Supplementary Information for Projected changes in crop yield mean and variability over West Africa in a world 1.5 K warmer than the pre-industrial

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1 Crop models

GLAM is the Global Large Area Model for annual crops (Challinor et al., 2004), it is a process based crop model that simulates the growth of a crop on the scale of grid cells used in climate models (Challinor et al., 2004) (Parkes et al., 2015). GLAM uses four meteorological inputs: maximum and minimum daily temperatures, downwelling shortwave radiation and precipitation, all at the surface. GLAM used the maize yield data as an input, along with soil quantities taken from the Digital Soil Map of the World using the approach described in Vermeulen et al. (2013). GLAM uses an intelligent planting system to wait for soil moisture to reach a pre-defined limit before planting occurs. The parameter set for maize used in this study is based on the one used in Vermeulen et al. (2013). The high temperature stress at flowering routine was enabled, if the maximum daily temperature is above 37 °C the yield is reduced, above 45 °C the yield is set to zero (Challinor et al., 2005, 2015). The rainwater harvesting routine used in GLAM stores any runoff from the top layer of the soil in a reservoir, the reservoir is tapped when the soil moisture falls below the wilting limit. The amount of water released from the reservoir is enough to bring the soil up to 80% of the drained upper limit or the totality of the water stored. GLAM does not have a parameter set for sorghum or millet and therefore was not used to simulate those crops. The carbon dioxide fertilisation effect is simulated by increasing the transpiration efficiency of the crop, this is based on the mean carbon dioxide concentration for the simulated time period.

ORCHIDEE-crop model is a land surface crop model, based on the generic vegetation model ORCHIDEE (Krinner et al., 2005), simulating carbon, water and energy fluxes (e.g. photosynthesis, respiration and evapotranspiration) and modules specifically designed to represent crop processes. The version of ORCHIDEE-crop used in this study includes crop phenology module (Wu et al., 2016) and crop management modules (Wang et al., in prep), which has also submitted results for global gridded crop model intercomparison (Müller et al., 2017). ORCHIDEE-crop calculates thermal unit accumulation, photosynthesis and energy exchange on a half-hourly time step, while leaf area dynamics, carbon allocation and biomass and soil organic carbon change are simulated on a daily time step. The daily climate variables driving the model includes: maximum and minimum daily temperatures, downwelling shortwave rand longwave adiation, surface pressure, wind speed and precipitation. The parameter set of maize was tested against a field experiment site in Ghana (Larvor, 2016).

SARRA-H (System for Regional Analysis of Agro-Climatic Risks), developed by the CIRAD, is a simple deterministic crop model for cereals operating at daily time steps (Dingkuhn et al., 2003; Baron et al., 2005; Kouressy et al., 2008) that simulates the growth of a crop on an adaptive scale of grid cells depending on the input data for Sorghum (90, 120 days or photoperiodic), Millet (90, 120 days or photoperiodic) and Maize (90 or 120 days). The performance in the analysis of climate impacts on tropical cereals is good (Mishra et al., 2008; Oettli et al., 2011). The yields are simulated under water-limited conditions by simulating the soil water balance, potential and actual evapotranspiration, phenology, potential and water-limited carbon assimilation, and biomass partitioning (see (Kouressy et al., 2008) for a detailed review of model concepts). The carbon dioxide fertilisation effect is not yet simulated. The optimum temperature is between 34 and 36°C and the limit temperature is between 44 and 46°C following the crop spices. SARRA-H model does not explicitly simulate the effects of fertilizer, manure application, or residue on crop yields but reproduce different level of fertility (F1=>F4). The ratio between F1 to F4 rate is calibrated with a field survey in Burkina Faso. For the sowing it starts when plant-available soil moisture is greater than 8 mm at the end of the day and after the date determined by krigged field farmers survey. The establishment of the crop is monitored during the followed 20 days and if the condition is not correct during this period, the juvenile crop died and a re-sowing is automatically done. SARRA-H (Sultan et al., 2014) SARRA-H uses five daily meteorological inputs: maximum and minimum temperatures, downwelling shortwave radiation, precipitation and PET (Hargreaves formula), all at the surface. Others inputs are also used: soil depth and soil water holding capacity, and sowing density and depth.

Author contributions. BP acquired the data and performed the simulations in GLAM, ORCHIDEE-Crop and the Linear models. DD ran the Sarra-H simulations. XW provided technical support for ORCHIDEE-Crop. All authors contributed to the manuscript.

Competing interests. The authors declare no competing interests.

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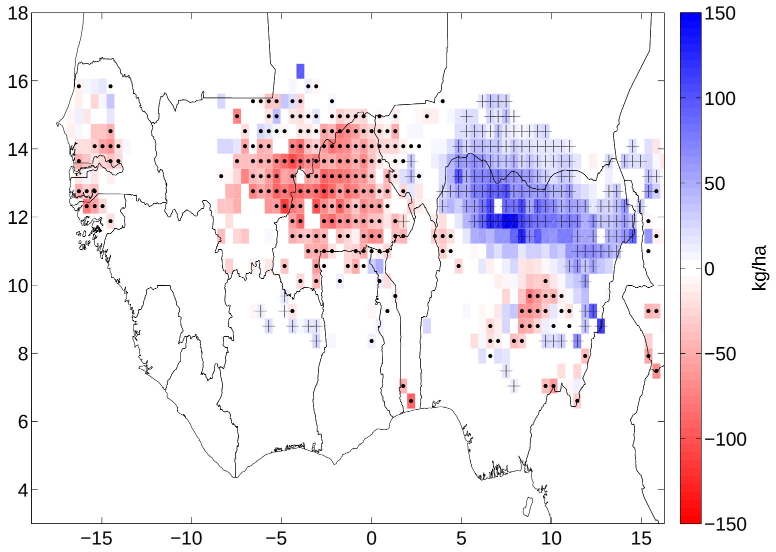

Figure 1. Multi model mean change in millet yield between control and future climates over West Africa in a world 1.5 K warmer than pre-industrial. Where + indicates three crop models agree the change will be positive and · indicates three crop models agree the change will be negative.

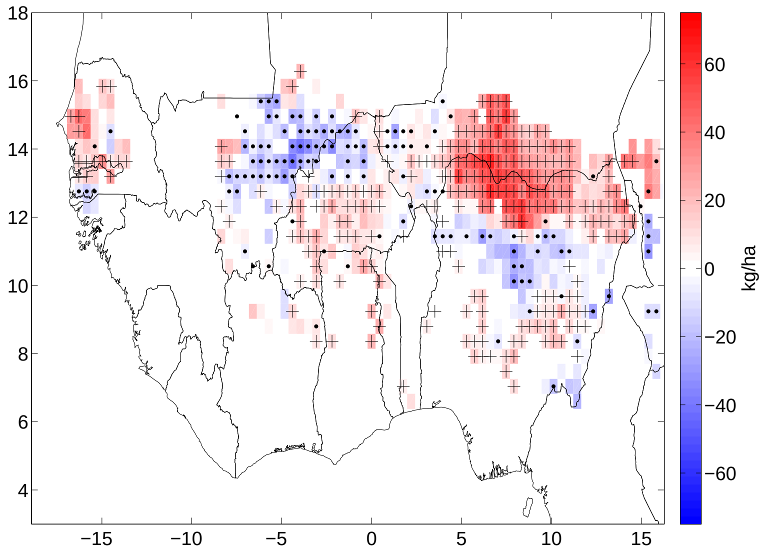

Figure 2. Multi model mean change in millet IAV between control and future climates over West Africa in a world 1.5 K warmer than pre-industrial. Where + indicates three crop models agree the change will be positive and · indicates three crop models agree the change will be negative.

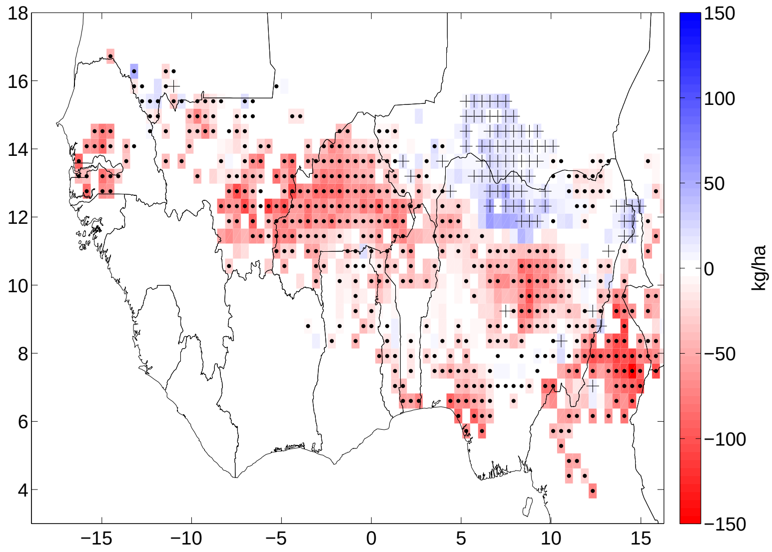

Figure 3. Multi model mean change in sorghum yield between control and future climates over West Africa in a world 1.5 K warmer than pre-industrial. Where + indicates three crop models agree the change will be positive and · indicates three crop models agree the change will be negative.

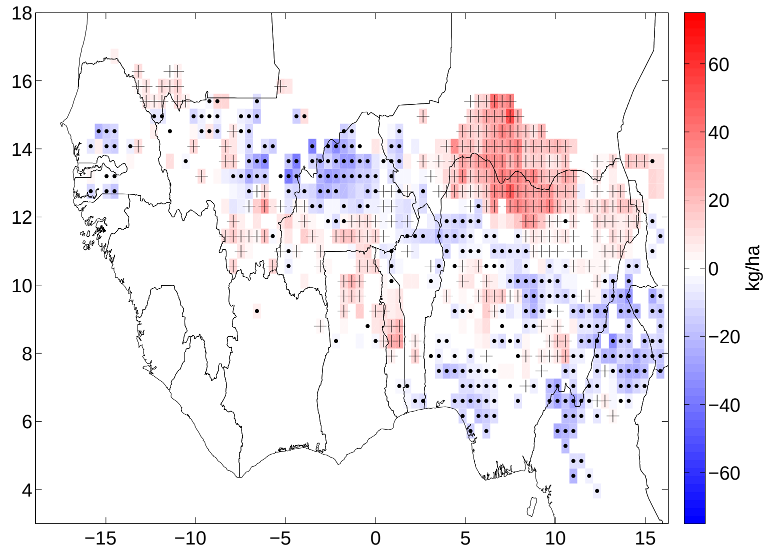

Figure 4. Multi model mean change in sorghum IAV between control and future climates over West Africa in a world 1.5 K warmer than pre-industrial. Where + indicates three crop models agree the change will be positive and · indicates three crop models agree the change will be negative.

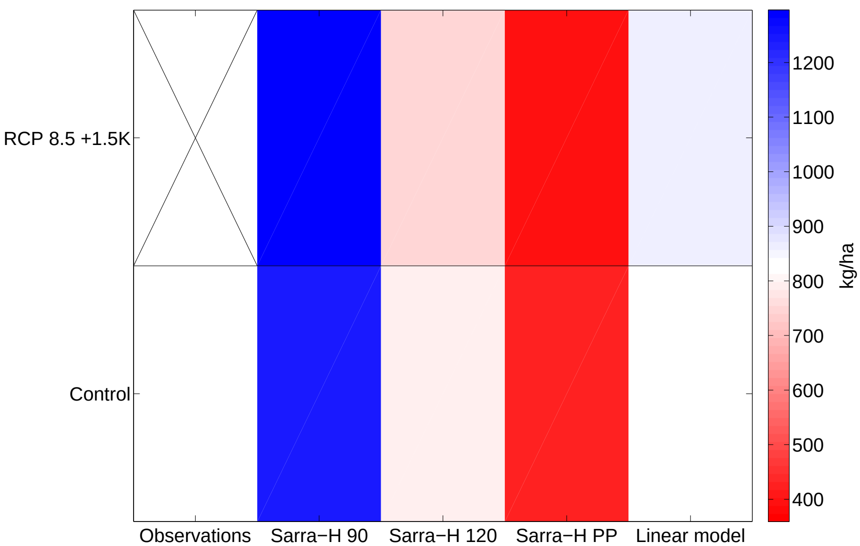

Figure 5. Heatmap of millet yields for four models for the control time period and at 1.5 K.

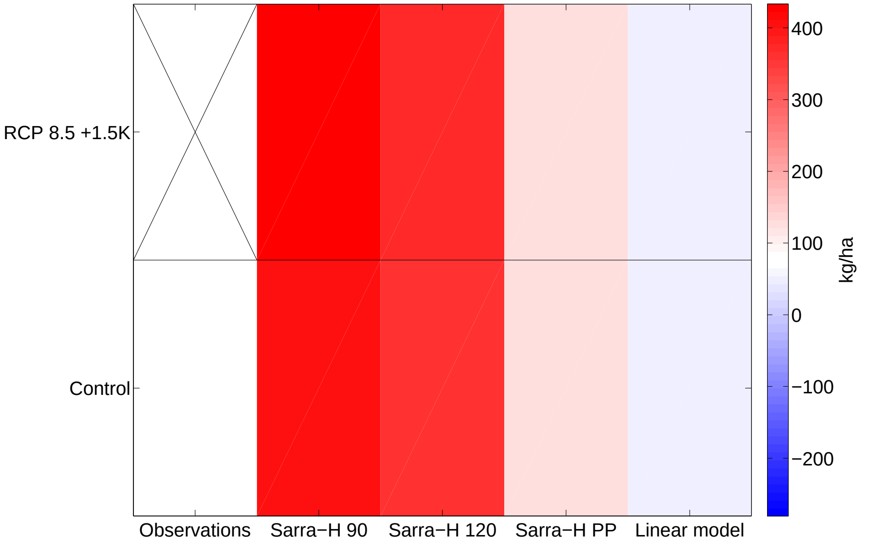

Figure 6. Heatmap of inter annual variability of millet yields for four models for the control time period and at 1.5 K.

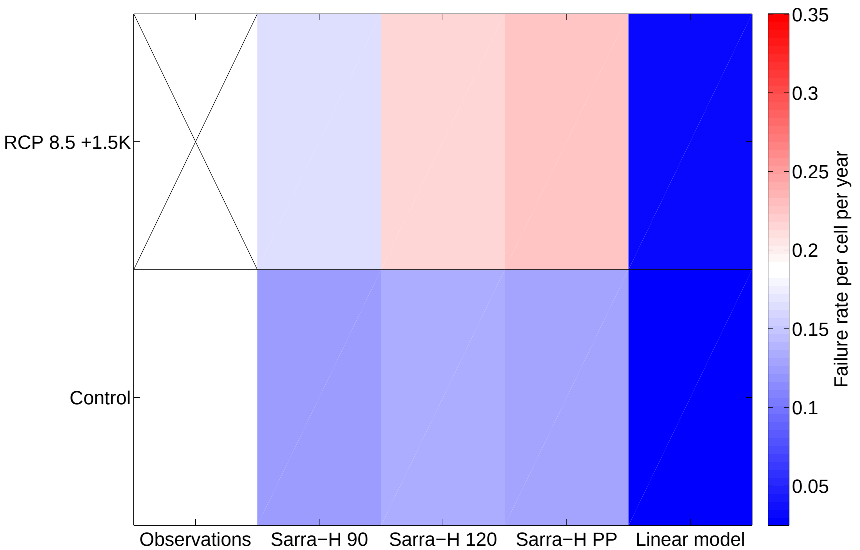

Figure 7. Heatmap of mild crop failure rate of millet for four models for the control time period and at 1.5 K.

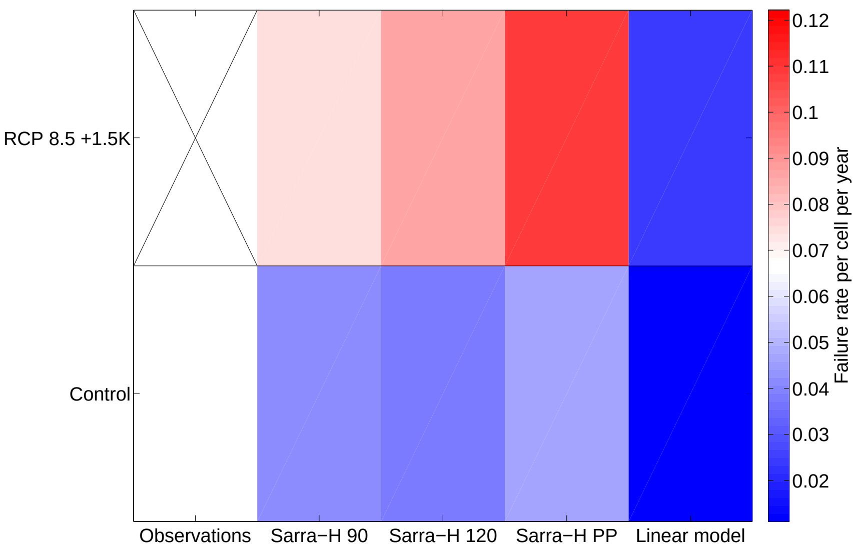

Figure 8. Heatmap of severe crop failure rate of millet for four models for the control time period and at 1.5 K.

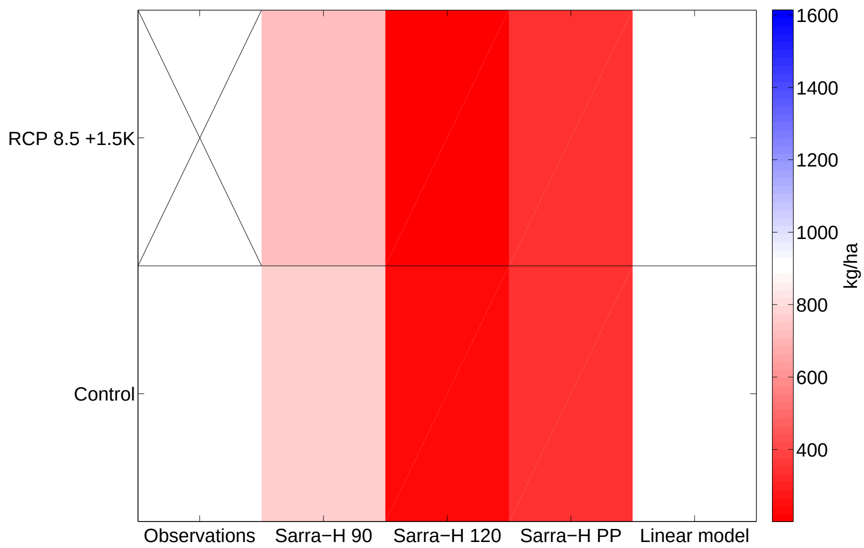

Figure 9. Heatmap of sorghum yields for four models for the control time period and at 1.5 K.

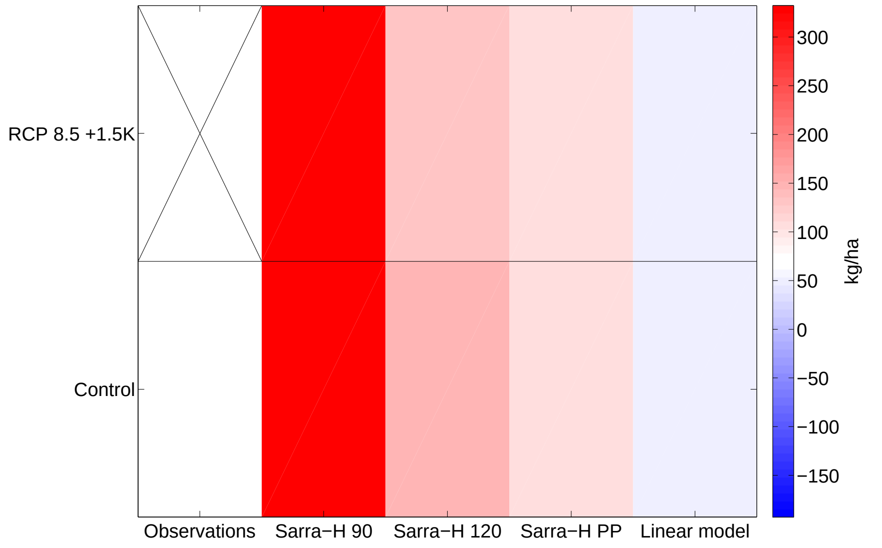

Figure 10. Heatmap of inter annual variability of sorghum yields for four models for the control time period and at 1.5 K.

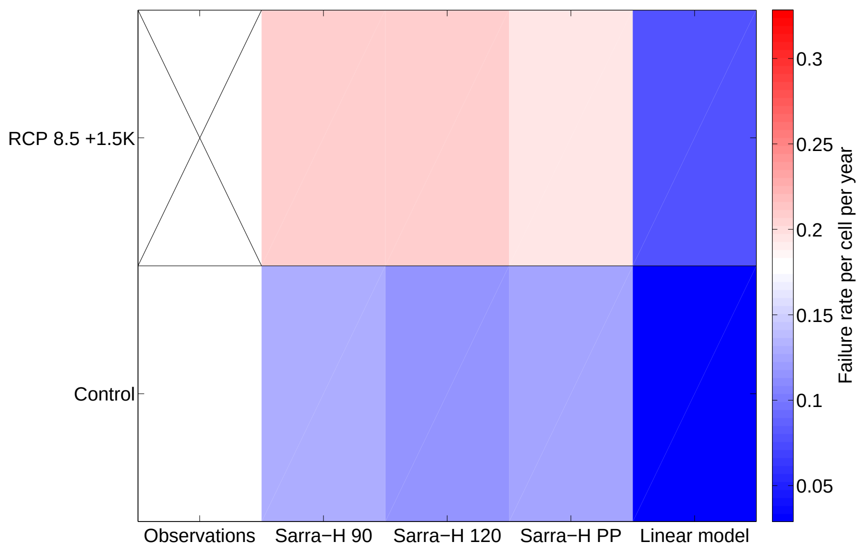

Figure 11. Heatmap of mild crop failure rate of sorghum for four models for the control time period and at 1.5 K.

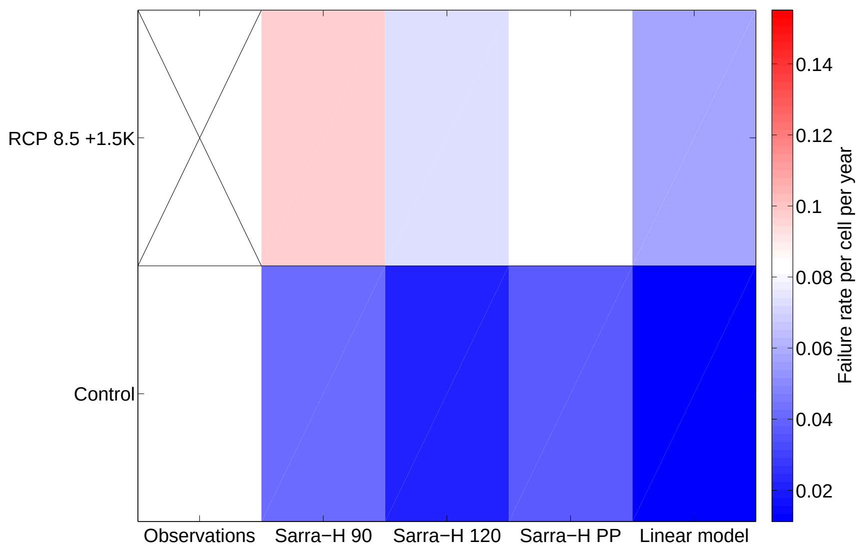

Figure 12. Heatmap of severe crop failure rate of sorghum for four models for the control time period and at 1.5 K.

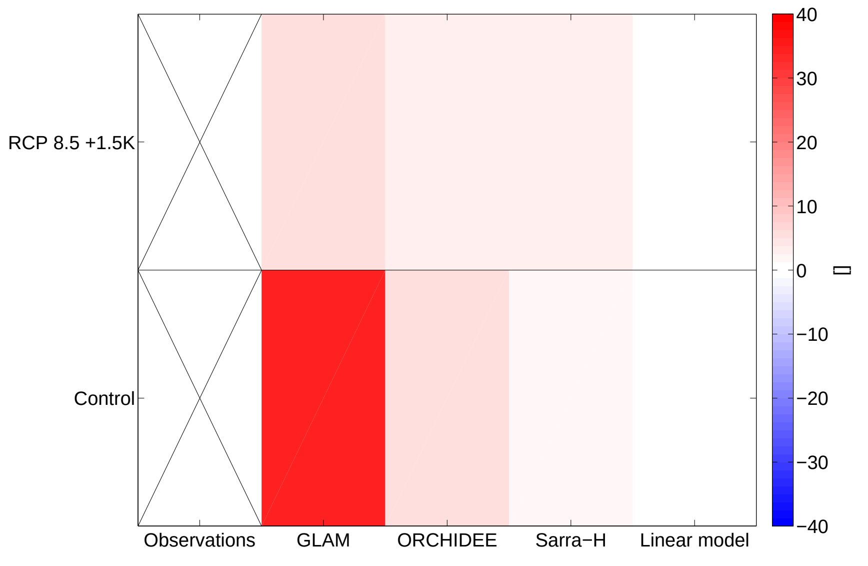

Figure 13. Ratio of IAV to model spread for maize for four models for the control peroid and 1.5 K

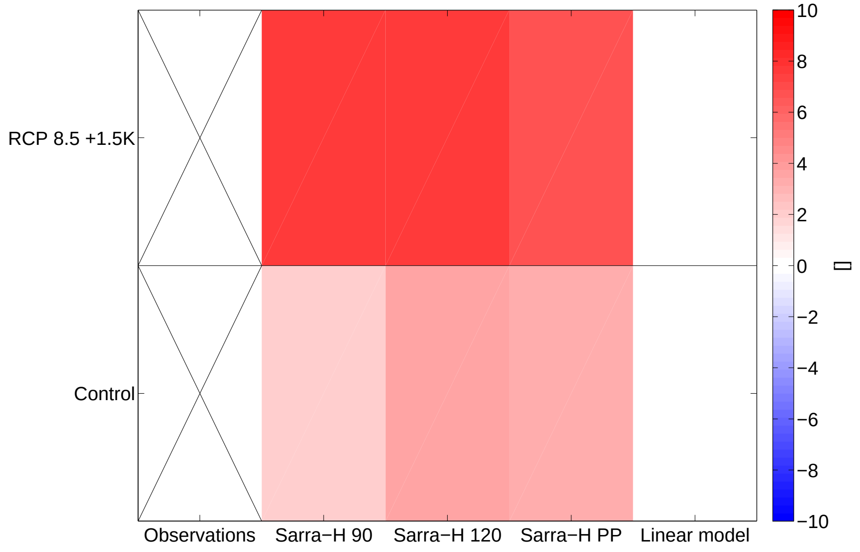

Figure 14. Ratio of IAV to model spread for millet for four models for the control peroid and 1.5 K

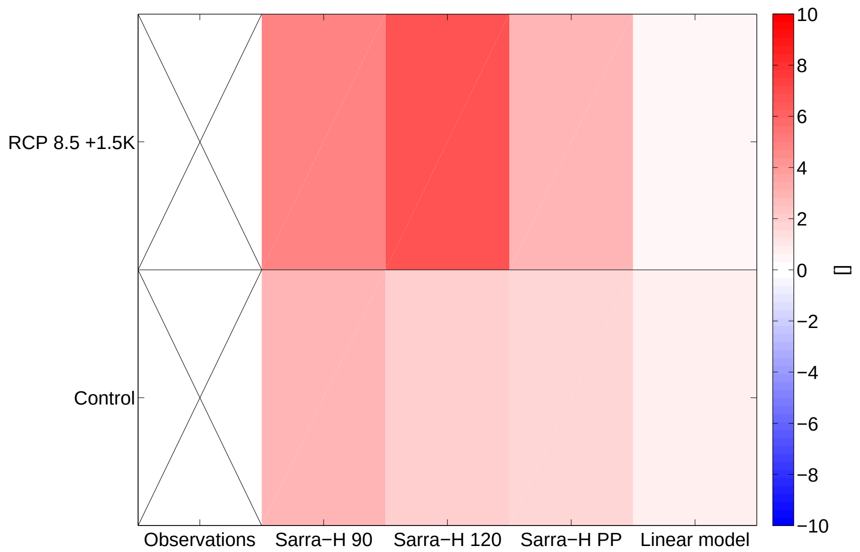

Figure 15. Ratio of IAV to model spread for sorghum for four models for the control peroid and 1.5 K