Using Hydro-Economic Modeling to Analyze the Allocation of Agricultural Water in the Southeastern U.S.

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Abstract

This paper summarizes the modeling framework used to determine the economic value of water for row crops using a partial equilibrium agricultural sector model designed for Tennessee and the Tennessee River Basin (TNAP). The objective of the paper is to outline a framework for determining water use by Tennessee's agricultural sector, the relative value of water used by agriculture, and potential technology options for adapting to water scarcity with TNAP. The focus is on the major row crops produced in the region, specifically corn, soybeans, wheat, and cotton. Estimates of water availability are generated with predictive water balance models. Metrics for water use and demand are developed from three sources of data: a) primary and secondary farm-level data, b) regional economic-sectoral data, and c) cost-of-production data for crops commonly produced in the region. Shadow prices of water will be estimated by adjusting water quantities available for agricultural activities with the marginal productivity value of farm and non-farm activities.

Introduction

Water availability has not historically received the attention in the Southeastern United States (US) that it has in the arid Southwest. However, the stress on Southeastern water resources is increasing due to expansion in irrigated acres, urbanization, population growth (Seager et al. 2009) and economic development (McNulty et al. 2008), coupled with a relatively constrained storage capacity, an aging infrastructure, and reliance of large inland population centers on relatively small watersheds with limited water supplies. As a result, conflicts over water use are increasingly common in the Southeastern US and communities and industries have occasionally found themselves without adequate water supplies (e.g., Morrison et al. 2009). Climate change threatens to exacerbate this stress, with uncertain rainfall patterns and the amplified risk of extreme weather, including both droughts and high rainfall events. These changes also imperil the resiliency of agricultural and forestry economies and the jobs and businesses that depend on these sectors. This concern is particularly relevant for the southeastern US where plentiful water resources have enabled the development of a “highly water-dependent regional economy” (EPRI 2009). Hence, communities in the region face a range of undesirable consequences, including: 1) Higher prices to ensure continued access to a reliable and safe supply of water (Copeland 2008); 2) Increases in the frequency of water use restrictions to manage water use during shortages (Thompson 2014); 3) Seasonal loss of aquatic recreational opportunities and associated loss in economic activity (e.g., Bleakly Advisory Group, Seaman, and PBS&J, Inc., 2010); 4) Expensive projects to transport and store freshwater when local demand exceeds water availability (Emanuel and Hoffner 2012); 5) Capital investment in new or expanded water treatment facilities as drought conditions increase pollutant concentrations from treatment plant discharges; 6) Loss of energy production when adequate supplies of water for cooling are not available

(Clark et al. 2013); and 7) Increased conflict within and across communities and economic sectors.

The effects of climate change on water availability could impact many economic sectors in the southeastern US, perhaps none more than agriculture. Cost-effective adaptation to climate change, along with increased water demand due to population growth, increased irrigation, and economic development is contingent upon sufficiently understanding the complexity characterizing land use and water availability dynamics. The southeastern US has an opportunity to consider proactive measures to prepare for these changes and address concerns over the allocation and conservation of water before water resources become fully allocated and opportunities for cost-effective adaptation to these changing conditions evaporate.

This research develops an agricultural sector model (ASM) for the Tennessee River Basin, extending the Statewide Agricultural Production Model (SWAP, Howitt et al., 2010) to Tennessee row crop production. The study area is comprised of the six Crop Reporting Districts (CRDs) located in Tennessee (Figure 1). Of the approximately eleven million acres of farmland in the study area, a little over three million acres are planted to corn, cotton, soybeans, sorghum or wheat and another four million acres are in hay and pasture (Bowling et al. 2016, USDA-NASS, 2013) The majority of these crops are rain-fed, especially in the eastern part of the state, while irrigated acres are primarily concentrated in the western part of the state (i.e., CRD 62) (Table 1). The objective of the modeling effort is to determine the economic value of water by maximizing producer profits, subject to water availability. Adaptive technologies, including irrigation, cover crops, and crop rotations are decision variables, along with the acres allocated to row crops commonly produced in the region. This paper summarizes the ASM currently under development.

Methods

The Tennessee Agricultural Production Model (TNAP) was developed to estimate the economic value of water in row crop (corn, soybeans, wheat, cotton, and sorghum) and pasture production. The core of the TNAP model is based on California's SWAP model (Howitt et al, 2001; Medellin-Azuara et al., 2012). TNAP is used to induce the economic value of water resources in contrasting agricultural regions and to analyze management strategies that could mitigate the impact of water scarcity on the economic performance of the agricultural sector in the Tennessee River Basin.

TNAP is benchmarked using Positive Mathematical Programming (PMP) (Howitt, 1995; Howitt, 2005). PMP is a calibration method that reproduces exactly the observed levels of agricultural production prior to policy analysis or exogenous shock, such as a change in input or output price, or water availability. Data requirements include agricultural output, variable costs of production, and input demand, including land, water, chemicals, fertilizers, energy, labor and capital. TNAP uses Constant Elasticity of Substitution (CES) production functions in the calibration routine (Manete et al, 2009; Medellin-Azuara et al. 2012), allowing for substitution effects between water and other input factors. This constraint augmentation enables identification of locations where the productive factors analyzed are more (or less) resilient to changes in water availability and additional resource constraints. In the current specification, the decision-making units are representative farms corresponding with Crop Reporting Districts. In a given season, producers allocate the expected seasonal water supplies to maximize gross margins subject to physical, technological, water quantity, and stream flow constraints. The marginal (economic) values of productive factors, such as land and water, are determined by incrementally changing the resource availability constraints. The model integrates the marginal value of resources (derived from shadow prices) to augment average cost and revenue information to calibrate the CRD-level models to observed baseline conditions. This process allows the aggregated regional model to estimate a more diverse set of activities than would be possible with linear production technologies.

There are two stages to calibrate the model using PMP. The first stage applies linear programming (LP) to calculate the dual values of the resource and calibration constraints. The LP model is:

$$\max_{z} \sum_{j} p_j \cdot q_j - \sum_{ijklm} c_m \cdot a_{ijklm} \cdot z_{ijkl} \tag{1}$$

Subject to:

$$\sum_{ijkl} a_{ijklm} \cdot z_{ijkl} \le b_m \qquad [\lambda_{1m}] \tag{2}$$

$$z_{ijkl} \le \hat{x}_{ijkl} + \varepsilon \qquad [\lambda_{2ijkl}] \tag{3}$$

$$q_j = \sum_{ikl} z_{ijkl} \cdot \hat{y}_{ijkl} \tag{4}$$

where:

p_j is the output price of crop *j* ($j =$ corn, soybean, wheat, sorghum, cotton, hay);

q_j is total output of crop *j*;

c_m is per acre cost of input *m* ($m =$ irrigated land, rainfed land, water, fertilizer, chemical, energy, labor, and capital);

a_{ijklm} is per acre use of input *m* for production region *i* ($i =$ CRD62 ,…, CRD67), crop *j*, tillage practice k ($k =$ conventional tillage, no-till), and irrigation option l ($l =$ irrigated, rainfed);

z_{ijkl} is acres in production region i, planted in crop j, using tillage practice k, and irrigation option l; and

b_m is the quantity of input m available for use (right hand side of the resource constraints).

The first stage LP model maximizes the total profit of regional row crop production, subject to a resource constraint (equation (2)) and a calibration constraint (equation (3)). The choice variable of the model is land allocation z in production region i of crop j with tillage practice k and irrigation option l. The observed baseline land allocation (in acres) is $\hat{x}$ and the (per acre) yield level is $\hat{y}$. For each resource and calibration constraint, the dual variable λ is obtained after solving the LP model. These dual values are then used, along with acreage supply elasticities η, to calculate the quadratic cost function parameters υ and φ for the second stage of the PMP procedure. The supply elasticities were estimated using an econometric model (Table 2, Lambert et al, 2015). The CES production function parameters α and β are estimated following Howitt (2005) with a given elasticity of substitution γ and the known input factor price and usage.

The second stage of the PMP procedure maximizes a non-linear objective function subject to resource constraints, and the parameterized variables resulting from the first-stage calibration:

$$\max_{x} \sum_{ijkl} Q_{ijkl} \cdot p_j - \sum_{ijklm} \upsilon_{ijklm} \cdot x_{ijklm} - \frac{1}{2} \sum_{ijkln} \psi_{ijkl} \cdot x_{ijkln}^2 \qquad (5)$$

Subject to:

$$Q_{ijkl} = \alpha_{ijkl} \cdot \left(\sum_m \beta_{ijklm} \cdot x_{ijklm}^{\gamma}\right)^{\frac{1}{\gamma}} \qquad \forall\ i, j, k, l \qquad (6)$$

$$\varphi_{ijkl} = \frac{p_j}{\eta_j \cdot \hat{x}_{ijkl}} \quad \forall\, i, j, k, l \tag{7}$$

$$\upsilon_{ijkln} = c_n + \lambda_{1n} + \lambda_{2ijkl} \quad \forall\, i, j, k, l, n, l = n \tag{8}$$

$$\upsilon_{ijklm} = c_m + \lambda_{1m} \quad \forall\, i, j, k, l, n \notin m \tag{9}$$

$$\sum_{ijkl} a_{ijklm} \cdot x_{ijklm} \leq b_m \quad \forall\ m \tag{10}$$

where p_j, c_m, a_{ijklm}, b_m, and $\hat{y}_{ijkl}$ are as before; Q_{ijkl} is total output in region *i* of crop *j* produced using tillage method *k* and irrigation option *l*; α_{ijkl}, β_{ijklm} are estimated CES production function parameters; and x_{ijklm} are the choice variables of the land and other resource allocations. The output of crop commodity Q is now specified as a CES function (Equation 6). The intercept υ and slope φ of the quadratic cost function are estimated in Equations (7)-(8) taking into consideration the dual values from the first-stage LP model. The solution of the model should produce exactly the baseline input and output level.

Yield Benchmarking

The interaction between water stress on crop production and adaptive practices (irrigation, cover crops, and crop rotation) are simulated using the Environmental Policy Integrated Climate (EPIC) cropping systems model (http://epicapex.tamu.edu/epic/). EPIC's agro-ecosystem model is a daily time step process-based model of agricultural crops that can be applied at any spatial scale and for a wide range of crops, cropping systems, and agricultural management practices. A management practices database representing baseline management activities is constructed where agronomic and economic information can be obtained and where EPIC provides the crop yield and environmental performance indicators. Yields generated under the different management practices are simulated for 100 time steps and according to the dominant soil types observed in each region (Figure 2). These yields are used in the calibration procedure for $\hat{y}$.

Simulating Water Scarcity

Water availability is simulated using the Variable Infiltration Capacity (VIC) model (Liang et al., 1994). VIC is a semi-distributed, macroscale hydrologic model used to quantify water and energy balances for larger river basins at a daily or sub-daily time step. The model was originally developed as a soil-vegetation-atmosphere transfer scheme for Global Circulation Models (GCMs) (Nijssen et al., 1997) and is based on work performed by the Tennessee Valley Authority (TVA). The VIC model has the ability to consider spatial heterogeneity in precipitation from storm fronts, local convection, or topographic heterogeneity (Liang et al., 1996) by designating a time-varying wet/dry fraction in each geographical area. Additionally, the VIC model can account for snow both delivered from the atmosphere and already on the ground surface.

To estimate water availability and scarcity across the study region, the VIC model will be used to perform water balance, and water routing, by considering surface water impoundments (i.e., lakes or wetlands) and losses due to irrigation and increased evaporation due to droughts and rising temperatures in the region. Irrigation water can be taken from river runoff or from reservoirs, so irrigation is restricted by water availability. Irrigation demands are calculated based on simulated irrigation water requirements downstream of the reservoir VIC uses the Tennessee Valley Authority algorithms (TVA, 1972) to handle lake evaporation with the approach of Bohn et al. (2013).

At a minimum, VIC needs daily precipitation, maximum and minimum air temperatures, and wind speed to run a simulation; however, sub-daily meteorological values from point observations, gridded observations, or reanalysis fields can be used. As mentioned above, VIC will use the TVA algorithms for all other needed forcing (Bohn et al., 2013). Other important data includes latitude/longitude, soil texture and other characteristics, available land cover in a grid cell, and vegetation parameters (e.g., rooting depths and Leaf Area Indices), as well as elevation and soil moisture/temperatures.

The basic outputs from VIC include specific state variables and fluxes related to the water balance of the system. The water balance state variables include total soil moisture content, total interception in the canopy, the depth of the water table, and lake surface area/depth/volume. Water balance fluxes from VIC include precipitation net transpiration, total net evaporation, runoff/ channel inflow, baseflow, and the water budget error.

VIC model simulations of water scarcity scenarios are upscaled to the regional level because the benchmark production data of the sectors analyzed are recorded at this level of aggregation. These shocks from status quo conditions will enter the water resource constraints of each agricultural sector to determine changes in gross sector income, changes in input use, crop mix, and changes in the economic value of water attributable to these shocks. An interesting output directly relevant to producers is examples of proactive, cost-effective measurements that can be implemented on their operations to moderate the impact of prolonged water scarcity or acute inundations.

Results and Discussion

< Results will be presented during the conference presentation>

Acknowledgements

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Figure 1. Study Regions.

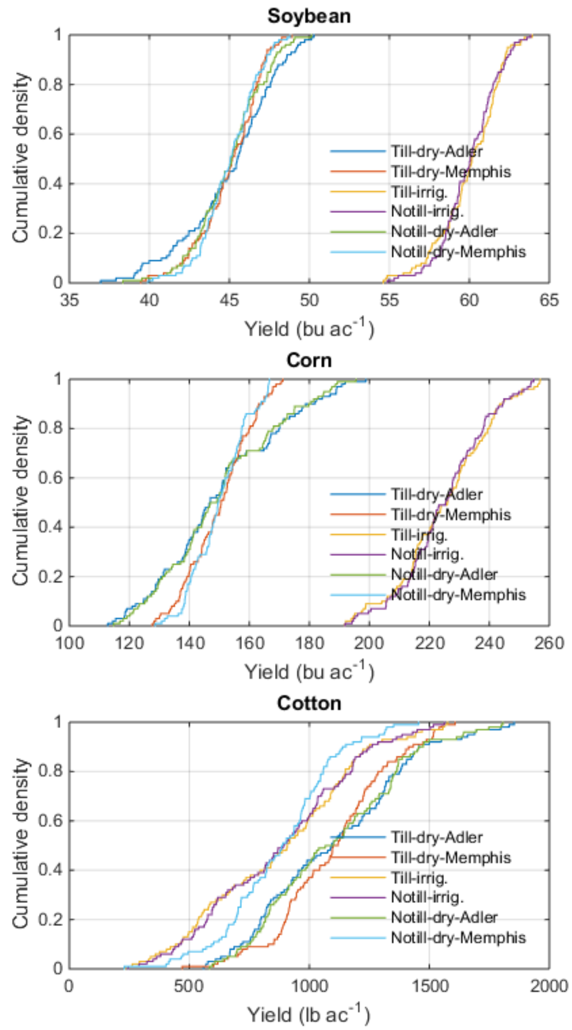


Figure 2. Example of Simulated Yields for till/no-till, irrigated/non-irrigated cotton, corn, and soybeans, Crop Reporting District 62.

Table 1. Distribution of irrigated crop and rainfed crop in Tennessee.

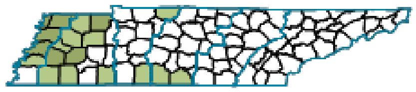
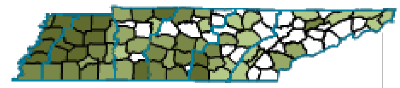
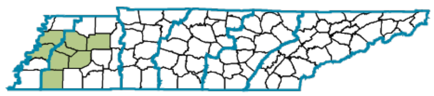
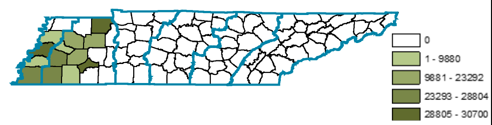
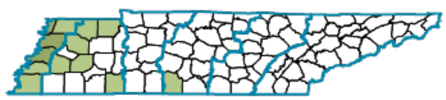
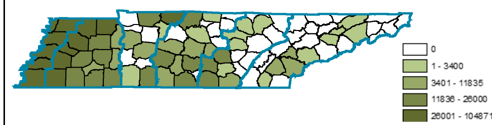
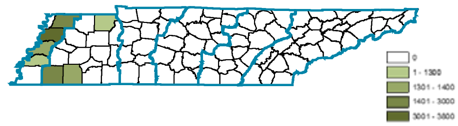
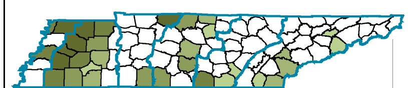
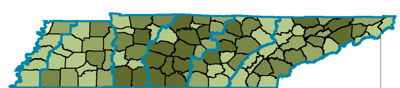
	Irrigated	Rainfed
Corn		
Cotton		
Soybean		
Sorghum	NA	
Wheat	NA	
Pasture	NA	

Table 2. Estimated acreage supply elasticities (η) for the Tennessee Basin

Activity	Point Estimate	Lower 5% CI	Upper 95% CI
Corn	0.17	0.12	0.19
Soybean	0.08	-0.03	0.20
Cotton	0.14	0.08	0.18
Wheat	0.21	0.14	0.23
Pasture	0.02	-0.03	0.07

Source: Lambert, Boyer, and He (2015).