AgScore – An Agricultural Perspective on Climate Model Skill

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Abstract
Crop yield forecasts are commonly based on models using historical climate, i.e. climatology. With increasing skill of seasonal climate models, these models are now becoming a feasible alternative to improve predictability. To facilitate this change of practice we have developed a web based tool to test yield prediction skill across climate models and identify agriculturally important problems in the forecasts. Our solution is a cloud based tool AgScore that is called from an R or Python session from which an ensemble of forecasts is uploaded for a location and crop (chosen from a broad, international predefined set). APSIM is executed with the uploaded climate model data, and AgScore analyses the results against identical APSIM simulations using baseline climatology for the same period. A standard suite of metrics are then sent back to the user giving them an indication of climate model performance. We are keen to hear feedback on how to develop this metric to best meet the needs of the agricultural and climate science communities. More details on the AgScore tool and how to use it can be found at https://research.csiro.au/agscore/.

Key Words
seasonal climate forecasts, yield forecasts.

Introduction
To estimate crop productivity during the coming season, decision-support-tools require information about the year-ahead climate as input. This is currently largely achieved by taking all past years of climate records as an ensemble of what the future might hold. Graincast, Yield Prophet, AussieGrass and CropARM are examples of such tools amongst many others. In some cases, statistical approaches are applied to narrow this range by picking appropriate analog years from the past according to the current El Niño or La Niña phase.

In recent years seasonal climate forecast models (SCFM) have received increased attention from the research community (WMO, 2018) and become more accessible to agronomists (McIntosh and Brown 2017) to use in agricultural models. This has led to a host of papers (including Rodriguez et al., 2018, Brown et al., 2018) and decision support tools (DSTs), such as AskBill and Yield Prophet Lite exploring this capability.

The utility of SCFM in place of climatology is still unclear. In some cases, climatology is a simpler, more pragmatic approach to providing input to cost effective DSTs especially where the skill of the seasonal climate forecast model is low.

It is expected that with continued research on SCFM, the skill of the forecast will improve much like the increases in the skill of shorter-term weather forecasts that have been achieved over recent decades. International efforts including the 'Subseasonal to Seasonal Prediction Project' (Vitart and Robertson, 2018) are an example of the growing interest in this field.

Improving our ability to forecast agricultural productivity will require specific improvements to SCFMs that are not always obvious. Climate scientists tend to focus on metrics such as the SOI or average seasonal rainfall. While these climate metrics are important for agriculture, to run agricultural productivity models daily time step weather predictions are required for six months in advance going out for at least six months. SCFM suffer from a bias of drizzle. That is, there might be relatively good skill in predicting the total rain for autumn, for example, but a tendency to simulate it as drizzle over many days rather that distinct rain events. Such differences can have profound effects on, for example, sowing date and yield. This is just one example of the climate subtleties required for an agricultural model like APSIM (Holzworth et al., 2018) to predict crop yield correctly.

Climate scientists do not necessarily have ready access or experience to run a system like APSIM to evaluate the forecast skill of the climate model. Our goal is to produce a series of metrics that are easily accessible and universal. These metrics can be applied to a climate model hindcast (historical forecast set) to see how successful the forecasts would have been in years past and highlight weaknesses. Our goal is to see climate scientists at international conferences comparing and rating their models by their 'AgScore' thereby generating model improvements that benefit the agricultural community.

Methods

The initial version of AgScore will be developed to test SCFMs for simulating wheat growth at pre-specified locations in Australia and with pre-set management rules. Having this consistency allows for comparisons to be made across different researchers and models using the tool. After this initial prototype is refined, the tool will be expanded to include other crops and locations around the world in key areas of interest.

An essential part of the project is user engagement to ensure that the tool is developed in a way that suits the operations of climate scientists and provides them with actionable information to help the development of forecasting.

Initial Prototype

The initial prototype of AgScore (Figure 1) will be called from a Python workspace for three Australian locations in a pre-specified framework. The user will upload an ensemble of climate hindcasts indicating which location they are targeting, the hindcast period of interest (e.g. 1980-2012), the time of year the forecast will start from (e.g. June 1st), with the relevant variables of rainfall, maximum temperature, minimum temperature and solar radiation.

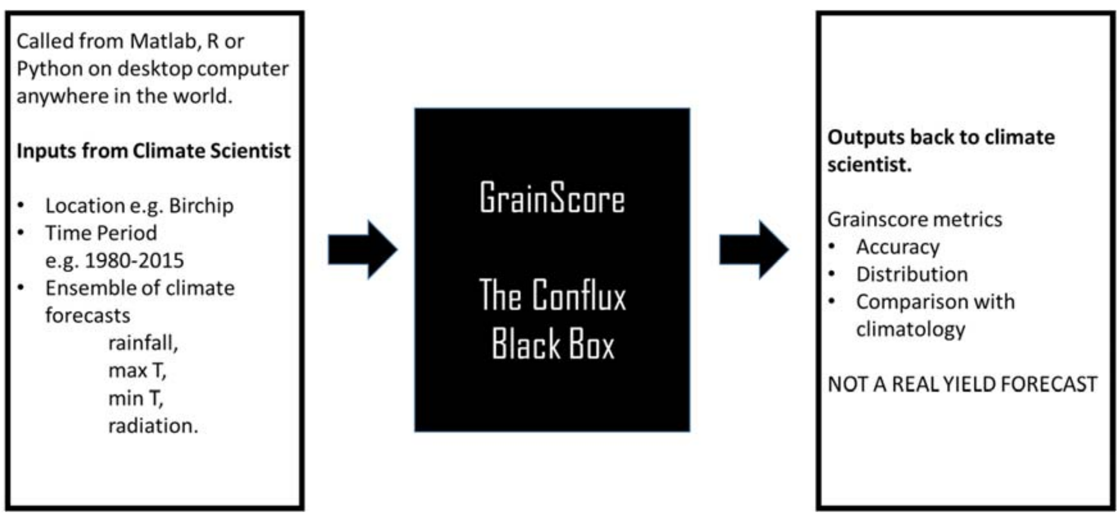


Figure 1. The AgScore System showing required inputs and possible outputs to the AgScore calculator.

The APSIM model was chosen as the agricultural production model for the Agscore tool, as it has international credibility for forecasting crop yields (Holzworth et al., 2018). Inside the AgScore tool (Figure 2), an APSIM appropriate weather file will be generated. This is a file that has historic observed weather data from January 1st to the 'start date' of the forecast (e.g. June 1st). The climate forecast is then patched on from January 1st until the end of the year and run through APSIM to generate a yield forecast and crop details of water stress and other productivity measures. This is repeated for each ensemble member and each year of the hindcast. In parallel, a series of runs is conducted using climatology.

The diagnostic calculator then conducts a skill assessment on the forecast detailing how well it was able to predict the potential yield in each year and delivers a 'skill score'. For the purposes of model development, the AgScore tool will determine whether there were any biases in features such as monthly rainfall, daily distribution of rain in dry days and drizzle days, targets in monthly temperature, and soil moisture accumulation.

It is important to note that this tool will not be appropriate for creating accurate future yield forecasts at new locations, as it will use a simplified agronomic system with predetermined locations and with soil and management options that might not be optimal for predicting crop yield. Its purpose is for climate scientists to assess model skill in simulation observed weather that is relevant to yield. It is not to assess how well the system can predict historical yield, and the relativities of outputs could be more important than absolute values when comparing different SCFM and climatology scenarios.

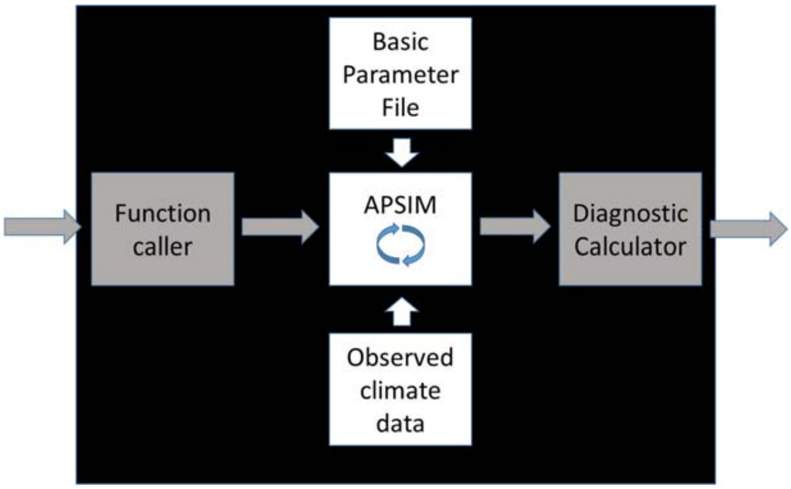


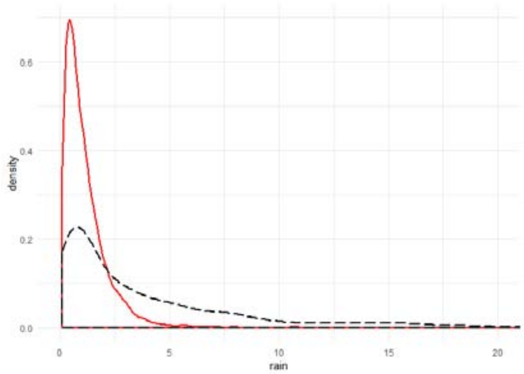
Figure 2. Inside the Agscore calculator. Climate data will be manipulated to feed into the APSIM program under a specified management option and consistent diagnostics run.

Results

The AgScore system is still under development. When fully operational it will provide assessments of rainfall, yield and other productivity measures. An example is given here for the types of rainfall metrics that might be included.

A common bias is too many drizzle days in model forecasts (Figure 3a). In this example at Birchip, the observed rainfall (dashed line) has just over 20% of days with 2 mm of rain and around 5% of days with 5mm. A typical climate model might produce something similar to the red line, the drizzle bias appearing as a higher frequency of days with 1 or 2 mm of rain and fewer days with 5 mm of rain or more. These biases are usually corrected in a post-processing method. How well they are corrected can significantly affect yield (Ines et al. 2011).

Total seasonal rainfall predictions are also crucial. If the total rainfall cannot be correctly simulated then yield cannot be accurately predicted irrespective of the frequency distribution discussed above. The Bureau of Meteorology's ACCESS-S model is run at Birchip for the period 1990-2012 and the results displayed in Figure 3b. The forecast start date at each year is March 1st and the rainfall is assessed over the autumn period in a tercile categorisation. In this scenario, the model picks the correct tercile in 30% of years. In 17% of years the model is 'wrong', i.e. it predicts the wettest or driest tercile when the opposite actually occurs. In 26% of years the ensemble spread is such that there is no clear prediction of which tercile rainfall totals will lie.



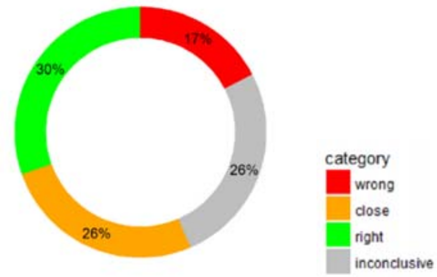


Figure 3. a) Rainfall frequency at Birchip comparing the frequency of different magnitude rain events from observations (black dashed line) and the ACCESS-S model. b) Rainfall skill assessment for Birchip for the 3 months starting on March 1st. The model is considered 'right' if at least 50% of ensemble members predict the correct category. It is deemed 'close' if it is one category out and wrong if 2 categories out e.g. predicts the wettest tercile when the actual rainfall was in the driest tercile. An inconclusive forecast is when the ensemble members are so disperse that no category is chosen. Figure adapted from Mitchell and Brown (Sub).

Conclusion

AgScore is a CSIRO initiative to provide leadership in the field of climate forecasting and agriculture. This new computational metric is being supported by the CSIRO Senaps compute platform and will initially be free to researchers to run computationally large assessments of their climate forecasts. The overarching goal is to improve the ability of seasonal climate forecasting models to provide meaningful and skilful data for generating grains and broader agricultural productivity metrics up to six months into the future.

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