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Crop response functions integrating water, nitrogen, and salinity

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ABSTRACT

Process-based simulation models are used to generate seasonal crop yield and nitrate leaching datasets for several important crops. The simulated data is then used to estimate novel three-input crop response functions that account for the effects of interactions and feedback mechanisms in the whole plant–water–nitrogen–salinity system. Comparisons with available field data show that this appears to be a reliable approach for estimating analytical crop response functions with water, nitrogen, and salinity as input factors. Results also demonstrate the shortcomings of using simpler two-input functions. The estimated functions are continuously differentiable and can be easily incorporated into comprehensive agricultural–economic–environmental optimization models, thus facilitating greater utilization of process-based models by a wider range of disciplines.

1. Introduction

Our ability to efficiently manage agricultural water has benefitted in recent years from the development of process-based simulation models that are capable of predicting the effects of varying conditions and management practices on crop yield and the environment. Examples of such models include GLEAMS, EPIC, APSIM, SMCR_N, CropSyst, SWAP, ENVIRO-GRO and HYDRUS (Knisel and Turtola, 2000; Williams et al., 1995; Keating et al., 2003; Zhang et al., 2010; Stöckle et al., 2003; Kroes et al., 2008; Pang and Letey, 1998; Šimůnek et al., 2008). Models such as these typically are based on the specific agronomic and biophysical processes that occur at the plant or plot level in short time steps throughout a growing season, and thus represent our best scientific understanding of those processes.

These models are potentially very useful for researchers in other disciplines who are investigating questions that require accurate representation of agronomic and biophysical processes, possibly at larger spatial and time scales. A prime example is economics which is often concerned with predicting the effects of changes in environmental, economic, or regulatory conditions on grower behavior and welfare, usually at the farm level and over multiple growing seasons. Such predictions invariably require solving a mathematical optimization problem that represents the grower's decision-making process. Although it is possible to link an economic optimization model directly with an external process-based simulation model such that the economic model calls the simulation model each time the optimization routine needs to calculate a level or derivative of one of the simulated variables, this is uncommon in practice due to the requisite programming skills and the substantial computational burden. A recent example of this approach is Lehmann et al. (2013) in which a genetic algorithm is used to bridge the models. Although the authors acknowledge that "the full potential of [process-based] models is only tapped when as many different management variables as possible are considered simultaneously" (p. 56), they must limit their choice set to twelve discrete decision variables in order to achieve reasonable computation times. While a decision set of this dimension may be adequate for some single period problems, notwithstanding the lack of continuous choice variables, multi-period problems can easily involve hundreds of decision variables (e.g. Baerenklau et al., 2008).

A far more common approach that is more widely accessible, more computationally feasible, and allows for a richer set of decision variables is to embed in the economic model analytical functions that have been fitted to data generated either from field experiments or by the external simulation model. This amounts to an indirect linkage of the models via the analytical functions, as shown in Fig. 1. A recent example of this approach is Finger (2012) who uses simulated yield data from CropSyst to estimate production functions that are then used to predict changes in water and

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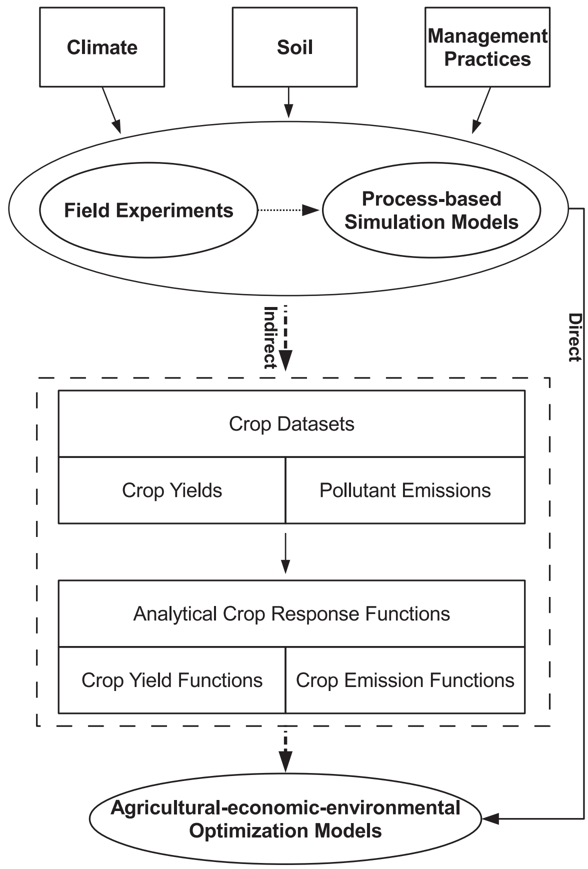

Fig. 1. Alternative approaches for linking process-based simulation models with optimization models.

fertilizer application rates by corn producers in response to changing economic conditions. In general terms, such crop response functions relate output variables (e.g., crop yield, pollutant emissions) to the quantity and/or quality of at least one input factor. Crop yield functions have a long history, likely dating back to von Liebig's "law of the minimum" in the mid-1800s, and continue to play an important role in economic analysis of agricultural production (Hexem et al., 1978; Lanzer and Paris, 1981; Letey and Dinar, 1986; Griffin et al., 1987; Berck and Helfand, 1990; Tembo et al., 2008). Tembo et al. (2008) provides an overview. Common applications include yield response to water, salinity, fertilizer, pesticide, or some combination of these.

As concerns about the effects of agricultural pollution have increased, emission functions have been developed to augment crop yield functions (Tanji et al., 1979; Peralta et al., 1994; Pang and Letey, 1998; Knapp and Schwabe, 2008). With both yield and emission functions in hand, economic analysis can be extended to include not only market inputs and outputs but also the non-market effects of agricultural production on natural resources and environmental quality. In the case of nitrogen fertilizer, nitrate leaching typically is estimated as a function of applied water and applied nitrogen. When the response functions are embedded in an economic optimization model, the effects of a fertilizer tax, for example, can be estimated on irrigation water use, fertilizer use, crop yield, farm income, nitrate leaching, and ultimately groundwater quality.

Standard practice for empirical specification of such agri-environmental crop response functions has converged on two-input models, typically either water and salinity, or water and nutrients (as in Finger, 2012), or water and pesticides depending on the desired application.[1] Incorporating multiple inputs allows modeling of potentially important interaction effects on crop yield and pollutant emissions. For example, applied irrigation water is at least as important as applied nitrogen for determining nitrate leaching because water is the main transport medium for dissolved salts (Pang and Letey, 1998). Therefore, in areas where nitrate pollution is a potential threat to public health and the environment, proper evaluation of pollution control policies requires information on the response of both crop yield and nitrate leaching to both water and nitrogen. Another example is the effect of saline irrigation water on nitrate leaching. Total leached nitrogen has been shown to increase due to the effects of salinity stress on water and nutrient uptake (e.g., Pang and Letey, 1998; Ramos et al., 2011).

We are not aware of any previously published crop response functions with three input factors, but such functions would be particularly useful for addressing persistent and emerging problems from irrigated agriculture. Therefore the purpose of this study is to develop, demonstrate, and test a methodology for estimating integrated crop response functions with three input factors; and to disseminate the estimated functions for several important crops that use water, nitrogen and salinity as inputs. In order to address the lack of field experimental data that would support estimation of such functions, we utilize simulations. Novel and generally applicable response functions are derived from the simulated data that account for the effects of interactions and feedback mechanisms in the whole plant–water–nitrogen–salinity system.

2. Methodology

2.1. Function inputs specification

Most studies estimate models of crop yield and nitrate leaching using *applied* water and nitrogen fertilizer as inputs (e.g., Helfand and House, 1995; Llewelyn and Featherstone, 1997). From an agronomic perspective, it is the combination of management practices like these and pre-existing soil conditions that determine yield and leaching; yet only a few studies include variables such as soil nitrogen stock as an additional input (Vickner et al., 1998; Martí nez and Albiac, 2006). Neglecting to account for soil conditions does not necessarily lead to biased estimation results but it does limit the transferability of the response functions to other regions or even to the same field under different conditions. Our crop response functions use available water, available nitrogen, and exposed salinity as inputs and are thus more general and transferable. Below we show how to navigate between our input variables and those that are more commonly used.

Water that is available for crop uptake includes irrigation (e.g., surface water, groundwater, recycled drainage water), precipitation, and initial water content in soil. Initial water content is relatively small compared to the amount of applied water, and thus can be assumed away from crop available water (Letey and Knapp, 1995). Denoting the remaining water sources as $w_i, i = 1, \ldots, I$ (cm), crop-available water, w (cm), can be specified as the summation shown in Eq. (1).

$$w = \sum_{i=1}^{I} w_i \tag{1}$$

[1] Here we refer to the variable inputs for which decisions must be made throughout a growing season. Many other choices by a producer affect yield and emissions, such as planting, harvest, and irrigation technologies. However, standard practice is to treat these as fixed factors of production and to estimate crop response functions conditionally on these choices.