DROUGHT IMPACT ASSESSMENT IN MONTANA USING A SATELLITE-DRIVEN HYDROECONOMIC MODEL

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Abstract

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1. Introduction

As climate change leads to unprecedented changes in natural systems, it is essential to encourage adaptation to offset the negative effects of those changes (Intergovernmental Panel on Climate Change 2014). Agriculture has a long history of adapting to variability in local conditions, but ongoing and substantial changes in climate are creating new challenges for farmers across the U.S. and globally [1, 2]. Evidence to date suggests that farmers have met these challenges by adapting with changes in crop mix and land use, for example (Schneider et al. 2000; Bryant et al. 2000; Menzel et al. 2006). However, little is known about how farmers adapt; to what extent adaptation mitigates economic losses from climate change; how adaptation in turn alters natural systems; and how

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policy instruments may encourage or impede adaptation (White et al. 2011). Understanding how farmers adapt to changing natural conditions is critical for developing efficient policies to support producer welfare, enhance food security, and protect the environment. The objective of this project is to develop a transformative decision support tool that will allow policymakers and natural resource managers to understand the incentives that drive farmers adaptation to changing natural conditions, as well as the environmental consequences of adaptive behavior. To do so, we propose a state-of-the-art integrated hydro-economic model that leverages recent advances in remote sensing science and in data assimilation methods to enable automatic model updates and refinements as new information on farming activity becomes available. Our methodology does not aim at optimizing the way farmers should allocate land, water, and other resources under different resource constraints. More importantly for policymaking is its capability to anticipate how they will allocate these resources, and the impact of their decisions on agricultural water demands, agricultural productivity and farm profits. Our methodology is designed for analysis at the farm or county scales and reveals how farmers react and reallocate resources seasonally when confronted with new climate, policy rules, or market signals. One reason current operational water management tools do not incorporate farmers behavior is because it is difficult to represent in models (Young et al. 1986). Agent-based models offer a very promising approach to simulate individual and collective action in response to changes in exogenous conditions. Unfortunately their complexity and computational requirements of these models limit their potential for operational water management and circumscribe their use to academic research (e.g. Yang et al. 2009 and references therein). Another limitation of current operational water management tools is that they often neglect the spatially explicit and dynamic nature of human action, often assuming that the behavior of one farmer does not affect the choices of farmers downstream. However, upstream decision-making is likely to influence the availability of water for downstream uses and the ability of downstream farmers to adapt to climate change (Maneta et al. 2009a; Maneta et al. 2009c). Hydro-economic models, such as the modeling approach we propose, overcome these limitations, and provide a promising basis for an operational water management tool. Hydro-economic models are integrated tools that incorporate the realities of water management systems, including spatial impacts and dynamic demands driven by economic and policy drivers (Harou et al. 2009). These types of models have been a subject of research since the late 1990s (Pulido-Velazquez et al.; Ward and Lynch 1996; Cai et al. 2003; Ward et al. 2006; Cai 2008; Brouwer and Hofkes 2008; Medelln-Azuara 2011) and are becoming one of the foremost tools for integrated water management in the future. Our group has extensive experience with these methods and our previous work shows that integrated hydro-economic modeling can simulate farmer behavior at a fraction of the complexity and computational requirements of agent-based models (Maneta et al. 2009a; Maneta et al. 2009b; Maneta et al. 2009c; Torres et al. 2011; Ghosh et al. 2014). In addition, hydro-economic models are more amenable to coupling with physical models that represent the distributed regional hydrologic system. This coupling is key to tracing the effects of farmer adaptation on natural systems over space and time. When applied to water management in agricultural regions, farmer behavior can be represented in hydro-economic models using response functions calibrated using positive mathematical programming (Howitt 1995). However, the predictive ability of these models is only as good as the quality of the behavioral observations used in the calibration. The availability of high-quality data for calibration has been limited by the availability of survey data on producer behavior. Data collection has often focused on specific watersheds, limiting the transferability and scope of these models. With the increased availability of high spatial resolution remote sensing data, we have an exciting opportunity to extend this approach to capture producer adaptation at a finer scale and across a broader geographic scope than has been possible to date. In this project, we propose to leverage and combine our diverse teams previous work in multiple disciplines (see section 1.2) to develop and calibrate a stakeholder-informed, innovative, and integrated hydro-economic model that incorporates three major advances:

1) We will exploit new satellite-based remote sensing methods and products to calibrate our hydro-economic model. Specifically, we propose to ingest remote sensing data into a positive mathematic programming (PMP; Howitt 1995) approach to capture previously underrepresented factors that influence farmer decision-making. This will allow us to operationalize a hydro-economic model that spans a wider geographic scope than previous studies, with the potential to move hydro-economic modeling from the watershed to the sub-continental scale. 2) We will implement a modeling approach based on recursive Bayesian inference that will permit us to evaluate the quality of the predictions based on the quality of the data (Maneta and Howitt 2014). It will also allow us to evaluate explicitly how changes in risk and uncertainty influence producer decision-making. This is a critical innovation given that the IPCC (2014) recently recognized that risk plays an important, and understudied, role in driving producer adaptation to climate change. 3) We will trace the effect of producer decision-making on regional hydrologic systems. This innovation allows us to understand how behavior affects the availability of water in the future, and also how the water-use decisions of individuals propagate through the hydrologic system to influence the behavior of downstream water users.

These innovations will advance hydro-economic modeling, overcome current limitations, and allow us to develop new insight into how famers behave under resource and policy constraints at unprecedented spatial extents and spatio-temporal resolutions. The resulting model will contribute to the next generation of decision support tools used in water policy analysis. Our proposed decision support tool is poised for use as a continuous, operational policy support system because the response of farmers to changing conditions can be continually updated using recursive inference methods from frequently available remote sensing information. This tool will support improved policy analysis to decide how to use water resources, including where to invest in water development infrastructure, how to design adaptation pathways, how to estimate water value, and how to manage water banks and other water marketing tools. The model will be applied, and its accuracy defined, for Montana agricultural systems.

These systems span a representative range of conditions in the western U.S., including extensive dryland agriculture that is particularly vulnerable to climate fluctuations, the existence of shared water governance with native groups and compacts with neighboring states, constraints imposed by legacy water rights and prior appropriation laws. 1.1. Preliminary work Most models that integrate water resources and agricultural economics are composed of an economic optimization component linked to some type of hydrologic model that provides physical constraints on the amount of water and land available for agricultural production (Harou et al. 2009). Classic linear optimization models of agriculture implemented to simulate agent behavior often produce unrealistic results because it is not possible to explicitly account for all of the variables affecting farmer decisions. To overcome this problem, many modern economic optimization models used in policy analysis are based on a methodology called positive mathematical programming (PMP, Howitt (Howitt 1995)). PMP reduces the amount of data and artificial restrictions needed to calibrate classic optimization models. It also avoids overspecialization in crop production (Howitt 1995) and ensures that the model calibrates to observed conditions. An important characteristic of models calibrated using PMP is that they relate agricultural production (yield and profit) to agricultural input variables (e.g. crop mix, acreage, water applied) using observed farmer response, not the physiology of the crop or other agronomic information. This is important because, when calibrated this way, the model captures the actual behavior of farmers and their actual reaction to external factors, such as droughts and risk, rather than the behavior that would be optimal from a purely agronomic point of view. The economic behavior of farmers is motivated by a desire to maximize profit but also driven by culture, personal experience, and tradition, among other factors, which are often developed to reduce risk. These important features that drive the economic behavior of farmers are captured using the PMP methodology. Models based on PMP have been used intensively in drought analysis and policy design in California (Connell-Buck et al. 2011; Medelln-Azuara et al. 2011). These models are at the heart of the Statewide Agricultural Production Model (SWAP, Howitt et al. (Howitt et al. 2012)), which is used in the agricultural economic component of the CALVIN model of the California water system (Draper et al. 2003). SWAP is also used for policy analysis by the California Department of Water Resources (Department of Water Resources 2009) and the U.S. Department of the Interiors Bureau of Reclamation (US Bureau of Reclamation 2011). Our team members have also used it to calibrate spatially-explicit, coupled hydrologic-economic models (Maneta et al. 2009a; Maneta et al. 2009c; Cobourn and Crescenti 2011). PMP is a well-established method of calibrating hydro-economic models, but its predictive ability hinges on the quality and quantity of the data that it uses to reflect observed farmer behavior. To date, PMP-based hydro-economic models are calibrated using costly survey data. This project will capitalize on the wealth of operational remote sensing data products and algorithms that are becoming available at little to no cost to improve the PMP calibration. Our team contains extensive experience in the design and application of remote sensing algorithms for regional to global scale assessment and monitoring of vegetation. Relevant experience includes the development and use of satellite microwave sensor based parameter retrievals for ecosystem studies (Jones et al. 2010; Jones and Kimball 2010; Jones et al. 2012); development of enhanced retrieval of plant biomass and phenology by fusing synergistic satellite optical-infrared and microwave remote sensing information (Kimball et al. 2009; Mu et al. 2009); documenting and improving the accuracy of satellite based time series of vegetation productivity (Heinsch et al. 2006; Kimball et al. 2007; Zhang et al. 2007) and evapotranspiration (Zhang et al. 2010). To take advantage of the high temporal frequency of remote sensing information we will leverage a second key enhancement of the PMP method (Maneta and Howitt 2014). This methodological extension permits recursive assimilation of remote sensing information using a stochastic data assimilation framework that overcomes two major limitations of classic PMP: 1) it now permits more robust model calibration by blending new and past information during the calibration process, avoiding over-calibration for the conditions of a single year; and 2) it generates predictions of resource allocation in terms of probability distributions that reflect the quality of the calibration and the uncertainty in the observations of agricultural activity. The stochastic data assimilation framework is based on the equations of the ensemble Kalman filter (Evensen 2003) , which permits recursive updates of the mean and covariance of the economic model parameters as new observations of agricultural activity become available (Error: Reference source not found). As more information is assimilated, the algorithm will improve the identification of the model parameters, which over time will converge to a distribution that reflects the quality of the observations being assimilated. Uncertainty in the model parameters and in the hydrologic conditions are also reflected in the prediction of resource allocation in the form of probability distributions (Error: Reference source not founda). Once the model is calibrated, it can be used to predict and study how farmers are likely to reallocate resources under various conditions by running the model under different scenarios of crop prices and costs of agricultural inputs, or under different levels of water and land restrictions due to environmental or policy factors (Error: Reference source not foundb). The probability distribution of the model parameters also permits an interpretation that provides insight into how risk influences producer decision-making and adaptation. We propose to build on this model component to identify and understand how the variance of critical economic and hydrologic parameters affects producer decision-making about resource use and the corresponding

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References

[1] A. B. McCarl, Elaborations on climate adaptation in U.S. agriculture, Choices 30 (2) (2015) 1–5.

[2] S. Rose, The inevitability of climate adaptation in U.S. agriculture, Choices 30 (2) (2015) 1–5.

[3] S. Bergstrm, The HBV Model, in: V. P. Singh (Ed.), Computer models of watershed hydrology, Water Resources Publications, Highlands Ranch, Colorado, 1995, pp. 443–476.

[4] S. Bergstrom, A. Forsman, Development of a conceptual deterministic rainfall-runoff model, Nordic hydrologydoi:10.2166/nh.1973.013.

[5] V. T. Chow, D. R. Maidment, L. W. C. N. P.-G. G. e. G. s. e. G. s. G. e. G. k. G. n. w. n. w. G. Mays, Applied hydrology, McGraw-Hill, New York, 1988.
URL http://uclibs.org/PID/115947

Appendix A. Hydrologic model

The hydrologic system is simulated using a rainfall runoff model coupled to a routing component that simulates the regional stream network. We use an adaptation of the HBV model [3, 4] to simulate subcatchment-scale hydrologic processes (snowmelt, evapotranspiration, infiltration) and to transform precipitation into runoff and streamflow. Runoff that reaches the channel is routed through the stream network using the Muskingam routing algorithm [5]. We provide here a description of the implementation of the algorithms.

Appendix A.1. Rainfall Runoff component

The HVB model is implemented as a mixture of gridded and vector-based operations to leverage the distributed nature of gridded meteorological datasets and the reduced computational burden of operating over polygons that aggregate processes over uniform hydrologic response units (HRU).

Snowpack processes and soil processes are calculated over the uniform grid imposed by the meteorological inputs (precipitation, air temperature, and potential evapotranspiration). In the next two paragraphs subscript i indicates that the variable is spatially distributed and occurs at grid point i. Superscript t indicates that the variable is dynamic and varies with the time step. Variables with no script or superscript indicate that the variable is spatially constant or time invariant.

Precipitation and snowpack processes. Precipitation is partitioned between snowfall and rainfall using minimum and maximum daily air temperatures and a critical temperature threshold Tc defining the snow-rain transition:

$$Snow_i^t = \begin{cases} P_i^t & Tmax_i^t < Tc_i \\ P_i^t * \frac{Tc_i - Tmin_i^t}{Tmax_i^t - Tmin_i^t} & Tmin_i^t < Tc_i < Tmax_i^t \\ 0 & Tmin_i^t > Tc_i \end{cases} \quad (A.1)$$

$$Rain_i^t = P_i^t - Snow_i^t \quad (A.2)$$

Snowfall during day t contributes to the snow water equivalent of the snowpack:

$$SWE_i^t = SWE_i^{t-1} + Snow_i^t \quad (A.3)$$

The snowpack melt process is simulated using a degree day factor model occurs when average air temperature exceeds a air temperature threshold (Tm):

$$Melt_i^t = ddf_i * (Tav_i^t - Tm_i)] \text{ for } Tav_i^t > Tm_i \tag{A.4}$$

$$Rain_i^t = P_i^t - Snow_i^t \tag{A.5}$$

Any melt form the snowpack during time t is subtracted from the snowpack storage and added to the amount of water ponded in the surface:

$$Pond_i^t = Pond_i^{t-1} + Melt_i^t + Rain_i^t \tag{A.6}$$

$$SWE_i^t = SWE_i^t - Melt_i^t \tag{A.7}$$

Soil processes. Recharge into the soil system occurs when ponded water infiltrates into the soil. Ponded water that is not infiltrated becomes overland flow. The fraction of ponded water that infiltrates into the soil is a exponential function of the relative water storage in the soil.

$$\Delta SM_i^t = Pond_i^t * \left(1 - \frac{SM_i^t}{FC_i^t}\right)^{\beta} \tag{A.8}$$

$$SM_i^t = SM_i^t + \Delta SM_i^t \tag{A.9}$$

$$OVL_i^t = Pond_i^t - \Delta SM_i^t \tag{A.10}$$

Actual evapotranspiration is also controlled by the degree of saturation and reduces the amount of water storage in the soil:

$$AET_i^t = PET_i^t * \left(\frac{SM_i^t}{FC_i * LP_i}\right)^{\beta} \tag{A.11}$$

$$SM_i^t = SM_i^t - AET_i^t \tag{A.12}$$

$$\tag{A.13}$$

Percolation and runoff generation. Once water enters the soil it percolates and produces outflow in two soil layers. These processes are implemented at the HRU level. For this, calculations about overland flow generation and soil moisture performed at the grid level are averaged over subwatersheds representing HRUs. Spatial arithmetic averaging of soil water storage over all grid cells i contained within a given HRU j is represented using angle brackets $< . >$. Mass balance and percolation of water from the soil upper to the soil lower zone is given by:

$$Rech_j^t =< OVL_i^t >_j + < max(SM_i^t - FC_i, 0) >_j \tag{A.14}$$

$$SUZ_j^t = SUZ_j^{t-1} + Rech_j^t + Pond_j^t - Q0_j^t - Q1_j - PERC_j \tag{A.15}$$

$$SLZ_j^t = SLZ_j^{t-1} + PERC_j - Q2 \tag{A.16}$$

The generation of output from the soil surface, and the upper and lower soil zones is given by:

$$Q0_j^t = max((SUZ_j - HL1_j) * CK0_j, 0.0) \tag{A.17}$$

$$Q1_j^t = SUZ_j * CK1_j \tag{A.18}$$

$$Q2_j^t = SLZ_j * CK2_j \tag{A.19}$$

$$Qall_j^t = Q0_j^t + Q1_j^t + Q2_j^t \tag{A.20}$$

The total outflow from HRU j on day t is distributed over time to produce the catchment response by convoluting the output of HRU j by triangular standard unit hydrograph with base M_{base}.

$$Q_j^t = \sum_{i=1}^{M_{base}} Qall_j^{t-i+1} U(i) \tag{A.21}$$

$$U(i) = \begin{cases} \frac{4}{M_{base}^2} * i & 0 < i < M_{base}/2 \\ -\frac{4}{M_{base}^2} * i + \frac{4}{M_{base}} & M_{base}/2 < i < M_{base} \end{cases} \tag{A.22}$$

where U is a triangular unit hydrograph of unit area with a duration MAXBAS.

Appendix A.2. Routing component

The response at the end of each HRU is routed through the stream network using the Muskingum routing model. In this model the storage in each stream reach k is given by the following discharge-storage equation:

$$S_k^t = K\left[eQ_{in} + (1-e)Q_{out}\right], \tag{A.23}$$

which has parameters K and e controlling, respectively, the celerity and dispersion of the wave routed through the channel.

Substituting this relationship in a finite-difference form of the continuity equation $\frac{S_k^{t+1} - S_k^t}{\Delta t} = Q_{in} - Q_{out}$ for a multi-reach system with lateral inflows injected upstream of reach k at average constant rate through time step t q_k^{t+1} yields:

$$Q_k^{t+1}\left[K_k(1-e_k) + 0.5\Delta t\right] + Q_{k-1}^{t+1}\left[K_k e_k - 0.5\Delta t\right] \tag{A.24}$$

$$= Q_k^t\left[K_k(1-e_k) - 0.5\Delta t\right] + Q_{k-1}^t\left[K_k e_k + 0.5\Delta t\right] \tag{A.25}$$

$$+ q_k^{t+1}\left[K_k(1-e_k) + 0.5\Delta t\right] \tag{A.26}$$

The equation is solved using an explicit finite difference scheme.

that becomes unstable if $\Delta t > 2 * K_k * (1-e_k)$, for this we implemented an adaptive time stepping scheme

$$a = (\mathbf{K} * (1-e) + dt * 0.5) b = (K * e - dt * 0.5) c = (K * (1-e) - dt * 0.5) d = (K * e + dt * 0.5) \tag{A.27}$$