Crop Modeling Activities at AgMIP-SS Africa Workshop

Mount Kenya, Kenya
January 16-20, 2012

Goals of the Crop Modelers during this Workshop: 1) to calibrate and intercompare multiple crop models against maize and sugarcane data at two or more sites in Africa, 2) to simulate growth and yield response to several climate scenarios compared to baseline for those selected sites, and 3) to demonstrate the process of scaling up or aggregating simulated outcomes for a region for use by the TOA economic model, considering the variability created by multiple soils, management, and weather. Data on growth, soils, management, and weather used during the Workshop were provided by the following African colleagues:

1. Maize – Jesse Naab, Wa, Ghana
2. Maize – K.P.C. Rao, Katumani, Kenya
3. Maize – Wiltrud Durand, Republic of South Africa
4. Sugarcane – Patrick Musinguzi, Uganda
5. Sugarcane - Simbarashe Chinorumba, Zimbabwe
6. Millet - Madina Diancoumba, Mali

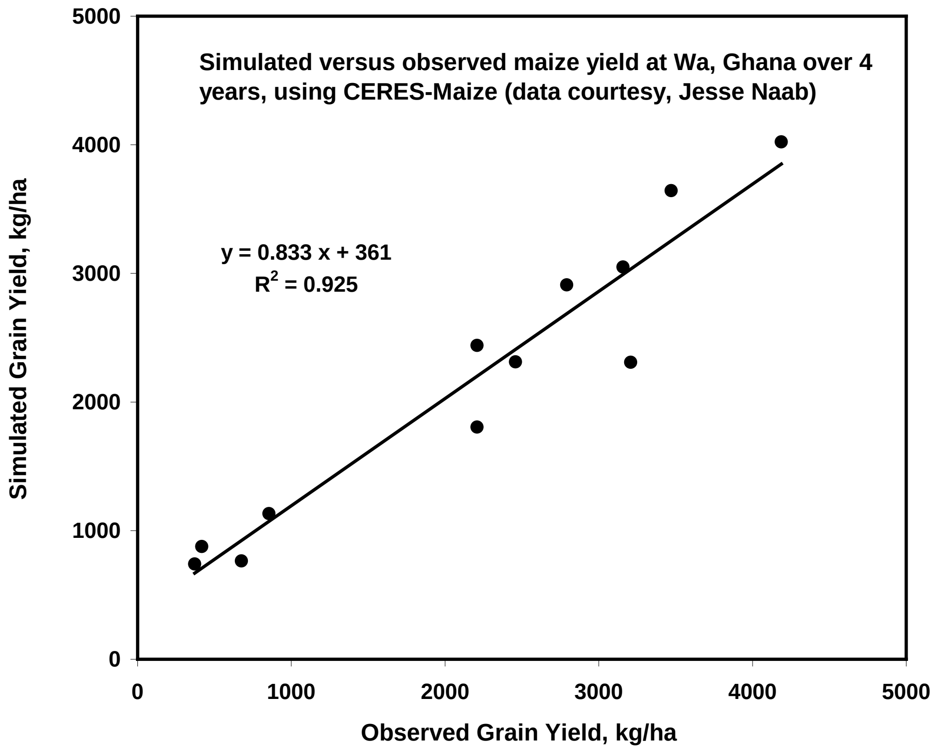
Three modeling groups were represented: **DSSAT** (Ken Boote, Jesse Naab, Wiltrud Durand, Jonathan Hickman with CERES-Maize; Mathew Jones with CANEGRO), **APSIM** (Peter Thorburn, K.P.C. Rao, John Hargreaves) and **AQUACROP** (Sue Walker and Yacob Beletse). A brief discussion on Monday afternoon identified the crops and the locations to concentrate on. The Ghana data provided by Jesse Naab had excellent time-series growth data along with phenology and end-of-season yield, biomass, and harvest index for treatments of zero N, 60 kg/ha N, and 120 kg/ha N in four seasons 2003, 2004, 2005, and 2006. The Katumani data did not have time-series growth or phenology (there was only harvest date, yield, biomass, and HI), but it had other advantages of multiple maize crops grown in long rainy season and short rainy season successively for 10 years (20 crops), for a zero N fertilization and a 100 kg/ha N plus residue treatment. Excellent data on soil carbon, initial soil water, initial nitrate, run-off, and water-holding traits (by neutron probe) were available. The data for Ghana and Kenya had been identified prior to the Workshop, allowing Alex Ruane to create baseline climate scenarios for these sites and allowing APSIM and DSSAT modelers to begin entering the data. Therefore we emphasized maize at Wa, Ghana and Katumani, Kenya, with calibrations and climate scenarios that were modeled by CERES-Maize, APSIM-Maize, and AQUACROP. In addition, sugarcane data was provided for Uganda by Patrick Musinguzi, and for Zimbabwe by Simbarashe Chinorumba, simulated with climate scenarios provided by Alex Ruane. Sugarcane simulations were assisted by Peter Thorburn for APSIM-sugarcane and Matthew Jones for DSSAT- CANEGRO. Scouting data with farmer maize yields for 47 fields over 4 seasons were provided by John Antle and Jetse Stoorvogel. Jim Jones, Jesse Naab, Wiltrud Durand, and John Hargreaves worked with that data to demonstrate aggregation, bias, and yield distributions created by the crop models with variable weather, soils, management, etc.

In addition, others came to the workshop with data in hand. Millet data for Mali was provided by Madina Diancoumba. Sibiry Traore assisted in calibrations and simulations for that site using CERES-Sorghum and SarraH millet models. Jonathan Hickman came with maize data from Malawi, and Wiltrud Durand came with maize data from Republic of South Africa. They worked independently with their data, but their activities were not concluded and are not reported here.

Participating crop modelers included: Myriam Adams, Andre Bationo Alhassane Agali, Yacob Beletse, Ken Boote, Regis Chikowo, Simbarashe Chinorumba, Lieven Claessens, Peter Craufurd, Olivier Crespo, Madina Diancoumba, Wiltrud Durand, John Hargreaves, Jonathan Hickman, Jim Jones, Matthew Jones, Job Kihara, Caroline Kirungu, Dilys Sefakor MacCarthy, Tamuka Magadzire, Ferdinand Mawunya, Patrick Musinguzi, Omari Mzirai, Jesse Naab, K.P.C. Rao, John Recha, Manuel Sitoe, Jetse Stoorvogel, Moses Tenywa, Peter Thorburn, Sedyou Traore, and Sibiry Traore.

Outcomes of the Crop Modeling Activities:

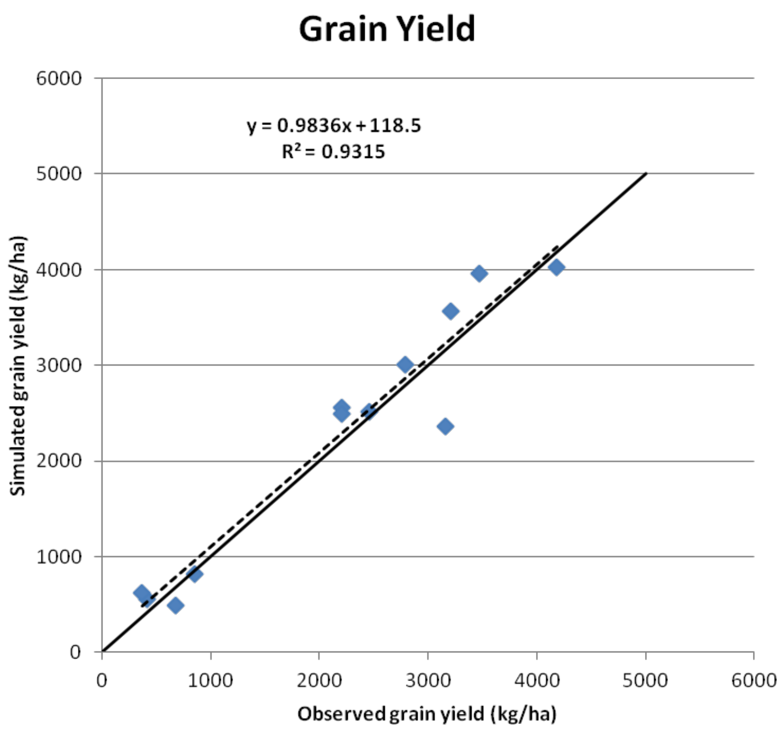
Calibration of the CERES-Maize model at Ghana: Only the high P fertilization treatments were used, to avoid complications from P infertility. Jesse Naab had previously calibrated the maize model for the cultivar Obatanpa with this data, thus we did relatively minimal calibration. Biomass had been overpredicted considerably, even though grain yield was well-predicted. To adjust this, the RUE was reduced from the default hybrid value of 4.2 to 3.7 g/MJ-par, with the justification that Obatanpa is not a hybrid, but an open-pollinated synthetic which would have less hybrid vigor. We further reduced the SLPF (soil fertility value for other than N, from 0.90 to 0.88, which is only slightly less than the default of 0.92 used for Florida soils). To bring yield and harvest index back up, the G2 was increased from 540 to 570 (maximum grains per plant) while G3 was reduced from 7.5 to 7.4 mg/grain/day to mimic correct grain size. The resulting root mean square error (RMSE) was 371 kg/ha and d-statistic was 0.97 (both very good).



Calibration of the APSIM-Maize model at Ghana: APSIM modelers were able to use the same soil water parameterizations as DSSAT. They set phenology coefficients from the observations. Minimal calibration was needed except for parameters affecting grain number. They modified the average growth rate per plant (g/day) during the grain-number sensitive phase to make potential grain number per plant to be less sensitive to very low growth rates to allow grain to be set under severe stress conditions (the data included a zero N treatment). The x-y parameter set is as follows:

- **grno_grate = 0.0 3 6**
- **grno_fract = 0.0 0.6 1**

The resulting successful calibration with the APSIM model resulted in an excellent 1:1 prediction versus observed, with a slope of 0.98 and an R2 of 0.93. Making potential grain number per plant less sensitive to very low growth rates (under zero N fertility) was important to correctly predicting yields at the low N stress stress conditions.

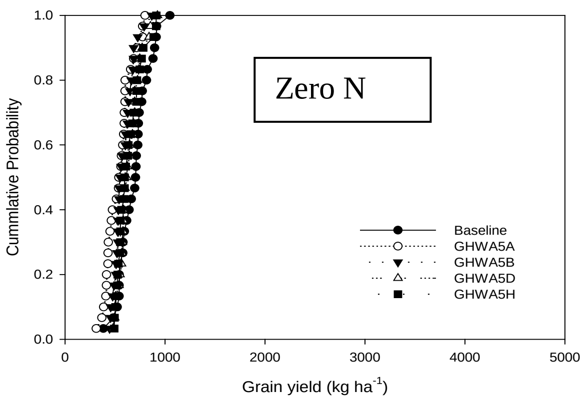


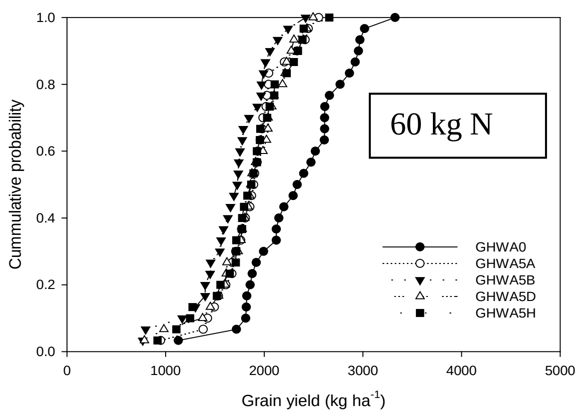
Calibration of AQUACROP model for Ghana:

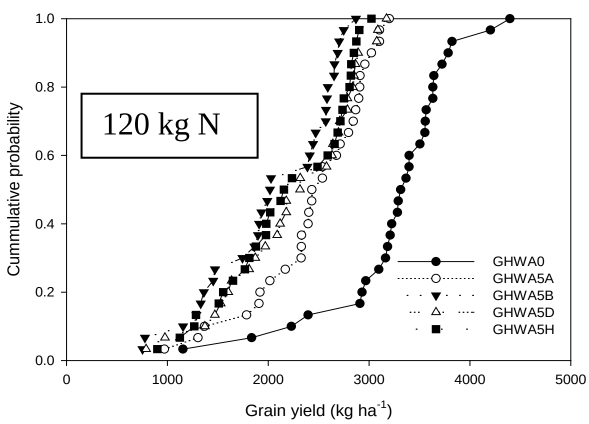
The AQUACROP model was was calibrated to one year of the Ghana data and tested against the others. The model is not responsive to N, but rather requires prior statement of poor, moderate, and good productivity (Results are not shown).

Climate Change Effects on Maize Yield under Zero, 60, and 120 kg N/ha in Ghana:

The CERES-Maize model after calibration was simulated with 30 years of baseline weather (at 369 ppm CO_2) compared to four climate change scenarios (at 734 ppm CO_2). In general, the seasonal temperature under climate change increased from 3.0 to 3.2C and remaining variation was attributed to rainfall. Yield variation caused by weather (primarily rainfall) was much greater for high N- treatment than at lower and zero N levels. ***The message is that weather effects are accentuated under high fertility and less expressed at low fertility***.

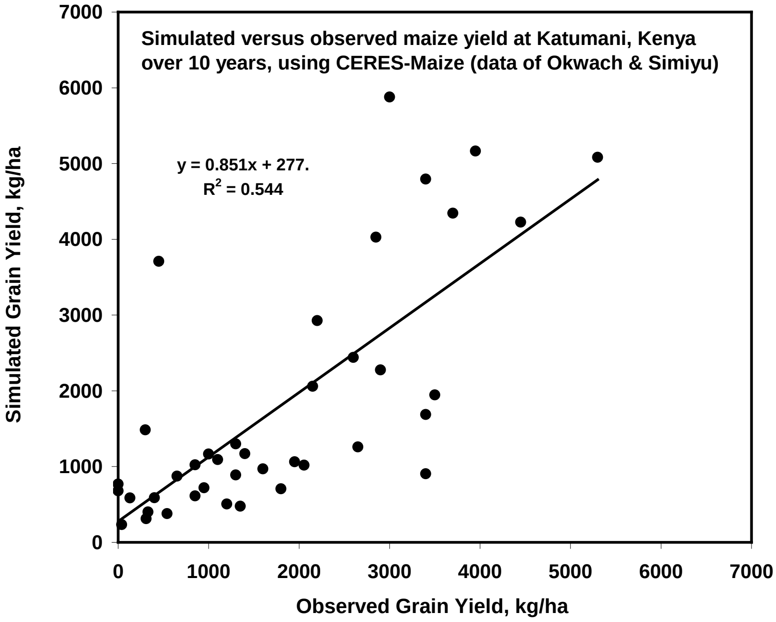




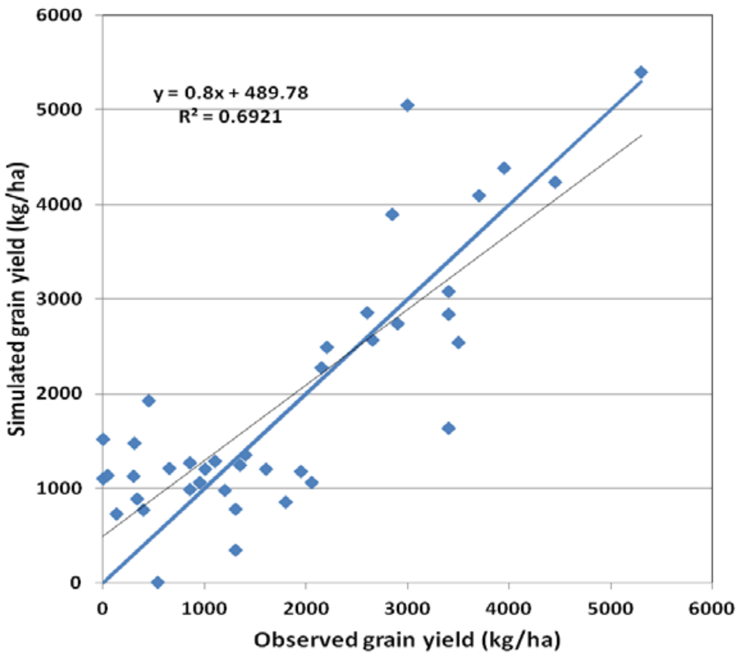


Calibration of the CERES-Maize model at Katumani, Kenya: Calibration of CERES-Maize for this site revealed several important steps. First, there was no phenology data, but just reported harvest date. We learned that Brian Keating had calibrated APSIM to this cultivar with good prior data, so the P1 and P5 of the CERES-Maize model were adjusted to mimic the APSIM-simulated anthesis date (52 days) and physiological maturity (113 days) averaged over the 20 maize crops. This contrasts to the mean harvest date of 124 days. There was a stated "Katumani" cultivar listed in the DSSAT, but retrospective analyses indicated that person's calibration was badly done (***Lesson # 1 – Don't trust a cultivar listed in the cultivar file***). Upon inspection of the crop biomass data, we determined that this was really stover (byproduct), because the reported biomass was sometimes less than the grain yield. So the true biomass was computed from stover mass plus grain. (***Lesson # 2 – Inspect data for reasonable values or talk to the data provider***), who was not present. Measured soil water data (LL, DUL, and SAT) was available in a spreadsheet from K.P.C. Rao and this was used directly in the DSSAT, with an exponential reduction in root length data from topsoil down. The curve number (CN) was taken from APSIM. (***Lesson #3, the soil water balance models of APSIM and DSSAT are quite similar and measured soil water traits are best***).

While this site was run as a continuous experiment by APSIM, we were not successful in using DSSAT's SEQUENCE method to run this as a continuous experiment. Rather we ran it as single simulations with re-initialization of soil water. This required entering the measured stover mass from the prior maize crop into the initial conditions for the subsequent maize crop. This worked well. In addition, the early simulations did not predict water stress when we knew it should have. To address this problem, we optimized (reduced) the fraction available soil water at sowing to improve the predictions, and settled on 40% available soil water at sowing. The published paper had given soil organic carbon as about 1.0% trending down to 0.5%, but this gave too much production at the zero N treatment when run with the CENTURY soil organic matter model. The spreadsheet of data had measured SOC values that were much lower, as well as measured soil nitrate values prior to sowing. After applying the observed stover, entering field-measured SOC and initial nitrate, and reducing the initial soil water at sowing, the model gave reasonable simulations. The rooting profile was reduced below 60 cm depth (as APSIM did) to create more water stress. Next the G2 and G3 and PHINT were optimized to predict grain yield and harvest index. The genetic coefficients for this cultivar were: P1=70, P2=0.3, P5=680, G2=590, G3=8.5, and PHINT=50. The resulting calibration gave an RMSE of 1095 kg/ha and d-statistic of 0.850.

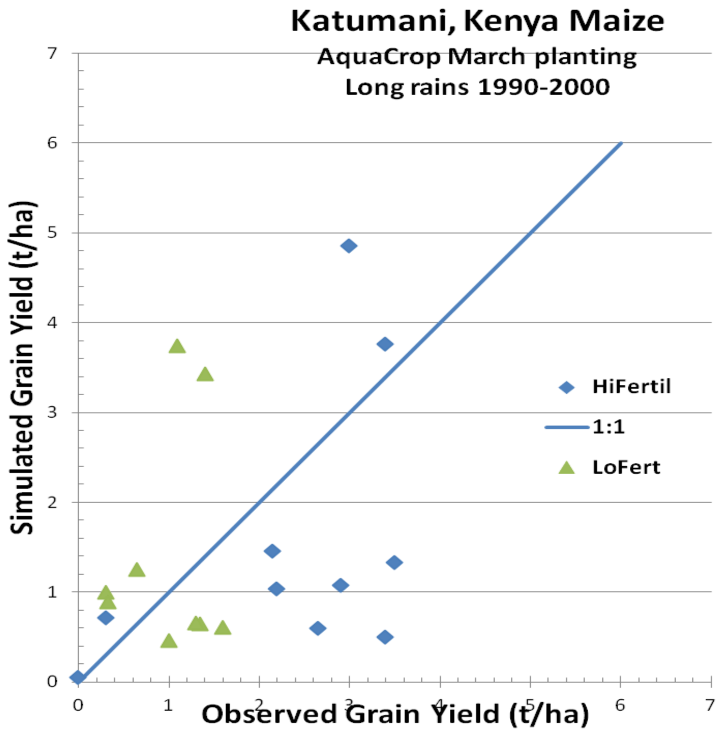


Calibration of the APSIM-Maize model at Katumani, Kenya:



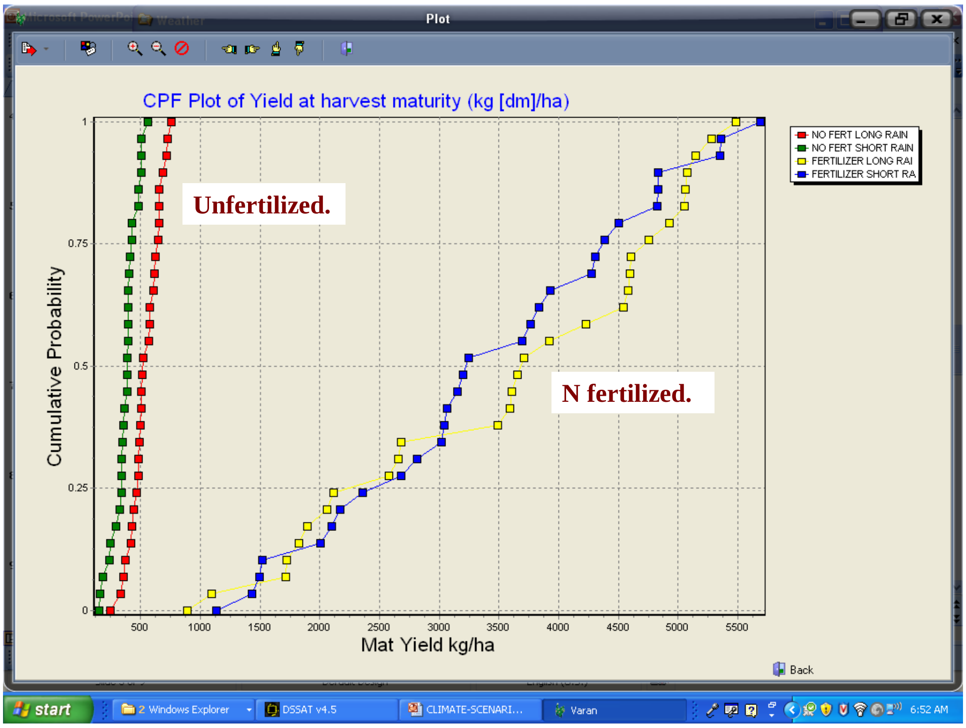
The APSIM model had been calibrated previously for this cultivar so phenology was predicted satisfactorily. The original authors (Okwach and Simiyu, 1999) used APSIM to simulate these data, but the prior calibrations were apparently lost. There was some difficulty in predicting the low input system, and modifications of the soil carbon pools were required, as well as adjustments in the soil water functions. After these modifications, prediction was good with an R^2 of 0.692.

Calibration of the AQUACROP model at Katumani, Kenya



AQUACROP modeling was slow to accomplish because runs needed to be made one at a time, and not in batch. So, only the long-rainy season was simulated. Results were mixed for grain yield, and biomass was overpredicted. The figure to the right illustrates AQUACROP prediction for low and high fertility cases in a 1:1 graph.

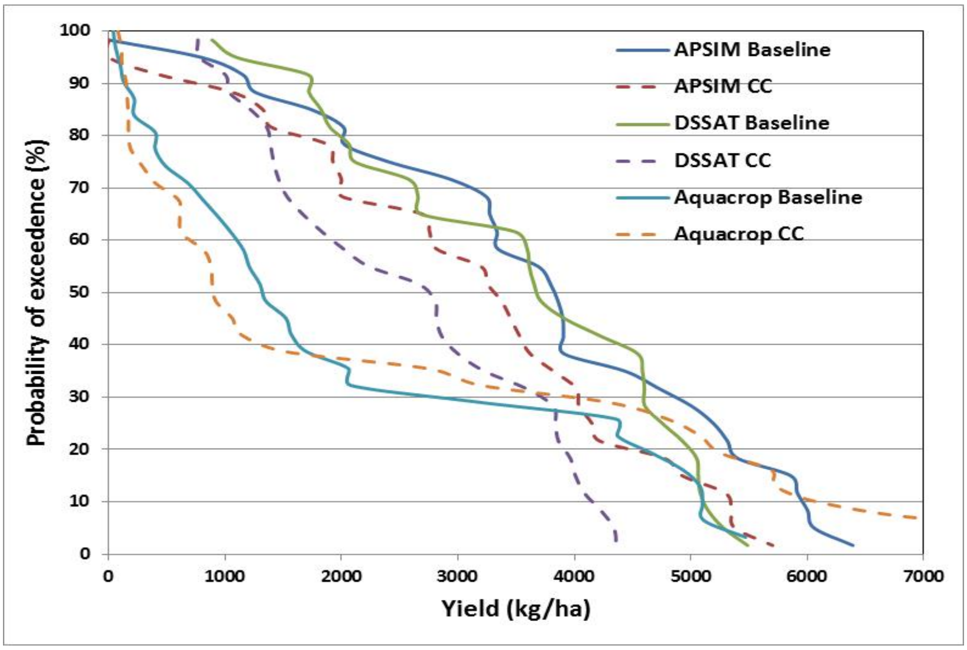
Weather Effects on N-fertilized Maize versus Non-fertilized Maize at Katumani: At Katumani, maize crops were grown successively in long rainy season and short rainy season for 10 years (20 maize crops) for a zero N fertilization treatment and a 100 kg/ha N plus residue treatment. Maize yield was simulated for the zero N and the high N-residue treatments for long and short rainy seasons using the calibrated CERES-Maize model with baseline weather. Yield variation caused by weather (primarily rainfall) was much greater for the N-fertilized treatment than the non-fertilized treatment (APSIM gave similar results, not shown). With fertilization, simulated yield ranged from 1000 to nearly 6000 kg/ha, with similar values in long and short rainy season. With no fertilization, yields were much higher in the long rainy season than short rainy season, varying from 200 to 800 kg/ha in the long rainy season and 0 to 600 kg/ha in the short rainy season. ***The message is that weather effects are muted under low fertility and more accentuated under high fertility***.



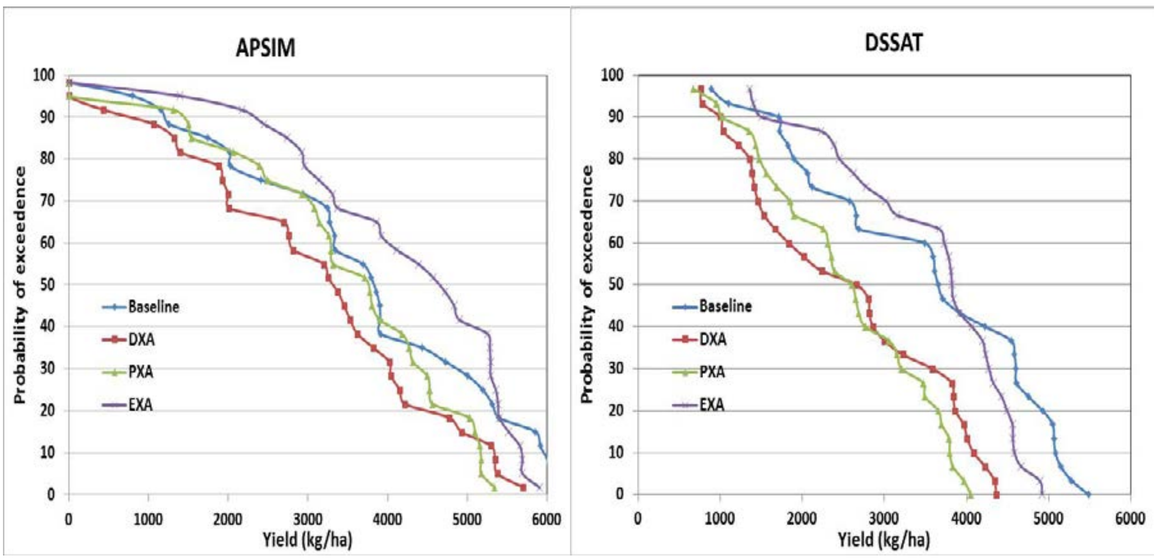
Probability of Yield Achievement under Baseline and Climate Change at Katumani, Kenya: An Intercomparison of the Maize Models:

After calibration to the 20 seasons of data for Katumani, the three maize models were compared to each other for the long rainy season maize cycle, with simulations of 30 years of baseline weather and 30 years of climate change scenario. APSIM and DSSAT gave quite comparable probability of yield attainment across the 30 years of baseline weather, with only minor wiggles in the line, although APSIM extended the range from low yield to higher yield compared to DSSAT-CERES. This central tendency was expected, as the models had been calibrated for 10 out of those 30 seasons of long rainy season. Simulated yields for the AQUACROP were consistently lower than the other two models, particularly at the low yield end. Causes were not understood or explored.

The simulated yields with APSIM and DSSAT models were both reduced by the climate change scenario, but the DSSAT model showed greater reductions in yield. Since the models were both giving good response to water deficit under baseline weather and 369 ppm CO_2, we speculate that differential modeling of CO_2 effects in the two models under water stress was the cause for these yield differences, as CO_2 was set to 734 ppm under the climate change scenario. Prior simulations with APSIM (Brazil AgMIP meeting) had shown considerable reductions in transpiration at elevated CO_2 (hence cause for less effect of low rainfall). At this point, we are not sure which model is more correct in this response, as the two models have not been tested under CO_2 enrichment with water deficit. AQUACROP, on the other hand, showed no reduction in yield under climate change and 734ppm CO_2; rather yields were increased considerably in some of the years. ***An important message is that we need better understanding and modeling of CO_2 effects on transpiration, which affects model response to rainfall variation.***

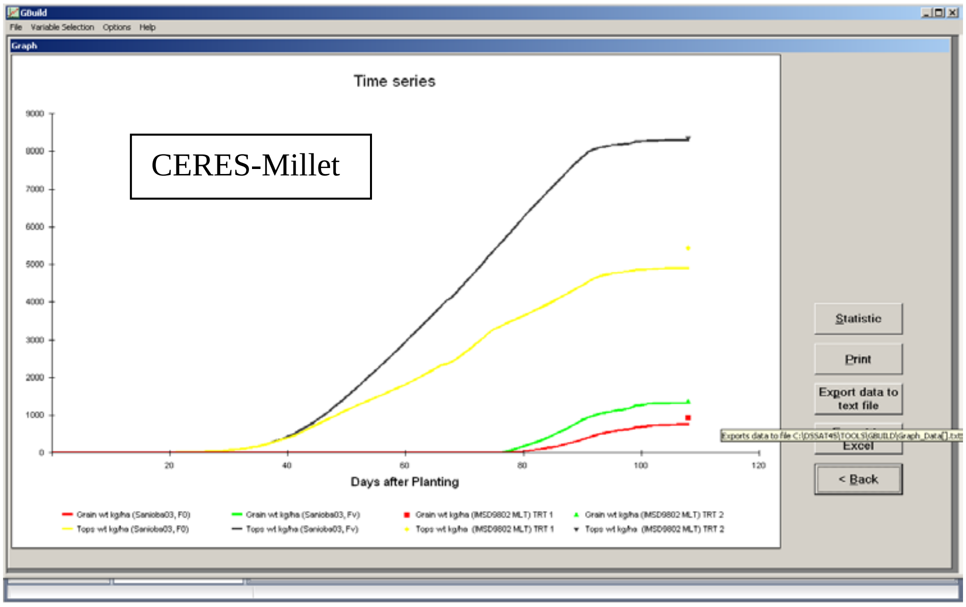


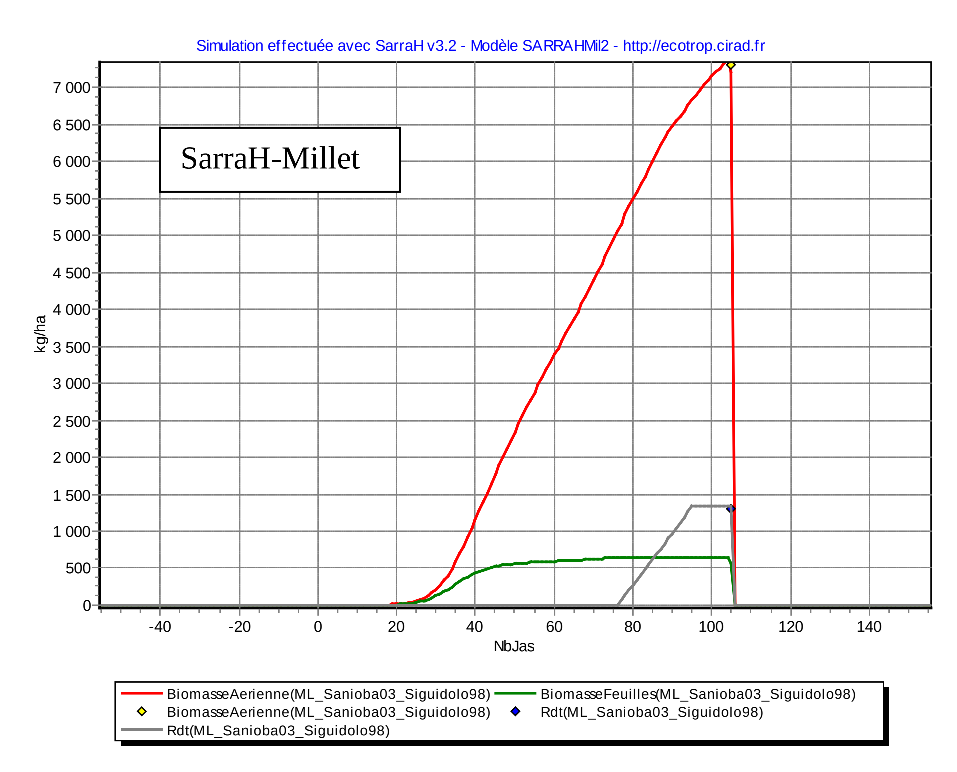
The APSIM and DSSAT maize models were simulated for the long rainy season with 30 years baseline weather compared to weather from three climate scenarios (DXA, PXA, and EXA) for Katumani. For APSIM, the EXA scenario increased yield during the long rainy season compared to the baseline. The PXA scenario gave results barely different from the baseline, while the DXA scenario consistently reduced yield. The DSSAT-CERES-Maize model showed somewhat different responses to climate scenarios. The simulated yield at EXA scenario was mostly comparable to the baseline, although showing cross-over, lower yields at the high end and higher yields at the low end. For DSSAT, simulated yields at the DXA and PXA scenarios were consistently lower than baseline. The yields in the short rainy season were consistently higher under the three climate change scenarios with the APSIM model (results not shown). Results for DSSAT for the short rainy season were not reported. ***An important message is that crop models can give different simulated outcomes to the same climate change scenarios.***



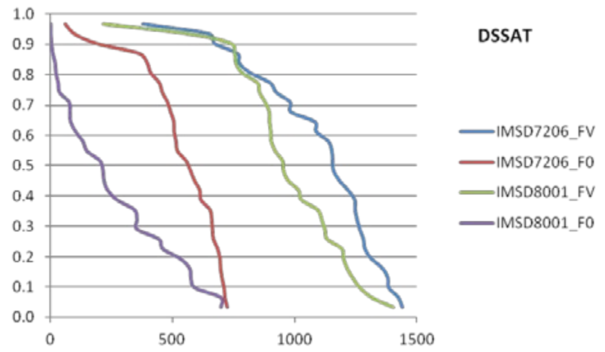
Calibrating the CERES-Millet and SarraH Models for Millet Grown at Sigidolo Ridge, Mali:

The millet crop was grown in 1998 at Sigidolo Ridge, Mali in an on-farm contour ridge tillage experiment. The Sanioba03 cultivar was grown in two treatments: no fertilization and organic manure (farmer practice). Madina Diancoumba and Sibiry Traore collaborated to simulate CERES-Millet and SarraH for millet. Growth and yield were simulated with the CERES-Millet model, using the Godwin soil organic carbon module (the CENTURY option simulated too rapid N availability). The simulations were started January 1, with 30% available soil water and 10 kg N/ha at initiation. In the calibration, the RUE was reduced from 4.0 to 3.8 g dry matter per MJ-PAR. The genetic coefficients were calibrated as follows: P1=413 GDD, Psat = 13.0 h, Pbase = 13.8 h, P5=500 GDD, G1=1.0, G4=0.3. After calibrations, the following prediction of biomass and yield was obtained for CERES-Millet and Sarra-H (successive figures).



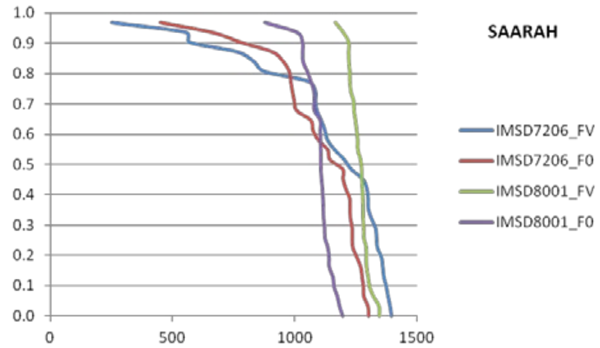


Fertility Effects on Yield Response to Weather with the CERES-Millet and SarraH Models:

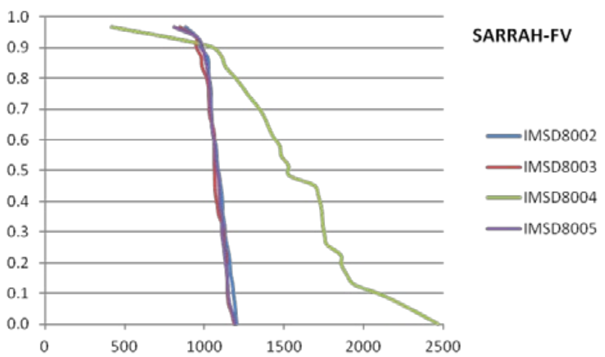


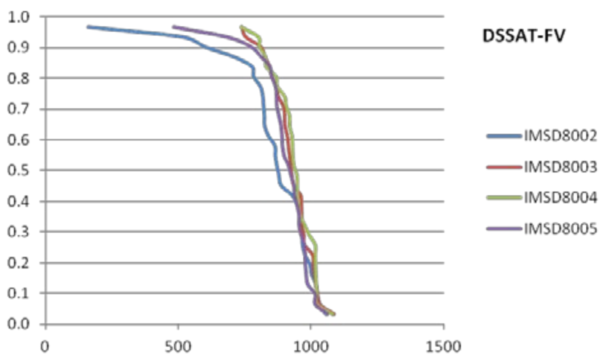
Yields of SarraH were greater than DSSAT when there was low input, but responses were more comparable with fertilizer input. Different responses are likely a rainfall x fertility interaction. This shows the need to review water and fertility aspects for these crop models.

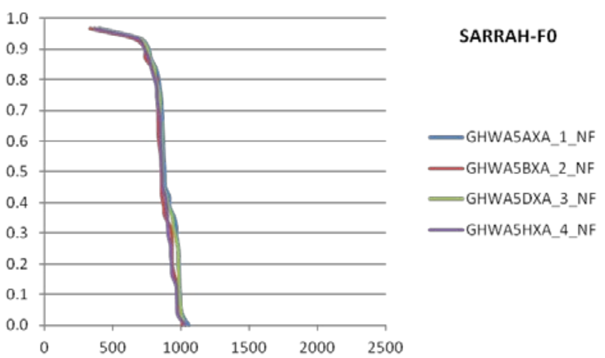
Climate Change Scenarios with the CERES-Millet and SarraH Models:

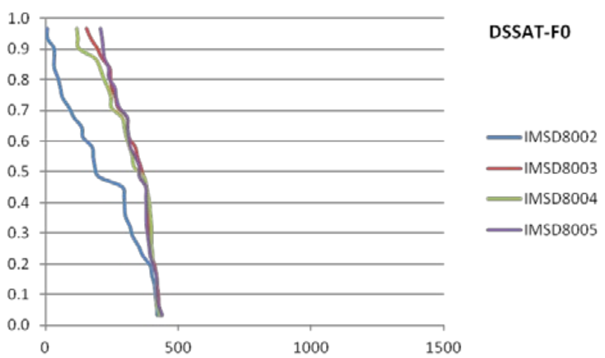


Under low input (F0), SarraH showed no climate scenario sensitivity, whereas CERES showed increased yield for three climate scenarios compared to baseline (using Wa weather site). With high input (Fv), DSSAT showed small increases in yield with three scenarios. SarraH showed increased yield under DXA scenario.





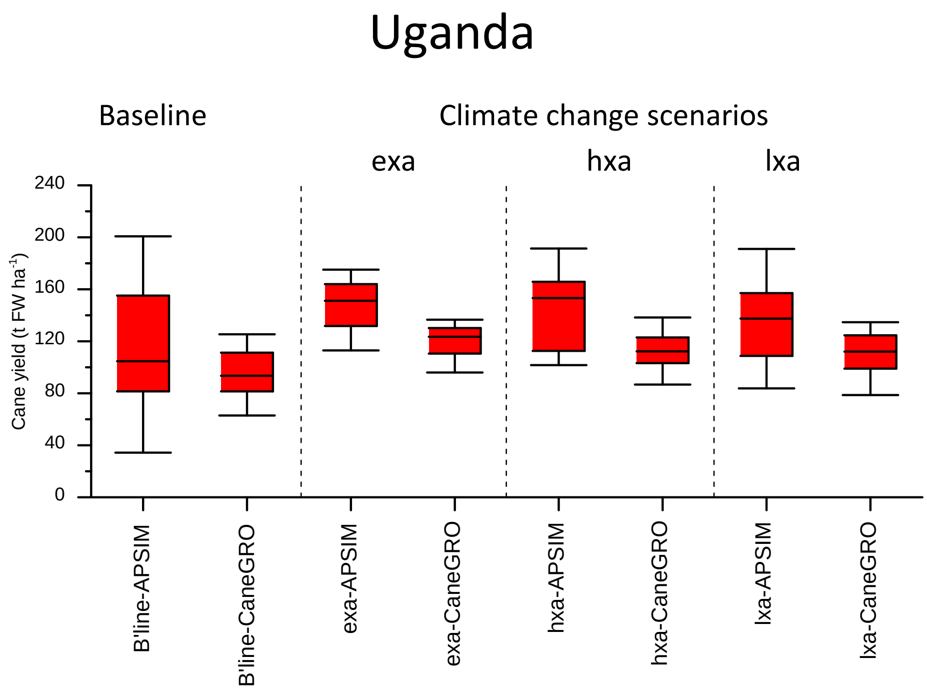




Calibration of the APSIM and CANEGRO models for Sugarcane:

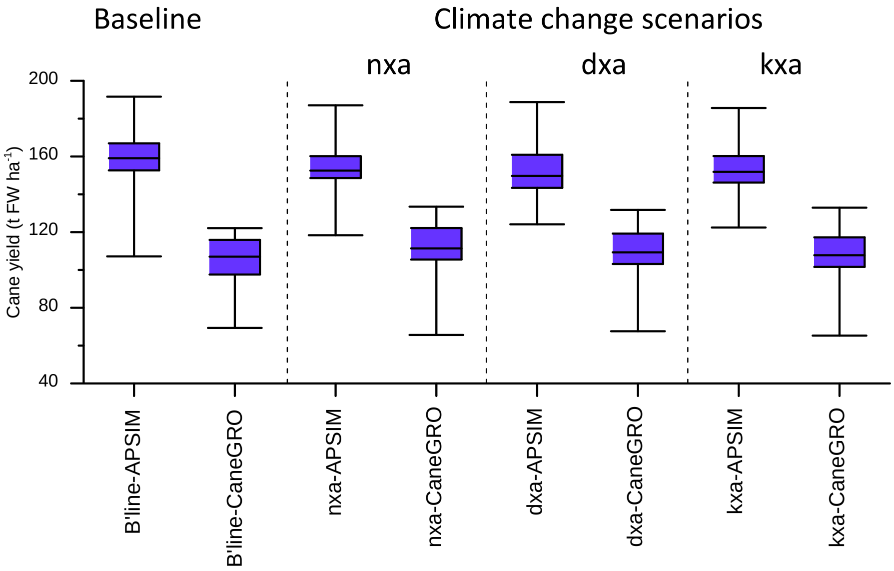
Sugarcane data was provided for central region of Uganda by Patrick Musinguzi, and southeast region of Zimbabwe by Simbarashe Chinorumba, and climate scenarios were created by Alex Ruane. The crop in Uganda was rainfed (under bimodal rainfall), and the crop in Zimbabwe was irrigated (under unimodal rainfall). Sugarcane simulations were assisted by Peter Thorburn for APSIM-sugarcane and Matthew Jones for DSSAT-CANEGRO. The models were calibrated to final yields using the NCO 376 cultivar traits present in APSIM and CANEGRO.

The APSIM and CANEGRO models were intercompared for simulated yield response to 30 years baseline weather, and for three climate change scenarios (EXA, HXA, and LXA). For the rainfed crop in Uganda, the CANEGRO model predicted consistently less cane yield than the APSIM model as well as much smaller yield variation (whiskers on the bars in the graph below). Causes for these cane yield differences between APSIM and CANEGRO are not known, unless it is the same CO_2 effect on transpiration as discussed previously for the APSIM maize model (except that CANEGRO is also lower than APSIM at baseline 369 ppm CO_2).



For the irrigated crop in Zimbabwe, the CANEGRO model consistently predicted much lower cane yield than the APSIM model for baseline and all scenarios. The reason for model differences is not understood, unless the defined irrigation record was questionable. There may be questions about how the irrigation was handled in the CANEGRO model, since this would need to be "automatic" to accommodate simulation with long-term weather records. The yield variation (whiskers on the bars in the graph below) was similar across the different climate change scenarios.

Zimbabwe



SUMMARY OF CROP MODELING ACTIVITIES:

1. Calibrated APSIM, DSSAT, and AQUACROP maize models for Wa, Ghana and Katumani, Kenya,
2. Simulated maize yield with the APSIM, DSSAT, and AQUACROP models for 30 years of baseline weather and 3 to 4 climate change scenarios for Wa, Ghana and Katumani, Kenya.
   a. Found that weather effects on maize yield were more accentuated under high fertility in both APSIM and DSSAT models.
   b. Discovered that the APSIM and DSSAT maize models differed in response to climate change scenarios.
3. Calibrated the CERES-Millet and SarraH models against a millet data set from Mali and simulated millet yield variation under baseline weather and several climate change scenarios for the Wa, Ghana location.
4. Calibrated the APSIM and CANEGRO sugarcane models against data from Uganda and Zimbabwe and simulated cane yield variation response to 30 years baseline weather and several climate change scenarios. Differences in mean yield and weather-induced yield variation were found.