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# Accurate crop yield predictions from modelling tree-crop interactions in gliricidia-maize agroforestry

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ABSTRACT

Agroforestry systems, containing mixtures of trees and crops, are often promoted because the net effect of interactions between woody and herbaceous components is thought to be positive if evaluated over the long term. From a modelling perspective, agroforestry has received much less attention than monocultures. However, for the potential of agroforestry to impact food security in Africa to be fully evaluated, models are required that accurately predict crop yields in the presence of trees. The positive effects of the fertiliser tree gliricidia (*Gliricidia sepium*) on maize (*Zea mays*) are well documented and use of this tree-crop combination to increase crop production is expanding in several African countries. Simulation of gliricidia-maize interactions can complement field trials by predicting crop response across a broader range of contexts than can be achieved by experimentation alone. We tested a model developed within the APSIM framework. APSIM models are widely used for one dimensional (1D), process-based simulation of crops such as maize and wheat in monoculture. The Next Generation version of APSIM was used here to test a 2D agroforestry model where maize growth and yield varied spatially in response to interactions with gliricidia. The simulations were done using data for gliricidia-maize interactions over two years (short-term) in Kenya and 11 years (long-term) in Malawi, with differing proportions of trees and crops and contrasting management. Predictions were compared with observations for maize grain yield, and soil water content. Simulations in Kenya were in agreement with observed yields reflecting lower observed maize germination in rows close to gliricidia. Soil water content was also adequately simulated, except for a tendency for slower simulated drying of the soil profile each season. Simulated maize yields in Malawi were also in agreement with observations. Trends in soil carbon over a decade were similar to those measured, but could not be statistically evaluated. These results show that the agroforestry model in APSIM Next Generation adequately represented tree-crop interactions in these two contrasting agro-ecological conditions and agroforestry practices. Further testing of the model is warranted to explore tree-crop interactions under a wider range of environmental conditions.

## 1. Introduction

In much of sub-Saharan Africa there is a projected decline in per capita food availability (Rosen et al., 2012) that is exacerbated by land degradation already affecting a third of the land area (Bai et al., 2008; Tittonell and Giller, 2013; Vågen et al., 2016). Yields of staple crops remain well below those in other continents and what could be obtained with better water and nutrient management (Mueller et al., 2012). The gap between actual and potential yields could be reduced through more efficient use of resources. Agroforestry is increasingly promoted as an important tool in addressing soil fertility issues in Africa (Glover et al., 2012). This is because trees, when incorporated in crop fields, are often able to reduce soil erosion, improve water and nutrient cycling and increase both soil organic carbon and the abundance and

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activity of beneficial soil organisms (Barrios et al., 2012). However, trees can also compete with crops for water and nutrients and reduce the land area available for crops, so that the net effect of agroforestry on crop yields over time will depend on attributes and interactions of the trees, crops, soil, climate, and management (Bayala et al., 2012).

Fertiliser trees including gliricidia (*Gliricidia sepium*), intercropped or in improved fallows, have been shown to increase maize (*Zea mays*) yield over current farmer practice across sub-Saharan Africa (Sileshi et al., 2008), but with different performance across soil types, climates and fertiliser application (Sileshi et al., 2010). This variation in performance presents a major challenge in scaling up adoption of fertiliser trees in Africa, because it implies that there is a need to take into account fine scale variation in context amongst smallholder farmers, so that appropriate fertiliser tree options can be matched to sites and farmer circumstances (Coe et al., 2014). Addressing this need could greatly accelerate scaling up, through accurate simulation of crop yields obtainable from alternative fertiliser tree options in different locations, thereby reducing the risk to farmers adopting agroforestry (Coe et al., 2016). A key constraint with respect to addressing food security in previous attempts to model gliricidia-maize agroforestry in Malawi, has been a difficulty in accurately predicting crop yields (Chirwa et al., 2006; Kerr, 2012).

Scaling up the use of other agroforestry practices in Africa could also benefit from a field scale modelling capability. For example, the ACIAR (Australian Centre for International Agricultural Research)-funded 'Trees for Food Security' project, implemented by the World Agroforestry Centre (ICRAF), is developing such capabilities for *Alnus*-potato and *Grevillea*-maize in Rwanda, and for *Faidherbia*, *Croton* and other tree species grown with wheat, maize, or teff in Ethiopia (Muthuri et al., 2016). Evaluation of such diverse tree, crop, climate, soil and management conditions requires a highly flexible and robust modelling framework to be developed (Luedeling et al., 2016). In the Trees for Food Security project, the Rwandan and Ethiopian governments are keen to extend the use of agroforestry, but are unable to test all possible tree-crop-management combinations across the agro-ecologies that occur in each country. With validation at some contrasting sites, virtual experiments could be conducted using simulation models, to predict performance in untested circumstances, with enough confidence to guide the development of agricultural policies and the promotion of agroforestry practices. Yield forecasting to guide operations is a common use of APSIM (Agricultural Production Systems Simulator, www.apsim.info) and similar models by consultants or governments for crops like wheat, maize and soybean (Holzworth et al., 2014; Hoogenboom et al., 2015) that could be extended to include situations where crops are grown in agroforestry combinations through the use of a robust tree-crop interaction model.

A recent evaluation of tree-crop interaction modelling at field scale (Luedeling et al., 2016), concluded that it would be useful to adapt the widely-used crop modelling framework in APSIM (Holzworth et al., 2014, 2015), that can reliably predict yields of major staple crops across a wide range of sites globally. Here we report on the first attempts to simulate tree-crop interactions and crop yield using APSIM Next Generation. The agroforestry practices that we simulated were gliricidia-maize intercropping at two contrasting sites in Kenya and Malawi, for which there were sufficient historical data to both parameterise the model and evaluate model performance. Gliricidia is a nitrogen-fixing tree native to Central America that is widely promoted as a fertiliser tree in Africa (Wise and Cacho, 2005). In Malawi and Zambia, gliricidia-maize intercropping is widely practiced (Akinnifesi et al., 2010; Sileshi and Mafongoya, 2006). The specific aim of the research reported here was to evaluate the new agroforestry model incorporated within the APSIM Next Generation modelling framework for simulating interactions in gliricidia-maize intercropping at two contrasting sites in Africa: Machakos in Kenya, and Makoka in Malawi, with a focus on maize yields, short-term soil water dynamics, and long-term soil carbon concentrations.

## 2. Materials and methods

### 2.1. Site description

#### 2.1.1. Machakos, Kenya

The Machakos site (1° 33′ S, 37° 08′ E, 1600 m elevation) is located 56 km southeast of Nairobi, Kenya. This site was chosen because water was usually more limiting to maize growth than nutrients. This is a semi-arid tropical site with mean annual rainfall of 740 mm. The climate is relatively cool, with an annual mean daily temperature of 20.1 °C. Rainfall has a bimodal distribution with one rainy season from October to December and the other from March to May. Soils are classified as Haplic Lixisols (WRB classification; Dewitte et al., 2013), which predominate in the area. Top soil (0–15 cm) comprised 1.0–1.5% organic carbon with a pH of 6.0 to 6.5, and base saturation ranging from 50 to 80% (Mathuva et al., 1998, Odhiambo et al., 2001, Wilson et al., 1998). Surface texture was sandy clay loam. The soil was of variable depth averaging 1.6 m, with bulk density increasing with depth from 1.19 to 1.67 g $cm^{-3}$ (Ong et al., 2000). The availability of nitrogen, phosphorus and other nutrients was considered adequate for maize, and generally the site was considered to be more water-limited than nutrient-limited for maize growth. Govindarajan et al. (1996) observed strong competition for water between the gliricidia and crops, because of the concentration of tree roots in the top 0.5 m of soil where crop roots are also predominantly found.

#### 2.1.2. Makoka, Malawi

The Makoka site (15° 30′ S, 35° 15′ E, 1030 m elevation) is located 20 km south of Zomba, Malawi. This site was chosen because N was more limiting to maize growth than other nutrients or water. This is a sub-humid sub-tropical site with mean annual rainfall of 1024 mm. Mean daily temperature varies between 16 and 24 °C. Unlike the Machakos site, Makoka has a unimodal distribution of rainfall from November to April. Soils are classified as Ferric Lixisols (WRB classification). Top soil (0–20 cm) comprised 0.88% organic carbon, with total N at 0.07%, and pH 5.9 (Ikerra et al., 1999). Surface texture was sandy clay. Soil was at least 1.2 m deep, with plant available water capacity 118–161 mm (Robertson et al., 2005). Low availability of nitrogen was the main limitation to maize growth, as well as seasonal variations in soil water content (droughts and saturation). Phosphorus was thought to be non-limiting to maize growth during the first few years of the experiment, but became co-limiting during the last few years (Akinnifesi et al., 2007).

### 2.2. Experiments

#### 2.2.1. Machakos, Kenya

The experiment at Machakos consisted of three treatments in a randomized block design with four replicates. Two treatments are considered in this paper: (1) sole maize crop, and (2) maize grown between gliricidia trees. A treatment not used was maize grown with grevillea trees. There were two crops per year: maize (cultivar Katumani composite) during the long season, and beans during the short season. The experiment commenced in 1993, but only the two maize crops in the period March 1996 to July 1997 were reported by Odhiambo et al. (2001) and used here. Plots were 20 m × 18 m with maize planted 1 m apart between rows and 30 cm apart within rows. In plots with gliricidia, trees replaced the middle row of maize. No fertilisers were applied, and weeds were removed manually, twice each season. Gliricidia was side-pruned to leave branch-free stems to a height of 2.5 m; residues were removed from the experiment. Between March 1996 and July 1997, gliricidia grew in height from about 4.0 to 4.5 m (Wilson et al., 1998). Key measurements for this paper included maize germination percentage (1996 only) and grain yield, gliricidia height and root-length-density, and soil water content at 35 cm depth. Data were provided by Wilson et al. (1998) and Odhiambo et al. (2001).

**Table 1**
Soil parameters used for simulations at the Machakos and Makoka sites.

| Depth (cm) | Bulk density ($g{\cdot}cm^{-3}$) | Water Content[a] (cm·cm$^{-3}$) Air dry | Drained lower limit | Drained upper limit | Saturated | Maize lower limit | Initial | PAWC[a,b] (mm) | Fractional water extraction[a] ($mm\ mm^{-1}\ d^{-1}$) | C (%) | FBiom[a,c] | FInert[a,d] | pH | $NH_4$ initial ($\mu g{\cdot}g^{-1}$) | $NO_3$ initial |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Machakos | | | | | | | | | | | | | | | |
| 0–20 | 1.35 | 0.04 | 0.10 | 0.20 | 0.35 | 1.35 | 0.130 | 20.0 | 0.7 | 1.10 | 0.030 | 0.600 | 6.5 | 0.1 | 5.0 |
| 20–40 | 1.35 | 0.04 | 0.10 | 0.20 | 0.35 | 1.35 | 0.130 | 20.0 | 0.7 | 0.80 | 0.020 | 0.600 | 6.5 | 0.1 | 2.0 |
| 40–60 | 1.35 | 0.14 | 0.14 | 0.22 | 0.37 | 1.35 | 0.160 | 16.0 | 0.7 | 0.60 | 0.010 | 0.600 | 6.5 | 0.1 | 0.5 |
| 60–80 | 1.40 | 0.15 | 0.17 | 0.24 | 0.37 | 1.40 | 0.176 | 14.0 | 0.7 | 0.60 | 0.010 | 0.900 | 6.5 | 0.1 | 0.5 |
| 80–100 | 1.40 | 0.16 | 0.17 | 0.24 | 0.38 | 1.40 | 0.170 | 14.0 | 0.7 | 0.20 | 0.010 | 0.950 | 6.5 | 0.1 | 0.2 |
| 100–120 | 1.40 | 0.16 | 0.17 | 0.24 | 0.38 | 1.40 | 0.170 | 14.0 | 0.7 | 0.10 | 0.010 | 0.950 | 6.5 | 0.1 | 0.2 |
| 120–140 | 1.40 | 0.16 | 0.17 | 0.24 | 0.38 | 1.40 | 0.170 | 14.0 | 0.7 | 0.10 | 0.010 | 0.990 | 6.5 | 0.1 | 0.1 |
| 140–160 | 1.40 | 0.16 | 0.17 | 0.24 | 0.38 | 1.40 | 0.170 | 14.0 | 0.7 | 0.10 | 0.010 | 0.990 | 6.5 | 0.1 | 0.1 |
| Makoka | | | | | | | | | | | | | | | |
| 0–20 | 1.42 | 0.16 | 0.17 | 0.38 | 0.40 | 0.170 | 0.250 | 42.0 | 0.08 | 0.88 | 0.010 | 0.660 | 5.9 | 1.0 | 3.0 |
| 20–40 | 1.45 | 0.17 | 0.18 | 0.38 | 0.41 | 0.180 | 0.250 | 40.0 | 0.08 | 0.63 | 0.010 | 0.660 | 5.6 | 1.0 | 2.0 |
| 40–60 | 1.47 | 0.18 | 0.19 | 0.37 | 0.42 | 0.190 | 0.250 | 36.0 | 0.08 | 0.40 | 0.010 | 0.900 | 5.8 | 0.5 | 1.0 |
| 60–80 | 1.31 | 0.20 | 0.22 | 0.36 | 0.43 | 0.220 | 0.270 | 28.0 | 0.08 | 0.23 | 0.010 | 1.000 | 5.9 | 0.1 | 1.0 |
| 80–100 | 1.42 | 0.23 | 0.25 | 0.33 | 0.44 | 0.250 | 0.270 | 16.0 | 0.06 | 0.22 | 0.010 | 1.000 | 6.1 | 0.1 | 1.0 |
| 100–120 | 1.38 | 0.23 | 0.25 | 0.28 | 0.44 | 0.250 | 0.290 | 6.0 | 0.04 | 0.11 | 0.010 | 1.000 | 6.3 | 0.1 | 0.5 |
| 120–140 | 1.32 | 0.26 | 0.27 | 0.29 | 0.44 | 0.270 | 0.300 | 4.0 | 0.03 | 0.05 | 0.010 | 1.000 | 6.2 | 0.1 | 0.1 |
| 140–160 | 1.30 | 0.27 | 0.27 | 0.30 | 0.44 | 0.270 | 0.300 | 6.0 | 0.02 | 0.05 | 0.010 | 1.000 | 6.4 | 0.1 | 0.1 |
| 160–180 | 1.31 | 0.28 | 0.29 | 0.30 | 0.44 | 0.290 | 0.300 | 2.0 | 0.02 | 0.05 | 0.010 | 1.000 | 6.3 | 0.1 | 0.1 |
| 180–200 | 1.31 | 0.28 | 0.29 | 0.29 | 0.44 | 0.290 | 0.300 | 0.0 | 0.02 | 0.05 | 0.010 | 1.000 | 5.9 | 0.1 | 0.1 |

[a] These parameters were adjusted during model tuning.
[b] PAWC = plant available water content.
[c] FBiom = fraction of carbon in microbial biomass.
[d] FInert = fraction of inert carbon.

### 2.2.2. Makoka, Malawi

This experiment consisted of a factorial combination of two agroforestry practices (maize monoculture and gliricidia-maize intercropping), three rates of N (0, 25% and 50% of the recommended 92 kg N ha$^{-1}$), and three rates of P (0, 50% and 100% of the recommended 40 kg P ha$^{-1}$ for hybrid maize growing in Malawi). Nitrogen fertiliser was applied at a rate of 0, 24 or 48 kg N ha$^{-1}$ as calcium ammonium nitrate four weeks after sowing. Phosphorus fertiliser was applied at a rate of 0, 20 or 40 kg P ha$^{-1}$ as triple superphosphate at sowing. We simulated four treatments: sole maize (Sm), Sm with 48 kg N ha$^{-1}$ (Sm48N), gliricidia-maize (Gm), and Gm with 48 kg N ha$^{-1}$ (Gm48N). There was one crop per year of maize (cultivar NSCM 41) sown in December and harvested April–May. Gliricidia was established during 1992, and the first maize crop sown in December that year. Plots were 6.75 m × 5.1 m with maize sown on ridges 0.9 m between rows and 0.15 m within rows. In plots with gliricidia, trees were planted in every second furrow 0.9 m apart, cut back to 0.3 m high stumps three or four times per year, and residues retained. Manual weeding occurred twice each season. Annual biomass and nutrient content of gliricidia residues are reported in Makumba et al. (2006), along with annual maize biomass and grain yield. Makumba et al. (2009) reported rooting patterns.

## 2.3. Modelling

The Next Generation version of the APSIM modelling framework (Holzworth et al., 2014, 2015), which includes the maize model used here in its release version, was used to simulate the long and short term interactions amongst maize and gliricidia. Other crops included in APSIM Next Generation are wheat, oil palm, and pasture, with teff, potato and cowpea under development, and the number of crop options is expected to increase during coming years. All APSIM one-dimensional (1D) crop and pasture models simulate the growth of plants using the key processes of phenology, soil water availability, soil nitrogen availability, climate and management. For example, radiation, leaf area and photosynthetic efficiency are the main determinants of carbon fixation, but these processes can be limited by sub-optimal nitrogen and water availability. Phosphorus or other nutrients potentially limiting growth were not included in this version of the maize model.

A pre-release version of an agroforestry model developed within the APSIM Next Generation framework was used for two-dimensional (2D) representation of gliricidia-maize intercropping. In this model, the maize model, as available in the release version of APSIM Next Generation, was used in conjunction with a static proxy of the gliricidia trees. In the tree model, there was no process-based simulation of gliricidia growth. Instead, the tree interacted with adjacent widths of crop zones via user-defined inputs that affected resource availability in these zones. Interactions spatially and temporally with crop zones were specified for the tree for shading, rainfall interception, N demand, water demand (as a result of temporal leaf area inputs), root distribution, and additions of pruned gliricidia biomass (C and N) where those that actually occurred (at Makoka only). Tree leaf area determined water demand using standard APSIM algorithms (Snow and Huth, 2004). Below-ground interactions between trees and crops were calculated by the APSIM SoilArbitrator model (http://www.apsim.info/ApsimxFiles/SoilArbitrator576.pdf). The model calculates N uptake using the equations of De Willigen and Van Noordwijk (1994) as formulated in the model WANULCAS (van Noordwijk et al., 2011). Water uptake is calculated using an adaptation of the approach of Meinke et al. (1993) where the extraction coefficient is assumed to be proportional to root length density (Peake et al., 2013). In the version of the agroforestry model used here, it was assumed that there were no fluxes of water, C or N between zones. The model can incorporate standard management practices such as plant spacing, sowing and harvesting rules, organic and inorganic fertiliser rates, and irrigation. A standard APSIM meteorological file was used that contained daily inputs of radiation (MJ m$^{-2}$ d$^{-1}$), maximum and minimum temperatures (°C), and rainfall (mm).

### 2.3.1. Model setup for Machakos, Kenya

Climate, crop and tree parameters, and soil physical and chemical properties were available from Odhiambo et al. (2001), Wilson et al.

(1998), and Ong et al. (2000). Daily weather data were compiled from measurements at the site (Jackson and Wilson pers. comm.) and a nearby government meteorological station. A tabulation of key soil inputs is provided in Table 1. The same soil and climate inputs were used for all simulations; soil C:N ratio was 12. The bean crop grown between the two maize crops was simulated as an additional maize crop because no legume crops were available in APSIM Next Generation. The additional maize was harvested (terminated) prior to grain formation. This ensured that water use by the additional crop approximated reality. If this crop had not been simulated, there would have been a risk that water and available N effects would have carried over to the second crop of maize and artificially enhanced the simulated growth. However, very few details were available in the original publications to guide simulation of this additional crop. Assuming a small amount of N was fixed by this bean crop, which then enhanced N availability, 5 kg N $ha^{-1}$ was added as nitrate at all distances from gliricidia trees during sowing of the second maize crop.

Simulations commenced 1st March 1996 and ran to 31st December 1997. Sowing and harvesting dates specified were those provided in the original publications. No fertilisers were applied. Tree height was set in the simulations to be the same as those measured; that is increasing from 0.9 m in December 1993 to 4.9 m in August 1997, with a concurrent increase in leaf area from 0.5 to 1.0 $m^2$, and constant gliricidia N demand of 0.1 $g{\cdot}m^{-2}$. Canopy width extended to one tree height (h), with 50% shading 0–0.5 h, and 25% shading 0.5–1.0 h. Roots were assumed to extend to 2.5 h radially, and to 1.6 m depth. Approximately consistent with measurements, root-length-density ($cm{\cdot}cm^{-3}$) was set in the 0–0.5 h zone to 2.0 at 0–20 cm depth, 2.5 at 20–40 cm, 1.6 at 40–60 cm, and 0.5 for the rest of the soil profile. Root-length-density decreased radially, e.g. to 0.3 at 2.0–2.5 h at 0–20 cm depth.

Calibration of the model was required only for soil water and nitrogen parameters, which was justified because the values of several parameters were not provided in the literature. An iterative process of parameter adjustment was used for maize in the 8 m crop zone. Parameters were adjusted within reasonable limits based on previous experience to achieve an approximate match between observed and predicted grain yield. Values provided in Table 1 are those arrived at by calibration or as provided in the literature. The release version of the maize model was used and, therefore, not recalibrated. As the gliricidia proxy was user-defined, it did not require calibration.

### 2.3.2. Model setup for Makoka, Malawi

Climate, crop and tree parameters, and soil physical and chemical properties were available from Makumba et al. (2006), Akinnifesi et al. (2007), Chirwa et al. (2007), Ikerra et al. (1999), and Robertson et al. (2005). Daily weather data were provided by the Malawi meteorological service (courtesy of B Nyoka, ICRAF). A tabulation of key soil inputs is provided in Table 1; soil C:N ratio was 14.3. The same soil and climate inputs were used for all simulations. Treatment-specific or year-specific inputs were as follows.

1. Biomass and N in gliricidia residues – annual inputs were available, which were assumed to be split and applied equally four times per year, i.e. on the 15th day each of February, August, October and December. These dates of application approximated actual practice, but amounts applied on each occasion were unlikely to be have been simulated exactly as they occurred.
2. A sowing rule was used in the simulation, that resulted in simulated sowing dates within the period described in references about these experiments (12th to 27th December), except for one year. The sowing rule operated from 15th November to 30th December and required minimum extractable soil water of 30 mm, and accumulated rainfall of 30 mm over 5 days to trigger sowing, but this rule did not lead to sowing in the unusually dry December of 1999. Although there was maize sown at 4.44 plants $m^{-2}$ in the experiment that season, it is expected that there would probably have been high maize mortality (Chirwa et al., 2007), but plant population density was not measured. As APSIM did not provide stress-modified germination or mortality, a specific operation was included in the simulation for that December to sow at a reduced population density that was tuned to match observed yields. Population densities (plants $m^{-2}$) used were Sm 0.5, Sm48N 1.2, Gm 1.2, and Gm48N 2.0. This operation was required in the simulation to ensure that maize growth in this season did not affect subsequent simulated maize crops via soil properties that could have been affected by a yield pattern that did not represent reality. Yields from this sowing (harvested in 2000) were excluded from observed versus predicted statistics.

Simulations commenced 1st September 1992 and ran to 31st August 2014 (22 years); simulations were extended beyond observations to determine the likely temporal patterns in grain yield and soil C. Simulated sowing was as described above. Nitrogen mineralization and nitrification parameters were set to those used by Asseng et al. (1998), which was required to achieve the higher rates of these processes than default values provided by APSIM. Where fertilisation occurred (SM48N and Gm48N treatments), urea N was applied at the required rate 30 days after sowing.

Gliricidia N demand was based on measured N content, and ranged from 0.005 g $m^{-2}$ at planting to c. 0.05 $g{\cdot}m^{-2}$ at 6 years of age, and thereafter remained approximately constant. As water availability had previously been found to be non-limiting, gliricidia was assumed to have no water demand, with no leaf area, canopy width, shading or rainfall interception. Roots were assumed to extend radially in a uniform manner to a width equivalent to one tree height (1 m) and to 2 m depth. Consistent with measurements, root-length-density ($cm{\cdot}cm^{-3}$) was set to 0.2 at 0–40 cm depth, 0.8 at 40–60 cm, 0.6 at 60–100 cm, 0.5 at 100–120 cm, 0.4 at 120–140 cm, 0.3 at 140–160 cm, and 0.1 at 160–200 cm.

Calibration of the model for the Makoka site was similar to that for the Machakos site, but the iterative process of parameter adjustment was used for sole maize (unfertilized and fertilised) during the first five years.

### 2.3.3. Model Evaluation

Values predicted by the model were compared to observed values (a) graphically using 95% confidence intervals of prediction (SigmaPlot©) and $R^2$ values (while recognising that assumptions of its use may have been violated, i.e. autocorrelation, normality, and heteroskedasticity), and (b) using a combination of statistics as recommended by Yang et al. (2014). Statistics chosen were mean absolute error (MAE), mean error (ME), index of agreement (IoAd), and Nash-Sutcliffe efficiency (NSE), which were calculated using the 'HydroTest' software (Dawson et al., 2007). Evaluation statistics were calculated with and without calibration data. Critical values for satisfactory performance were taken as $d > 0.8$ for plant properties or $d > 0.60$ for soil properties, $NSE > 0.65$, and $R^2 > 0.70$ (Dawson et al., 2007; Ritter and Muñoz-Carpena, 2013).

## 3. Results

### 3.1. Machakos, Kenya

In both years, highest maize yields were observed at 8 m horizontal distance from the gliricidia trees although a plateau in yield versus distance had not been reached at this distance (Fig. 1). Yields progressively decreased to approach zero at 1 m from the tree rows. This variation in maize yields with distance was accurately simulated by the model, where 99% of variation was explained with calibration data excluded from the evaluation statistics (MAE = 7.46 $g{\cdot}zm^{-2}$, ME = 2.37 $g{\cdot}m^{-2}$, IoAd = 1.00, NSE = 0.98, $R^2$ = 0.99, Fig. 2) and a similar result with them included

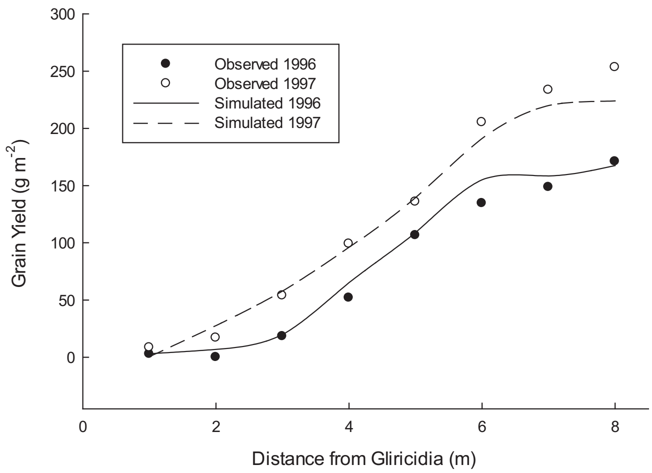


**Fig. 1.** Observed and simulated maize grain yield in relation to distance from gliricidia during 1996 and 1997 at Machakos, Kenya.

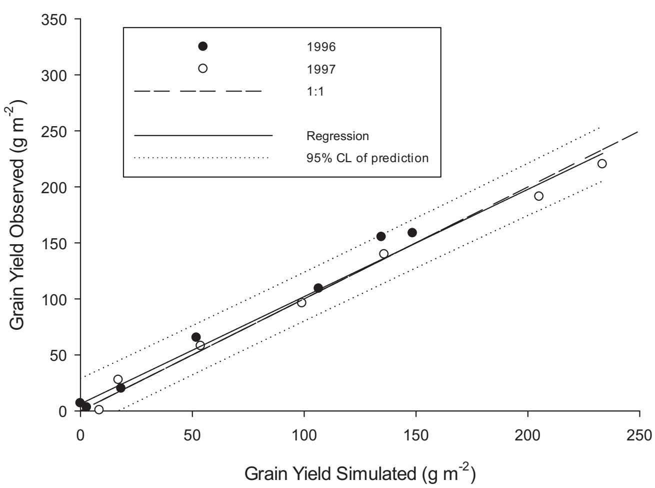


**Fig. 2.** Observed versus predicted maize grain yield during 1996 and 1997 at Machakos, Kenya ($R^2$ = 0.99) in relation to the 1:1 line. Evaluation statistics are provided in the text with and without data excluded for the 8 m zone for both years, because they were used for model calibration.

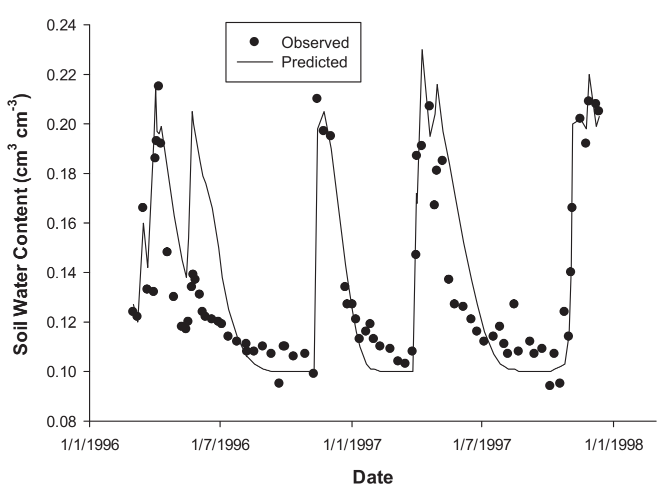


**Fig. 3.** Temporal pattern of observed and predicted volumetric soil water content at 35 cm depth at Machakos, Kenya, at 2 m from gliricidia. Evaluation statistics are provided in the text.

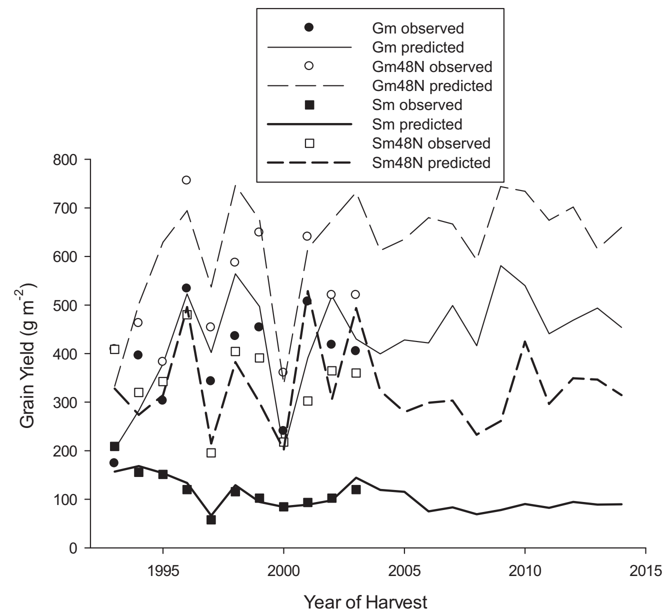


**Fig. 4.** Temporal patterns of observed and predicted maize grain yield at Makoka, Malawi. Treatments shown are: Sm = sole maize without fertiliser, Sm48N = sole maize receiving 48 kg·N·ha$^{-1}$; Gm = gliricidia-maize without fertiliser; Gm48N = gliricidia-maize receiving 48 kg·N·ha$^{-1}$. Observed data are shown as points and predicted data as lines.

(MAE = 23.47 g·m$^{-2}$, ME = −15.89 g·m$^{-2}$, IoAd = 0.96, NSE = 0.79, $R^2$ = 0.90, Fig. 2). The success of the model was underpinned by generally adequate simulation of soil water dynamics (temporal pattern shown for one depth and location in Figs. 3, 20–40 cm depth, 2 m zone, MAE = 0.017 cm3 cm$^{-3}$, ME = 0.0087 cm3 cm$^{-3}$, IoAd = 0.91, NSE = 0.58, $R^2$ = 0.75), which was the main limiting factor for maize growth at this site. There was, however, a tendency towards over-prediction of intermediate soil water contents as seasonal decreases occurred.

### 3.2. Makoka, Malawi

Maize yield at Makoka in sole maize (Sm) ranged between 0 and 2 t·ha$^{-1}$, with yields tending to be higher early in the measurement period 1993–2003 (Fig. 4). Maize yields in most years of the Sm treatment were well simulated ($R^2$ = 0.76). Observed and predicted yields increased in response to factorial combinations of fertiliser and gliricidia residues. Highest yields occurred in the combined treatment (Gm48N), which, in the 11th year, provided an observed 333% increase over those in the Sm treatment, and was simulated as a 250% increase. There was a bias towards over-prediction of yields from 1997 to 2003 in the Gm and Gm48N treatments. The ranking of yields in year 2000 was correctly simulated, but absolute values were initially substantially over-predicted (data not presented) because the simulation had not accounted for resowing at a later date and population density differences. Therefore, the simulation was coded to end the crop soon after sowing and then to resow it at a maize population density that provided simulated yields close to observed yields. Excluding 2000 and calibration data from evaluation of the model, observed yields were adequately simulated (MAE = 82.0 g·m$^{-2}$, ME = −49.9 g·m$^{-2}$, IoAd = 0.90, NSE = 0.67, $R^2$ = 0.73, Fig. 5), with a similar result when they were included (MAE = 71.4 g m$^{-2}$, ME = −32.4 g m$^{-2}$, IoAd = 0.94, NSE = 0.78, $R^2$ = 0.81). Sowing rate adjustments for that year were justified, as it was particularly dry immediately after planting, necessitating reseeding in an adjacent experiment (Chirwa et al., 2007). Although the current experiment was not resown, we were unsure what effect there had been on maize survival.

Measured soil carbon concentrations (0–20 cm depth) were 8.8 g·kg$^{-1}$ at commencement of the experiment, and those in the Sm treatment decreased to 8.2 g·kg$^{-1}$ after 9 years and 5.5 g·kg$^{-1}$ after

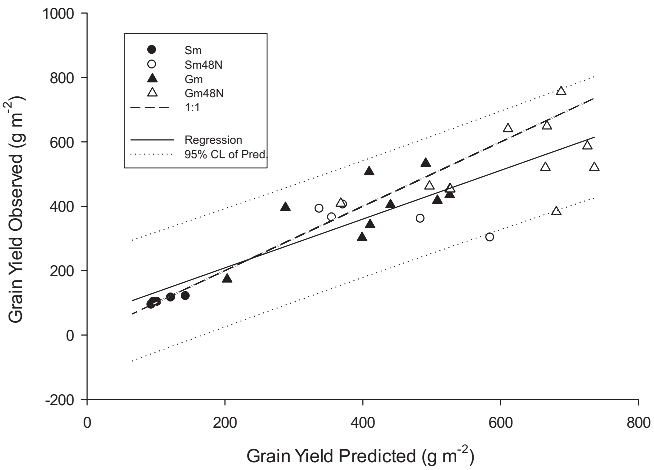


**Fig. 5.** Observed versus predicted maize grain yield 1993–2003 at Makoka, Malawi, showing a linear regression ($R^2$ = 0.73) and its band of 95% CL of prediction, in relation to the 1:1 line. Sm = sole maize without fertiliser, Sm48N = sole maize + 48 kg N $ha^{-1}$; Gm = gliricidia + maize without fertiliser; Gm48N = gliricidia + maize + 48 kg·N·$ha^{-1}$. Evaluation statistics are provided in the text. Data were excluded for the first five years for the Sm and Sm48N treatments, which were used for model calibration.

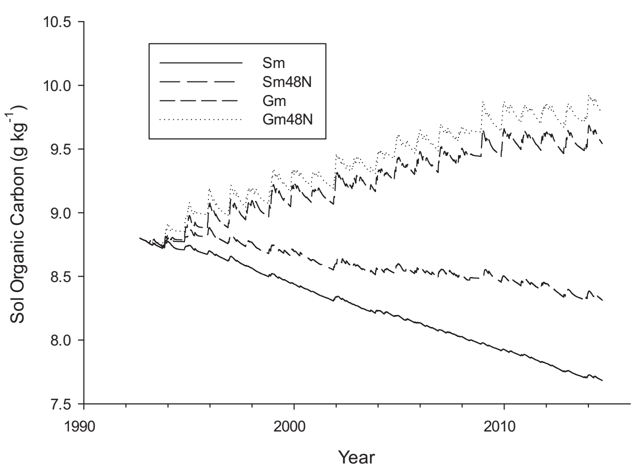


**Fig. 6.** Simulated trends in soil carbon concentrations at 0–20 cm depth at Makoka, Malawi. See Fig. 1 for treatment definitions.

12 years. In contrast, soil C increased to 10.0 g·$kg^{-1}$ with gliricidia-maize intercropping, and N fertiliser further increased soil C concentrations after 12 years. Observed soil C trends in surface soil were reflected at depth but with smaller changes. Observational errors were, however, apparent that could not be resolved. Hence, simulated concentrations of soil C (Fig. 6) followed the same general pattern as observations; that is gliricidia residues and N fertiliser both increased soil C, but evaluation statistics could not be calculated. Although the range of predictions did not fully reflect measured site variability, simulated trends in soil C were within the 95% confidence interval of prediction for the 2004 means (data not presented). Small increases in soil C were simulated at deeper depths (data not presented).

## 4. Discussion

The APSIM maize model has been validated and used in many contexts globally (Holzworth et al., 2014). In the present simulation, maize yield and water availability were used as the indicator of short-term gliricidia effects under water-limited conditions at Machakos, while maize yield and soil carbon concentration were used as indicators of long-term effects under N-limited conditions at Makoka. The APSIM agroforestry model adequately simulated the relative and absolute values of maize grain yield in these two contrasting gliricidia-maize intercropping contexts, with accompanying short-term trends in soil water and long-term trends in soil C. N dynamics were also simulated by APSIM and were consistent for Machakos with observations that competition for nutrients and light had a minor influence on maize yield in Machakos. For Makoka simulated results were consistent with observations that N was the main limiting factor.

Soil at Makoka was observed to change during 14 years of measurement for properties such as organic matter, nutrient availability, pH, and soil water characteristics (Akinnifesi et al., 2007). However, simulations did not cater for changes in these soil properties, apart from C and N concentrations. As simulations adequately reflected treatment effects on maize grain yield and soil C, this result further suggests that the main limiting factor for yield at Makoka was N availability as affected by gliricidia residues or fertiliser.

Potential sources of simulation error other than N need to be considered. Responses in maize yield to N and P fertilisers in factorial combinations with gliricidia at Makoka were modelled empirically by Akinnifesi et al. (2007) for the years 2002 to 2006. A small response in maize yield to P fertiliser was detected, which contrasts with the lack of response to P during the first year of the experiment (1992). This indicates that a P limitation developed in the intervening period that could account for some discrepancy between observed and predicted maize yield, including the tendency towards over-predicted yields later in the simulation (from 2002 to 2003) in the more high-yielding treatments Gm and Gm48N (Fig. 4). Another factor potentially contributing to prediction error was speculation that heavy rains, slow drainage and perched water tables at the site could suppress maize growth through water logging, but there was no clear relationship between high annual rainfall and low crop or gliricidia production in the observations and APSIM lacked the capability to model this effect.

Projected yields of the gliricidia-maize system at Makoka with possible changes in future climate (years 2040 to 2069) were estimated by Kerr (2012) using three global climate models, sub-daily interpolations of precipitation and temperature, and yields that were assumed to be directly related to growing degree days (GDD). Yields were assumed to decline by 1% for every GDD > 30 °C. Precipitation was estimated to remain adequate, and although high temperatures were projected to decrease yields, this result depended largely on the assumptions underlying the sub daily interpolations of temperature. A crop production model dependent only on GDD is unlikely to capture tree-crop interactions because it would not take account of daily variations in N and water availability, temperature and light that determine maize growth and yield.

The gliricidia-maize system at Makoka has been previously simulated by Chirwa et al. (2006) using an early version of the WaNuLCAS model, with a focus on biomass production in the sole maize and gliricidia-maize treatments, and for predicting possible trends in leaching, soil surface evaporation, drainage and water uptake. Results showed that WaNuLCAS either underestimated or over-estimated crop production compared to field observations. Model outputs were unaffected by applications of green leaf manure as it assumed continuous availability of soil nutrients over several seasons, even when no fertiliser or green manure was applied. The lack of model fit was also ascribed to the model not considering crop phenological and physiological parameters, which are catered for in the APSIM framework. Muthuri et al. (2004), when simulating maize interactions with *Grevillea robusta*, *Alnus acuminata* and *Paulownia fortunei* in Kenya, also observed that improved cultivar information for maize was needed in WaNuLCAS to avoid over- or under-estimates of yield.

The results of this simulation and earlier empirical studies (e.g. Chirwa et al., 2007; Sileshi et al., 2012) indicate that combining maize with fertiliser trees results in greater water availability and crop utilization of water than in sole maize. According to a study at Makoka (Chirwa et al., 2007), water use efficiency (WUE) was higher in maize intercropped with gliricidia than in sole maize. In another analysis

(Akinnifesi unpublished), gliricidia-maize intercropping was more stable (lower coefficient of variation) in terms of rain use efficiency than unfertilized sole maize. This result indicates that, where N is more limiting than water, gliricidia-maize intercropping can significantly increase WUE and stabilize crop yields.

The ability of the Next Generation version of APSIM to simulate short- and long-term tree-crop interactions suggests that it would be useful to further develop the model to include a broader range of tree and crop species and evaluate performance across a broader range of environmental and management contexts. Such developments need to occur in the context of the current and other relevant modelling activities. For example, WaNuLCAS was calibrated to model the productivity, carbon-stock dynamics and economic value of a gliricidia woodlot under a range of pruning and residue management decisions and for varying levels of land degradation (Wise and Cacho, 2005) but no validation was provided. The RothC model for soil organic carbon was used to simulate soil C turnover in Zambia (Kaonga and Coleman, 2008). RothC simulates the effect of annual above- and below-ground plant residue inputs to the soil on total organic C, microbial biomass, and radiocarbon age of the soil, over a period ranging from a few years to centuries. In Eastern Zambia, RothC estimated that soil C stocks increased by 29% (26.2 to 33.9 $t{\cdot}ha^{-1}$) where gliricidia was used, and that the decomposable:resistant plant material ratio needed to be increased (tuned) from 0.25 to 1.1 to achieve satisfactory simulation results. Comparable values for simulations at Makoka were a 22% increase in soil C (8.2 to 10.0 $g{\cdot}kg^{-1}$) with a decomposable:resistant ratio of 0.66. The RothC model is not designed to simulate crop production, but instead focuses on soil C dynamics with user-prescribed inputs, preferably of crop residues and other organic amendments. Although APSIM simulates both crop yields and soil C, it is likely to be useful to compare simulated soil C with RothC outputs where soil C is a major focus of research.

A maize agroforestry system was also simulated by Senaviratne et al. (2014), but this did not include crop or tree production. Instead, water quality of small catchments was simulated empirically using the APEX model. Sediment, total N and total P in runoff water were adequately predicted after an extensive parameter optimisation process. Although APSIM is not primarily a catchment model, it can be used to simulate water and nitrate leaching and salinity, and, as for similar field-scale models, it could be interfaced with catchment models to simulate stream-flow (Almeida et al., 2016) and contaminants (Wang et al., 2009).

Tree root behaviour is very important in determining tree-crop interactions, and so needs to be adequately dealt with in crop models. At the Makoka site, repeated coppicing would be expected to have kept tree root length density and distribution relatively stable during the study period. Whereas at the Machakos site where trees grew large, tree roots were extending laterally year-on-year, so that the zone of competition with crops would have increased correspondingly. In this situation, tree roots were already present and active when the crop was planted and could extract water before germinating seedlings. Tree water use and root distribution were important under semi-arid tropical conditions in Machakos, but were less of an issue in the frequently pruned and more N-limited sub-humid sub-tropical system in Makoka. In these contrasting agro-ecologies, the model was shown to integrate the distribution and density of tree roots with the availability and uptake of water and N reasonably well.

## 5. Conclusion

The agroforestry model in APSIM represents a major advance in being able to reliably predict the impact of trees on crop yield and water and soil carbon dynamics. The model demonstrated this capacity, in two contrasting African sites, even though there were some uncertainties in data inputs (exact planting and harvesting dates, exact gliricidia pruning dates and amounts of residues, and uncertainties for some soil water characteristics, tree root length densities, and soil C and N). This initial evaluation used a version of APSIM with N as the only nutrient under consideration, a proxy tree model that includes only limited dynamics in some tree variables (roots, shade), as well as fixed soil properties (BD, water characteristics, pH, FBiom, FInert), and no capacity to simulate the effects of waterlogging. There are few crops currently available in APSIM Next Generation, and no mechanistic modelling of crop germination and mortality. Hence, the model appears to work well for water and N limited situations, but it would benefit from further development to cope with other limiting nutrients and water logging, as well as including a broader range of trees and crops, before it can be widely used to help refine our understanding of how different agroforestry options will perform across different locations in Africa.

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