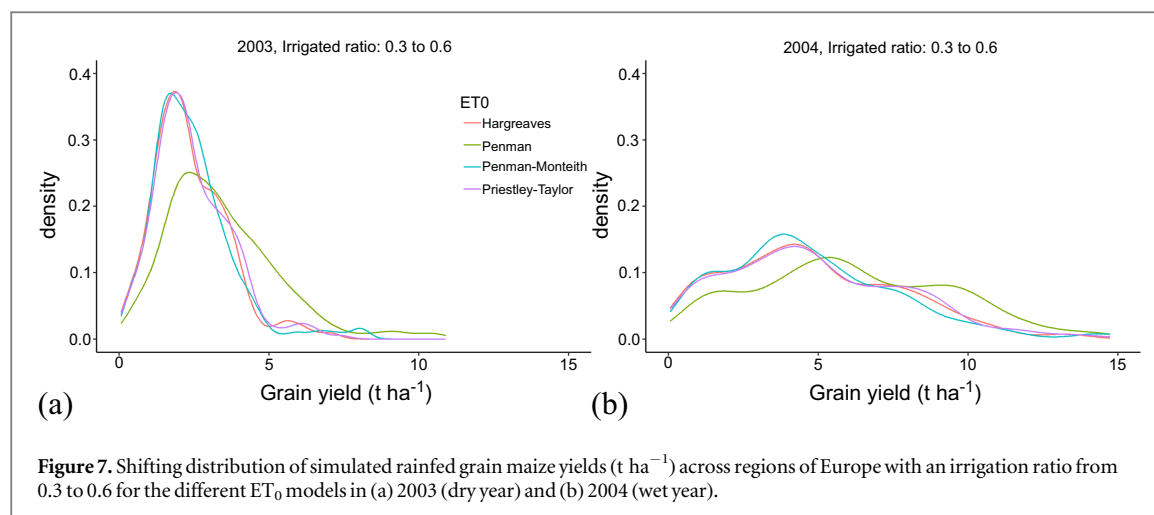


Figure 7. Shifting distribution of simulated rainfed grain maize yields (t ha⁻¹) across regions of Europe with an irrigation ratio from 0.3 to 0.6 for the different ET₀ models in (a) 2003 (dry year) and (b) 2004 (wet year).

methods without the neutral stability assumptions perform better.

Grain yields and risk of crop failure under rainfed conditions

Average yield levels and the risk of crop failure exhibited somewhat less variability across ET₀ method than NIR. The increase in average rainfed grain yields was largely due to our simulated autonomous adaptation (maintaining current growing season length through adoption of longer season varieties) and increased precipitation for all GCMs used in this study (SI appendix, figure S7). Differences in average rainfed yield levels are related to differences in average growing season crop water use, which varied across ET₀ methods to an extent similar to the fully irrigated case in most years (SI appendix, figure S8). We suspect that in regions where drought is more common, i.e. in regions with a larger share of irrigated production, we may expect more year to year variation in maize grain yields resulting from the ET₀ methods estimating higher water use. For example, the yield distributions of the ET₀ models in water limiting (2003) versus largely non-water limiting (2004) conditions for parts of France and surrounding regions (IR 0.3–0.6, SI appendix, figure S5) that suffered from the 2003 summer heat and drought event [45] are shown in figure 7. In 2003, the Penman model shows a lower frequency of very low grain yields, than the other models. In 2004, which was considered a relatively wet year, there was much less difference between the grain yields simulated by the four ET₀ models in the region.

The difference between ET₀ models in the expected rate of crop failure was approximately 30% and this was constant across the scenarios and periods considered. This translates into a crop failure once in 8 years for the Penman model as opposed to a crop failure once in 5.5 years for the other three for the 25 km² aggregate area. This may translate into much greater yield variability at the farm level [46, 47]. The 30% decrease compared to average yield levels was chosen

as a measure for crop failure following international standards. The WTO Uruguay Round Agreement on Agriculture, Annex 2 8(a), for example, defines '[...] a natural or like disaster [...] by a production loss which exceeds 30 per cent of the average of production [...]'. The WTO definition also shaped the crop failure definition of 'European Union Guidelines for State aid in the agricultural and forestry sectors' [48, 49]. The use of a lower threshold for crop failure may be more appropriate for risk analysis at aggregate scales. However, there are few instances of studies investigating crop failure [50], with some previous studies having used non-coherent indicators [51] such as standard deviation [52]. More broadly, it is hard to translate these yield shocks into risk for farmers [53], as farms vary in their sensitivity to yield shocks as compared to price shocks [54], and this depends on their production system, crop type, diversification strategies [55], crop insurance schemes [56, 57] as well as income support and off-farm income [54].

Conclusions

This analysis indicates that if we can improve our ET₀ and related soil evaporation estimates in crop models, building on knowledge from the irrigation scientific community, we can reduce uncertainty in irrigation water demand and yield estimates under drought. Improving modeling the dynamics of crop water movement or root growth seems only critical to estimate crop water use under drought conditions. While perhaps interesting from a scientific perspective, it is not as critical for planning irrigation infrastructure investments, nor estimating yield under drought.

Across Europe, there was considerable uncertainty in absolute estimates of net irrigation demand and, to a lesser extent in rainfed yield levels and the risk of crop failure across ET₀ models. However, there was relatively less uncertainty across ET₀ models in the relative changes in either crop water use or yield levels,

supporting the utility of crop models in assessing climate changes impacts. However, to enable crop models to be more useful in understanding adaptations such as irrigation or crop insurance, crop models will need to be improved regards to their estimates of crop water use. Obtaining experimental datasets at both the field and larger scale will be critical to support this model improvement. Finally, the on-going initiative in AgMIP to compare crop models for ET is a critical step in model improvement to support decision making AgMIP or similar networks.

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