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Field-scale modeling of tree–crop interactions: Challenges and development needs

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ABSTRACT

Agroforestry has attracted considerable attention in recent years because of its potential to reduce poverty, improve food security, reduce land degradation and mitigate climate change. However, progress in promoting agroforestry is held back because decision-makers lack reliable tools to accurately predict yields from tree-crop mixtures. Amongst the key challenges faced in developing such tools are the complexity of agroforestry, including interactions between various system components, and the large spatial domains and timescales over which trees and crops interact. A model that is flexible enough to simulate any agroforestry system globally should be able to address competition and complementarity above and below ground between trees and crops for light, water and nutrients. Most agroforestry practices produce multiple products including food, fiber and fuel, as well as income, shade and other ecosystem services, all of which need to be simulated for a comprehensive understanding of the overall system to emerge.

Several agroforestry models and model families have been developed, including SCUAF, HyPAR, Hi-SAFE/Yield-SAFE and WaNuLCAS, but as of 2015 their use has remained limited for reasons including insufficient flexibility, restricted ability to simulate interactions, extensive parameterization needs or lack of model maintenance. An efficient approach to improving the flexibility and durability of agroforestry models is to integrate them into a well-established modular crop modeling framework like APSIM. This framework currently focuses on field-scale crops and pastures, but has the capability to reuse or interoperate with existing models including tree, livestock and landscape models, it uses parameters that are intuitive and relatively easy to measure, and it allows scenario analysis that can include farm-scale economics. Various types of agroforestry systems are currently being promoted in many contexts, and the impacts of these innovations are often unclear. Rapid progress in reliable modeling of tree and crop performance for such systems is needed to ensure that agroforestry fulfills its potential to contribute to reducing poverty, improving food security and fostering sustainability.

Contents

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1. Introduction

1.1. Agricultural models for systems analysis and decision-making

Agricultural models are often used to support decisions regarding the management of food production systems. They serve a wide range of purposes, including planning day-to-day management of cropping activities on farms (Hochman et al., 2009), informing development initiatives for rural poverty alleviation (Thornton et al., 1997), and projecting the impacts of climate change on food security (Webber et al., 2014). They are applied in making operational, tactical and strategic decisions (de Koeijer, 2002) and are capable of projecting field, farm and food system performance across a wide range of environmental and socioeconomic conditions (Holzworth et al., 2014). The primary objectives of these models are a) to synthesize experimental and conceptual information on how system components interact in agricultural systems; b) to identify and prioritize gaps in knowledge; c) to test through 'virtual experiments' the effect of a large number of interacting factors such as soil, climate, species, and management, that are too numerous to be studied empirically; d) to provide decision support to policy makers, researchers and extension staff (Aumann, 2007) and e) to share knowledge amongst researchers and practitioners about determinants of productivity.

Most agricultural production models contain a process-based submodel at their core which simulates the growth of plants through their vegetative and generative stages on a particular unit of land (Steduto et al., 2009). This core model element is typically a crop model, which simulates production of a particular crop as a function of crop attributes interacting with environmental conditions, such as soil and weather, which are in turn influenced by climate, agricultural inputs and management. In most cases, the crop and soil components are the only ones that respond directly to changes in environmental or climatic conditions. A wide range of crop models have been developed, that simulate yields reasonably well for many crops. Examples of such models include WOFOST (Van Diepen et al., 1989), DSSAT (Jones et al., 2003), APSIM (Holzworth et al., 2014), the 'Wageningen crop models' (Van Ittersum et al., 2003), Hybrid-Maize (for maize only; Yang et al., 2004), STICS (Brisson et al., 2003) and AquaCrop (Steduto et al., 2009). Researchers have sufficient confidence in many of these models to routinely use them for projections of crop performance in places where the crop of interest has never been grown (McLaughlin et al., 2006), or in projected future climates under which crop performance has never been observed (Parry et al., 2004).

The availability of reliable crop models is mostly restricted to monocultures, where interactions between plants are limited to resource partitioning between individuals of the same species (Steduto et al., 2009). Models typically simulate attainable yield, considering potential yield, which depends on crop genotype, radiation, temperature, and management, that is constrained by limiting factors such as water and nutrients. They do not normally simulate actual yields, which are generally below that attainable because of pests, diseases and weeds. Some models allow simulation of systems that are more complex than a monoculture. Amongst these are the inclusion of weeds in monocultures (Deen et al., 2003; Grenz et al., 2006) and intercropping systems (Carberry et al., 1996). There have been several attempts to model tree–crop interactions at various levels of detail, including HyPAR (Mobbs et al., 1998), WaNuLCAS (Van Noordwijk and Lusiana, 1998) and the SAFE family of models, which consists of Hi-SAFE (Talbot, 2011) and Yield-SAFE (van der Werf et al., 2007), themselves forming the basis for plot-SAFE and Farm-SAFE (Graves et al., 2011). There are also models for windbreaks and crops in the Sahel (Mayus et al., 1998) and coffee agroforestry (Van Oijen et al., 2010), and there is basic functionality to model trees within the APSIM crop modeling framework (Huth et al., 2002). These tree–crop interaction models, while capturing interactions to variable degrees, often fall short of accurately predicting attainable yields for both tree and crop components simultaneously, over a wide range of conditions (Walker et al., 2007; Bayala et al., 2008b).