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Analyzing rainfall effects on agricultural income: Why timing matters

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Abstract

Water is a key input to agricultural production and therefore fluctuations in water availability may impact agricultural productivity and revenue. Climate science tells us that most of these fluctuations are increasingly resulting from intra-year, instead of interyearly, shifts in the timing and intensity of rainfall. Consequently predictions of the economic effects of these fluctuations would likely differ depending on how these shifts are taken into account by the empirical models. To investigate this, the present paper introduces a novel hydro-economic model in which the timing and intensity of rainfall affect the productivity of a partially irrigated agricultural system in Brazil. The specification of the production function is designed to reflect intra-year, in a monthly or seasonal basis, and interyearly shifts on rainfall to show how the opportunity cost of supplementary irrigation supply varies with changes in the timing and intensity of rainfall. Results suggest that the timing of rainfall is indeed an important economic variable and models that take into account shifts only on a yearly basis will tend to underestimate the impacts of water scarcity on agricultural income.

JEL Classification: Q10; Q25; Q54

Keywords: Applied microeconomics; Water resources; Agricultural income; Positive mathematical programming; Temporal resolution; Hydroeconomic modeling

1. Introduction

Climate change and shifts in the timing and intensity of rainfall is widely acknowledged as being already in evidence in many parts of the southern hemisphere. A common characteristic of these effects is that while the yearly mean rainfall quantity may be relatively unchanged, climate change will result in significant shifts in the timing of the rainfall and its variability intrayearly. In several regions this timing is predicted to be relatively subtle and may take the form of a one to two-month shift in the rainfall pattern. It follows that economic and social analysis to measure the impact of this important change must be able to reflect the differences in both the timing and quantity of rainfall.

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The effects of fluctuations in rainfall and water availability on agriculture have been recently investigated by a wide array of methods and approaches. Surveys of agricultural models that include rainfall, temperature and water as determinants of productivity, land price, profits and yields have been compiled in Dell et al. (2014) and in Booker et al. (2012). In the former, the focus is on econometric studies and in the latter, the focus is on constrained optimization models. A couple of examples are Hidalgo et al. (2010), Lobell et al. (2011), Deschênes and Greenstone (2007), Schlenker and Lobell (2010), Rosegrant et al. (2000), Cai et al (2003), Welch and Vincent (2010), Wang et al. (2016) and Olayide et al. (2016). On Brazil, more specifically, examples are Evenson and Alves (1998), Sangui and Mendelsohn (2008), Féres et al. (2011), Maneta et al. (2009), Haddad et al (2013), Masseti (2013), Cunha et al. (2014) and Torres et al. (2016). Other studies, outside the economic literature, show how crop productivity impacts estimates from changes in water availability and rainfall vary according to different spatial resolutions (global, regional etc), such as Carbone et al (2003), Mearns et al. (1999, 2001, 2003), Eastering et al (1998). In these papers, however, rainfall is generally specified on an yearly, or at best, a seasonal basis and thus they are unable to reflect the results of shifts in the timing of rainfall that climate modelers tell us will be one of the main results of global climate change (Feng et al., 2012; Carbone et al., 2003; Mearns et al., 1999 and Trenberth, 2005).

To examine whether the timing of water availability and rainfall is an important economic variable, this paper uses a novel hydro-economic model in which the timing of rainfall and supplementary irrigated water supplies can affect the productivity of a partially irrigated agricultural system. The specification of the production function and water supply either in the form of water stored in reservoirs or rainfall is designed to reflect shifts in monthly rainfall totals and to show how the opportunity cost of supplementary irrigation supply varies with changes in the timing of rainfall.

The paper opens with a discussion on estimation methods based on the specialized literature and then introduces the analytical model with a brief discussion of its calibration and verification against an empirical case study in central Brazil. In the empirical section the model is run to generate results that compare the costs of shifts in rainfall under the standard hydro-economic model, which is specified on a yearly or seasonal basis, with the new model that is able to analyze a monthly distribution of rainfall and its resulting opportunity costs. The results are followed by the conclusions section with a discussion of the policy cost of this particular aspect of climate change and the effects of shifting rainfall patterns on the increasing value of supplementary irrigation that may be able to offset some of the effects. Additional discussion explores the generality of the approach and the ability to extend it to areas other than Brazil.

2. Methodology

Generally researchers follow one of the two main approaches to model the effects of changes in rainfall and water supply on agricultural productivity and income: econometrics and mathematical programming. The first approach relies on cross-section or panel data econometric estimation of production functions, or Ricardian land price, profit and crop yield equations. Besides the usual production and crop output and input price data, researchers that follow this approach may complement their datasets with information on rainfall and temperature from gridded data, satellite data and reanalysis data, Dell et al (2014). Some examples of this approach are Kaiser et al (1993), Adams et al (1995), Deschênes and Greenstone (2007), Schlenker and Lobell (2010), Hidalgo et al. (2010), Welch and Vincent (2010), Fisher et al (2012), Wang et al. (2016) and Olayide et al. (2016).

As seen in Booker et al., empirical water researchers also rely on mathematical programming models that involve the maximization of an economic objective function (e.g., net-revenue) subject to a set of physical and institutional constraints including hydrological and agronomic factors. Two types of models can be highlighted: holistic and coupled. In the first, economic, hydrologic and agronomic aspects are spatially integrated in a single model characterized by a system of water supply and demand nodes. Examples of this approach are the SWAP model as in Howitt et al. (2001 and 2012), the WEAP model as in Yates et al. (2009) and the CalSim model in Draper and Lund (2004). In the coupled modeling approach, distinct economic, hydrological and agronomic models are built separately and integrated iteratively via linking equations. Examples of coupled models are Maneta et al (2009), Torres et al (2012) and Torres et al (2016).

For this study we follow the mathematical programming approach for two main reasons. The first is that when extensively reviewing the econometric studies on climate and agriculture, Dell et al. highlighted a couple of classical problems related to models based on cross-section data, such as inconsistent estimators and unobservable relevant variables correlated with climate, that can be smoothed out with the use of econometrically estimated fixed-effects panel data models. This latter approach, however, requires at least two years of observations, a condition that cannot be met by the database used here, which is based on a single year of farmer level primary data. Another reason is that mathematical optimization allows for a richer representation of the physical constraints that real farmers face when deciding on what and when to crop. The precise characterization of these constraints is key for this study as alternative timings regarding rainfall and irrigation water supplies imply different specifications for the set of constraints facing by the farmers.

The model is divided in two components: economic and hydrological. In the economic component, crop and farm specific production functions that characterize the agriculture system within a watershed, located near Brasília, Brazil, are parameterized using Positive Mathematical Programming (PMP), Howitt (1995), and adapted to the study site as in Torres et al (2016). These functions are then used in a regional net-revenue maximization model subject to a set of physical constraints. It is important to notice here that since our unit of observation, and the appropriate data, is at the farmer level, the crop and farmer-specific production functions are parametrized using PMP without having to incurr into maximum entropy methods to disaggregate production parameters from coarser (e.g.: regional) to finer spacial scales, such as the farmer level, as done in Howitt and Msangi (2014). The hydrological component uses a mass-balance model to estimate the monthly, seasonal and yearly water available for irrigation to farmers in the watershed. This information is than used to set the physical constraints on water and rainfall used in the economic component. These two components are then sequentially coupled to allow for the measurement of the effects of variations in rainfall and the volume of stored water in small reservoirs on agricultural income given alternative model timing resolutions.

2.1. Economic component

We make the usual assumption that the multiproduct and multi-input farmers maximize net-revenues associated with growing irrigated and rain fed crops, designated in the model by the superscripts *ir* and *r* respectively. For the *ith* irrigated crop, inputs used are land ($land_i$), applied water (aw_i), materials (mat_i) and labor (l_i). For the *jth* rain fed crop the input set includes land ($land_j$), materials (mat_j) and labor (l_j). Crop production is modeled by a Constant Elasticity of Substitution (CES) production function that yields the maximum output for a crop given the amounts of the inputs used to grow it. For irrigated crops (superscript *ir*) and rain fed crops (superscript *r*), the CES production functions are respectively specified as

$$q_i^{ir} = A_i\left(b_{land_i} land_i^{\gamma ir} + b_{aw_i} aw_i^{\gamma ir} + b_{m_i} mat_i^{\gamma ir} + b_{l_i} l_i^{\gamma ir}\right)^{\frac{\varepsilon_i}{\gamma ir}} \tag{1}$$

and

$$q_j^{r} = A_j Precip_j \left(b_{land_j} land_j^{\gamma r} + b_{m_j} mat_j^{\gamma r} + b_{l_j} l_j^{\gamma r}\right)^{\frac{\varepsilon j}{\gamma r}} \tag{2}$$

where A is a scale parameter and $b_{land}, b_{aw}, b_m, b_l$ are the share parameters. $\gamma ir = \frac{\sigma^{ir}-1}{\sigma^{ir}}$ and $\gamma r = \frac{\sigma^{r}-1}{\sigma^{r}}$ in which σ^{ir} and σ^r are the elasticity of input substitution for irrigated and rain fed crops, respectively. ε_i and ε_j are the parameter associated with returns to scale in the production of crops *i* and *j*.

Rainfall is handled as a shifter in the rain fed production function and is defined as

$$Precip_j = \frac{pr_j^a}{pr_j^e} \tag{3}$$

where pr_j^a and pr_j^e are the actual and expected amounts of rainfall to fall onto the area covered by crop *j*. In the irrigated production function rainfall is part of total applied water, that is $aw_i = sw_i + pr_i$. Where sw_i is the total amount of water stored in reservoirs used in the irrigation of crop *i*, which can be controlled by the farmer, and pr_i is the amount of rainfall that falls onto the area covered by crop *i*, and is assumed to be exogenous. Groundwater is not used for irrigation in the area of study.

The crop and farmer-specific share parameter estimates in the production functions are analytically calculated under the assumption that the farmers' objective is to maximize net-revenue. In other words, as a first-order condition for a maximum, farmers will choose the optimal amounts of the inputs under their control such that the value of the input marginal productivity equals input marginal cost. For instance, for an irrigated crop i, the first order condition for labor can be specified as

$$p_i \frac{\partial q_i^{ir}(land_i, aw_i, mat_i, l_i)}{\partial l_i} = MC_{l_i}, \tag{4}$$

where p_i is the unit price of the *ith* crop, and $\frac{\partial q_i^{ir}(land_i, aw_i, mat_i, l_i)}{\partial l_i}$ is the marginal product of labor in crop i and MC_{l_i} is the marginal cost of labor when used in crop i. Assuming constant returns to scale ($\varepsilon_i = \varepsilon_j = 1$), so that for each crop and farmer the sum over the estimated share parameters equals 1, expressions for the share parameter estimates can be analytically derived. These expressions are functions of input quantities, unit crop prices, marginal input costs and the elasticities of input substitution.[1]

For unrestricted inputs such as materials and labor, marginal costs are defined, respectively, as the unit prices of materials (fertilizers, pesticides, seeds etc) and the price of a man-hour of labor. For the restricted supply inputs such as land and stored water, marginal costs are constructed as follows. For the water withdrawn from the reservoirs, the marginal cost each farmer faces is a sum of its unit cash cost plus an estimate of the farmer's water scarcity shadow value. The idea here is that for whatever cash cost paid, markets for water are non-existent. By adding a measure of its scarcity value, we more accurately reflect its true cost.

For land costs, we follow the same reasoning. That is, to the unit land cash cost, a land shadow value is added to the measure of its marginal cost. Besides these two components of the marginal cost of land, a third component is added to it: the implicit marginal cost of land or the *PMP* term. This term represents all other marginal costs faced by the farmers when allocating land to the different irrigated and rain fed crops that cannot be directly observed by the researcher. In a nutshell, a farmer could have, in theory, allocated an additional unit of land to the nominally more profitable crop from the least profitable crop that was actually observed to be grown in the base year. Since the farmer didnt́ make this reallocation, under profit maximization, we can conclude that it was because there were some other costs associated with this land allocation to the nominally more profitable crop at the margin. Since each farmer has a different set of crops, with different profitability, the *PMP* term becomes crop ***and*** farmer specific.

The stored water and the land shadow values as well as the *PMP* term are estimated by a linear programming model (*LPM*). In the *LPM*, the goal is to find the allocation of land and all other input quantities, assumed to be in fixed proportions to land, across all farmers and crops that maximize regional net-revenue. This maximization is subject to a set of constraints on the amount of stored water available and land. The set also contains a calibration constraint that restricts the amount of land allocated to a given crop to be less or equal to the amount of land allocated in the base year. The value of the *Lagrange* multipliers associated with the water, land and calibration constraints are then used as the water and land shadow values and the *PMP* term respectively.

With data on input quantities, market input prices, shadow values for the limited availability inputs (land and stored water) and the *PMP* term, the only missing information necessary for the estimation of the share parameters in (1) and (2) are the elasticities of input substitution. There are several studies on estimates of elasticities of input substitution between owned and purchased inputs in agricultural production. Salhofer (2001), with his survey on 32 econometric studies, found the range of Allen elasticities to be between 0.3 and 1.5. Gomez et al (2004), Boyd and Newman (1991) and Seung et al (1998) also provide some estimates. Gomes et al., in particular, found an elasticity of input substitution for irrigated crops between land and an aggregate of capital-water of 0.7, within the range showed in Salhofer (2001). Based on these studies we use a value for the elasticity of input substitution of 0.7 for irrigated crops and 0.3 for rain fed crops, given the reduced ability for input substitution in the production of crops that rely solely on exogenous rainfall.

Once we have the values for the share parameters we substitute them in (1) and (2), along with data on output and input quantities and the values of the elasticities of input substitution, to derive the estimates for the rain fed and irrigated crops scale parameters A_i and A_j, respectively. With the parameterized production functions we can then

[1] A more detailed display of how the parameter estimates are derived can be seen in Maneta et al (2009).

define the non-linear regional net-revenue function that is subsequently used for simulations. The regional net-revenue function is specified as

$$\max_{\substack{land_{ig}, m_{ig}, l_{ig}, \\ land_{ig}, sw_{ig}, m_{ig}, l_{ig}}} net \sum_g \sum_{ij} [p_{jg}\hat{q}^r_{jg}(land_{jg}, mat_{jg}, l_{jg}) + p_{ig}\hat{q}^{ir}_{ig}(land_{ig}, aw_{ig}, mat_{ig}, l_{ig}) - p_{sw_{ig}} sw_{ig} - m_{ig} \\ - p_{l_g} l_{ig} - l\hat{c}^{ir}_{ig}(land_{ig}) - m_{jg} - p_{l_g} l_{jg} - l\hat{c}^r_{jg}(land_{jg})] \tag{5}$$

where p_{jg} and p_{ig} are respectively the unit price of the *jth* rain fed and *ith* irrigated crops received by farmer g. $\hat{q}^r_{jg}(land_{jg}, mat_{jg}, l_{jg})$ and $\hat{q}^{ir}_{ig}(land_{ig}, aw_{ig}, mat_{ig}, l_{ig})$ are the crop- and farmer-specific parameterized production functions for rain fed and irrigated crops. m_{ig} and m_{jg} are the costs with materials used in the *ith* and irrigated *jth* crops respectively. That is, instead of using prices separated from quantities, we use a measure of the total material expenditures per crop (the sum, by crop, of the unit price paid of each material used times its quantity).[2] p_{l_g} is the labor price defined as the price of a man-hour of work and p_{sw_g} is the unit price of stored water used by farmer g and is defined as the marginal cost of stored water discussed above. Since famers do not directly pay a unit fee for the water, we use, as a proxy for its cash cost, an average irrigation cost estimated as the sum, over all crops, of the irrigation costs with labor, electricity and yearlyized capital value divided by the number of crops irrigated.

Last, but not least, notice that in (5) two terms are added to the regional net-revenue function: $l\hat{c}^{ir}_{ig}(land_{ig})$ and $l\hat{c}^r_{jg}(land_{jg})$. These are parameterized functional forms for the cost of land a farmer g faces when allocating land to the *ith* irrigated and *jth* rain fed crops. By adding these terms, the model calibrates without the need to add calibration constraints, as done in *LPM* describe above.[3] More specifically, cost with land is assumed to follow an exponential functional form with respect to land. That is, $l\hat{c}^{ir}_{ig}(land_{ig}) = \hat{\delta}_{ig} e^{\hat{\gamma}_{ig} land_{ig}}$, and $l\hat{c}^{ir}_{jg}(land_{jg}) = \hat{\delta}_{jg} e^{\hat{\gamma}_{jg} land_{jg}}$ with crop- and farmer specific estimated parameters $\hat{\delta}$ and $\hat{\gamma}$.[4] The parameters δ and γ are estimated by finding their values that minimize the sum of squared errors associated with a system of two equations. One parameter is obtained by setting the land marginal cost equal to the derivative of $l\hat{c}^{ir}_{ig}(land_{ig})$ and $l\hat{c}^r_{jg}(land_{jg})$, respectively, while the other is derived from the definition of the elasticity of land use in crop i or j, with respect to crop prices. This requires prior information on the value of the elasticities. As done in Torres et al. (2016), we use a value of 0.7 for all crops.

Maximization of the problem represented by Eq. (5) is subject to the following set of constraints:

Land availability

$$\sum_{i,j} (Land_{i_g} + Land_{j_g}) \le b_{land_g} \tag{6}$$

Water availability and water application

Yearly

$$aw_{i_g} = sw_{i_g} + pr_{i_g} \tag{7}$$

$$\sum_i sw_{i_g} \le b_{sw_g} \tag{8}$$

$$pr_{i_g} \le P_{i_g} \tag{9}$$

$$\frac{aw_{i_g}}{land_{i_g}} \ge k * \overline{wuse}_{ig} \tag{10}$$

[2] Materials are composed by several inputs used in a single crop, including different types of pesticides and fertilizers used along the different stages of planting. To use a separate price for each material would leave the model intractable.

[3] By calibration we mean that the optimal results of the contrained maximization model in terms of the input and output quantities associated with each irrigated and rain fed crop match the values seen in the field in the baseyear.

[4] Assuming an exponential functional form for the land cost function allows us to restrict the estimated costs to be positive. A more detailed discussion on the exponential land cost function can be found in Medellín-Azuara et al. (2010) and in Howitt et al. (2012).

Seasonal

$$aw_{i_g} = \sum_s (sw_{i_g}^s + pr_{i_g}^s) \tag{11}$$

$$\sum_i sw_{i_g}^s \leq b_{sw_g}^s \tag{12}$$

$$pr_{i_g}^s \leq P_{i_g}^s \tag{13}$$

$$\frac{sw_{i_g}^s + pr_{i_g}^s}{land_{i_g}^s} \geq k * \overline{wuse_{ig}^s} \tag{14}$$

Monthly

$$aw_{i_g} = \sum_m sw_{i_g}^m + pr_{i_g}^m \tag{15}$$

$$\sum_i sw_{i_g}^m \leq b_{sw_g}^m \tag{16}$$

$$pr_{i_g}^m \leq P_{i_g}^m \tag{17}$$

$$\frac{sw_{i_g}^m + pr_{i_g}^m}{land_{i_g}^m} \geq k * \overline{wuse_{ig}^m} \tag{18}$$

Eq. (6) establishes that the total yearly amount of land farmer g can use in the production of crops i and j throughout the agricultural year must be less or equal to the yearly total amount of land available, B_{land_g}. With respect to water, three alternative sets of constraints are utilized. If the temporal resolution is yearly, seasonal or monthly, the constraints on water use are represented by Eqs. (7) – (10), (11) – (14) and (15)–(18), respectively. More especially, Eq. (7) shows that the total amount of water used by crop i throughout the agricultural year, aw_{i_g}, must be equal to the yearly amount of stored water farmer g decides to apply, sw_{i_g}, plus the total yearly amount of water in the form of rainfall that falls over the land area where crop i is grown, pr_{i_g}. Constraint (8) says that the yearly amount of stored water farmer g uses to irrigate all irrigated crops, $\sum_i sw_{i_g}$, must be less than or equal to the yearly amount of stored water available to farmer g, b_{sw_g}. Constraint (9) establishes the total amount used from rainfall pr_{i_g} must be less or equal to actual amount of rainfall that falls onto crop i, grown by farmer g, $P_{i_g}^a$. Constraint (10) puts an upper limit on the amount of water stress that can be applied to a given crop i. That is, the yearly ratio of applied water to a hectare of land, $\frac{aw_{i_g}}{land_{i_g}}$, cannot fall below a certain threshold, $k * \overline{wuse}_{ig}$, where k is a parameter ranging from 0% to a 100% and $\overline{wuse}_{ig}$ is the applied water to hectare of land ratio used by farmer g on crop i in the baseline year. In this study k is assumed to be 0.85.[5]

Constraints represented by Eqs. (11)–(14) set up the scenario for the seasonal temporal resolution. Now, with Eq. (11), the total amount of water used by crop i throughout the agricultural year (aw_{i_g}) must be equal to the sum of the seasonal amounts of stored water and rainfall used. Where s refers to one of the 2 seasons within the agricultural year: the wet season from October of a given year through March of the following year; and the dry season, from April through September. Eq. (12) says that the total amount stored water farmer g uses to irrigate its crops in season s, $\sum_i sw_{i_g}^s$, must be less than or equal to the amount of water stored in reservoirs at season s available to farmer g, $b_{sw_g}^s$.

[5] It is important to notice here that ideally not only the parameter should not be same across time scales but also not the same across different regions in the world due to differences in soil types and climate. However due to the lack of proper information to the study site at the time the paper was in development, we have decided, after discussions with the co-author Lineu Rodrigues, a hydrologist specialized in the area of study, to choose an ad-hoc, albeit conservative, value of 0.85. In this context, we are thankful to a referee that pointed out for the importance of doing a sensitivity analysis on the k parameter value in order to check for the robustness of the results. We have performed this analysis and a discussion on the issue can be seen in the Results section below.

Eq. (13) establishes that the total amount used from rainfall in season s, $pr^s_{i_g}$, must be less or equal to actual amount of rainfall that falls onto crop i, grown by farmer g, in season s, $P^s_{i_g}$. Eq. (14) assures that ratio of applied water to a hectare of land in crop i, in season s, $\frac{sw^s_{ig}+pr^s_{ig}}{land^s_{ig}}$, must be greater or equal to $k * \overline{wuse^s_{ig}}$, where k is defined as above and $\overline{wuse^s_{ig}}$ is the applied water to hectare of land ratio used by farmer g on crop i in season s during the baseline year. Finally, analogously to the seasonal temporal resolution, Eqs (14) – (16) set up the constraints at the monthly temporal resolution in which m refers to one of the 12 months of the year.

The economic model was calibrated with data on input and output (prices and quantities) collected *in situ* during the agronomic base year of 2007/2008 and validated to the values observed in the field. The amount of stored water used by farmer and crop was calculated based on information on the frequency and duration of irrigation, considering irrigation technology. Rainfall data in daily millimeters were drawn from Rodrigues et al. (2012). On total there were 26 farmers operating in the basin. Small farmers (4 ha on average) form the majority of farmers in the area. Most of them grow a mix of vegetables and fruits and can be considered as small for Brazilian standards (3–5 ha). The exception is the farmer that operates a center pivot that can be considered large (more than 100 ha under cultivation yearly). Estimates of the volume of water stored in reservoirs available to each farmer g represented by b_{sw_g}, $b^s_{sw\,g}$ and $b^m_{sw\,g}$ in Eqs (8), (12) and (16) respectively were fed by the hydrological model described below.

2.2. Hydrological component

With the regional net-income model calibrated, simulations of restrictions on the amount of water either in the form of rainfall or water stored in reservoirs are used to derive the estimates of impacts on net-revenue under different model timing resolutions: yearly, seasonal and monthly. The method of analysis is as follows. We first analyze the impacts by assuming that cuts in stored water volume are directly proportional to cuts in rainfall volume. For example, a 10% cut in rainfall implies a 10% cut in stored water volume for all farmers. Alternatively, we assume that they are not proportional and that they relate to each other in a non-linear manner. The idea behind the non-linearity is that although we assume that a given cut or increase in rainfall affects all farmers in the same way, in terms of how much rain falls onto their crops, the effect of this cut or increase on their access to stored water may not be the same across the basin. For example, let's assume that in a given period in time it started to rain more heavily on the river mouth area, which caused a 5% increase in the volume of water along the water stream. At first, a similar increase of 5% is then seen in the volumes of the reservoirs along the river. But part of the water that fell in the mouth area may infiltrate in the soil and percolates more heavily into the reservoir that is closest to the creek mouth. Therefore a 5% increase in rainfall may imply a more than a 5% increase in volume of stored water available to farmers that withdraw water from this closest reservoir.

How much and where water infiltrates and percolates depends on several variables such as geographic position, soil porosity and declivity etc. In order to more precisely measure the relationship between rainfall and reservoir volumes we build a hydrological model. The Fig. 1 below shows the Buriti Vermelho River watershed. Farmers located within the basin draw water for irrigation from three of the five reservoirs. The black and gray dots represent small farmers and CP3 represents the location of a center pivot managed by a larger farmer. From Reservoir #1 water reaches first the farmers located near Channels 1a and 1b. The remaining water goes first to Reservoir # 2 that feeds farmers through Channel 2, and then to Reservoir 5 used by CP3.[6]

The hydrologic model simulates the river discharge and a canal model is used to simulate the daily amount of water diverted from the small dam to the canal and the amount of water that each farm gets. In the Buriti Vermelho basin, infiltration rates are high and the storm durations short. Most of the saturation excess runoff infiltrates after the storm ends and before it reaches an open water body.

The daily river discharge was simulated using the procedure described by Steenhuis et al. (2009) and Liebe et al. (2009). Basically the overland flow from contributing areas starts when rainfall exceeds evapotranspiration and fully saturates the soil. In this case, any moisture above saturation becomes runoff that can be estimated by adding the change

[6] Reservoirs 3 and 4 are not shown in the map since they are in disuse.

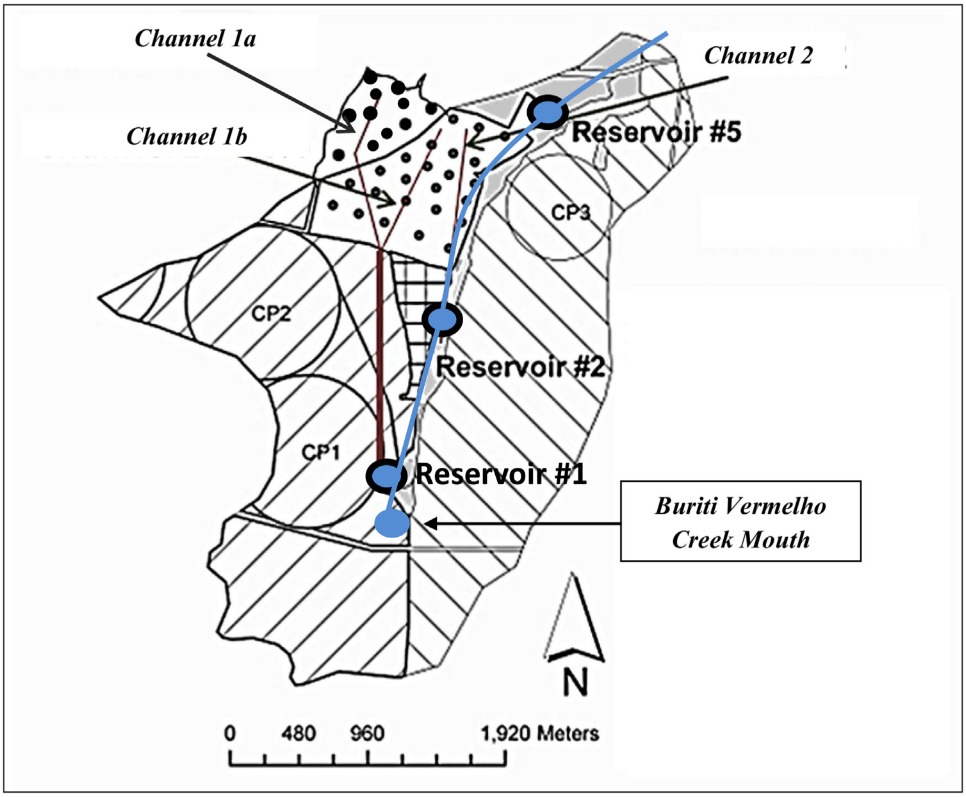

Fig. 1. The Buriti Vermelho watershed.

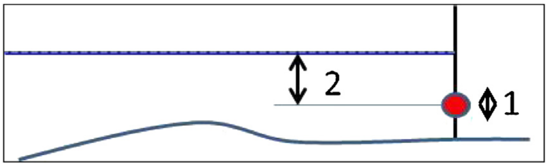

Fig. 2. Hydrological sequence.

in soil moisture from the previous time step to the difference between rainfall and actual evapotranspiration (Steenhuis et al., 2009), Eq. (19),

$$R = S_{t-\Delta t} + (P - AET)\ \Delta T \tag{19}$$

where P is the rainfall (*mm*/*day*), AET is the actual evapotranspiration (*mm*/*day*), $S_{t\_\Delta t}$ is the previous time step storage (*mm*), R is the saturation excess runoff (*mm*/*day*) and Δt is the time step.

The model was calibrated based on measured daily discharge for the period of 2005–2009 and validated for the period of 2010−2012. With the model validated, river discharge and the amount of water diverted to the canals was calculated. In particular, the canal model was built taking into account that the canals in the BV are not operated. This means that the amount of water diverted to the canals is a function of both pressure head and pipe diameter only (Fig. 2).

Where 1 is the pipe diameter and 2 is the pressure head. The pressure head was calculated daily for each reservoir using a stage discharge curve. The needed parameters were obtained from Rodrigues et al. (2012). The discharge in the channel was calculated using Manning equation with roughness coefficient for concrete.

Table 1
Regional net-revenue impacts under simulated cuts in rainfall.

% Cuts in rainfall from the Baseline	Yearly		Seasonal		Monthly	
	Value[a]	%	Value	%	Value	%
0	734.5	–	734.5	–	734.5	–
10	709.2	−3.4	709.2	−3.4	709.2	−3.4
20	684.3	−6.8	684.3	−6.8	683.8	−6.9
30	659.9	−10.2	658.3	−10.4	649.1	−11.6
40	632.7	−13.9	608.5	−17.2	569.8	−22.4
50	586.7	−20.1	529.1	−28,0	487.8	−33.6
60	514.2	−30.0	473.1	−35.6	425.5	−42.1
70	458.2	−37.6	401.7	−45.3	370.4	−49.6

[a] Values in thousands of Brazilian Reais.

3. Results

Table 1 shows the impacts on regional net-revenue from alternative cuts in rainfall (0–70%), assuming that they imply directly proportional cuts in the water volumes stored in the reservoirs. Impacts are displayed by the timing resolutions in which stored water and rainfall are modeled, namely: yearly, seasonal and monthly. In the baseline year, regional income was 734.5 thousand Brazilian reais. A 10% cut in rainfall volume however would imply, *ceteris paribus*, a decrease of 3.4% in net revenue no matter the timing resolution. When the cut in rainfall increases to 20%, the yearly and seasonal models predict a drop in net-revenue of 6.8% and the monthly model a slightly higher impact of 6.9%. As the cuts get deeper, impacts become more significant in magnitude, as expected. For example, with the yearly model, impacts increase from 3.4%–38%.

More interestingly, we can see how the impacts differ under alternative timing resolutions. Consider a 30% cut in rainfall. While the yearly model would predict a 10.2% drop in net-revenue, the seasonal model predicts a drop of 10.4% and the monthly model, 11.6%. And as the cuts get deeper, the differences in the predictions become higher. For example, in the event of a 50% cut in rainfall, the yearly, seasonal and monthly predictions would be 20%, 28% and 34% respectively. The same pattern is repeated in the successive cuts. In other words, the coarser the timing resolution of the model the more the regional impacts are underestimated.

It is important to check for the robustness of these results under different values for the *k* parameter, since from an agronomic point of view they should not be constant under different time scales to allow for differences in crop-water requirements and the levels of water stress a plant can handle during its growing cicle, as highlithed by Doorenbos and Pruitt (1977), Doorenbos and Kassam (1979) and Steduto et al (2012). To check for this, a sensitivity analysis was performed with the estimation of net-revenues under different values for *k* and alternative time scales and levels of rainfall. In all simulations, although net revenue estimates do change according to different values of *k*, the results consistently show that coarser time scales tend to underestimate the impacts of water scarcity on agricultural income. One elucidating simulation was performed by keeping a relatively more conservative value of *k* at 0.85, for the monthly time scale, and a less conservative value of *k* at 0.55, for the annual time scale (an unrealistic and extreme value of *k* to represent stress irrigation without assuming substantial yield losses). Under water scarcity (generally for levels of cuts in rainfall of 30% or higher), net-revenue estimates at the annual time scale with $k = 0.55$ would be 659.9, 635.5, 611.3, 584.6 and 534.8 for respective cuts in rainfall of 30, 40, 50, 60 and 70%. By looking at Table 1 above, we can see that under these same cuts, net-revenue estimates at the monthly time scale with $k = 0.85$ would range from 649.1–370.4. Now, had we also chosen 0.85 for the annual time scale, Table 1 also shows that the net revenue estimates would range from 659.9–458.2, under the same cuts in rainfall. Either 659.9–534.8 or 659.9–458.2 compared to 649.1–370.4 would lead to a conclusion of a significant underestimation of net revenue losses under the annual *vis-à-vis* the monthly time scale.[7]

This underestimation can also be seen by looking at Table 2 below which shows the months in which constraints start to become binding and positive shadow values are triggered.[8] For example, in the event of a 10% cut in rainfall the

[7] The full set of results of the simulations performed in the sensitivity analysis can be accessed upon request to the correspondent author.
[8] For farmers and months that do not appear in the table, shadow values are null.

Table 2
Monthly and yearly stored water shadow values in the event of a 50% cut in rainfall and stored water availability.

Monthly						Yearly	
Farmer	Month	Shadow Value	Farmer	Month	Shadow Value	Farmer	Shadow Value
v10	*Oct*	2.097	*v22*	*Oct*	0.778	*v10*	0.000
v13	*Dec*	4.002	*v23*	*Dec*	1.406	*v13*	0.009
v14	*Feb*	1.347	*v24*	*Feb*	5.403	*v16*	0.251
	Oct	0.510	*v25*	*Dec*	2.623	*v18*	0.015
v16	*Feb*	0.606	*v26*	*Oct*	1.082	*v24*	0.334
	Dec	2.954	*v27*	*Dec*	2.419	*v26*	0.015
v17	*Dec*	11.382	*v28*	*Feb*	1.314	*v27*	0.005
v18	*Oct*	2.274		*Oct*	1.543	*v28*	0.261
v19	*Dec*	4.718	*v31*	*Feb*	4.182	*v31*	2.513
v20	*Feb*	3.137		*Oct*	14.614		
	Dec	12.849	*v32*	*Dec*	4.210		
v21	*Dec*	4.695					

shadow values associated with the stored water constraints (Eqs. (8),(12) and (16)) are all zero, no matter the timing. While the shadow values associated to the rainfall constraints (Eqs. (9), (13) and (17)) are invariant to the temporal resolution. But as the cuts become larger, not only the shadow values on stored water and rainfall constraint costs become larger, but they also start to differ depending on the timing resolution. For example, consider a 50% cut in rainfall level and a specific farmer called *v10*. Under this 50% cut in rainfall and the directly proportional cut in stored water availability, the yearly model predicts that the yearly available stored water would be 10,655 m^3 and the farmer would use only 8297 m^3, triggering a null shadow value on stored water. Now if we consider the monthly temporal resolution model, we can see that stored water would be binding in the month of October, triggering a shadow value of 2.097.

For another farmer called *v13*, the yearly model would predict a shadow value of 0.009, while the monthly model would trigger a positive shadow value in December of 4.002. That is, under a 50% cut of stored water, the yearly model is saying that one additional unit of water per year for farmer *v13* would increase its net-revenue by 0.009 Brazilian Reais no matter the time the farmer applies it. Alternatively, the monthly model says that if the farmer had one more unit of stored water and applied it in December, their profits would increase by 4 Brazilian reais. In summary, the yearly model assumes that the impact of water scarcity is uniform throughout the year, or in other words that farmers can freely allocate water between the months. Under this assumption, water becomes artificially cheaper. There are several other examples with different farmers and different time periods in which the yearly model underestimates water scarcity values, particularly when water scarcity starts to become severe.

As already mentioned, the above discussion considers that cuts in rainfall imply a proportional cut in stored water volumes stored in the reservoirs. In order to allow for a non-linear relationship we consider the predicted stored water supply by farmer yielded by the hydrological model described above. Two scenarios are considered in the hydrological model predictions: a 30% and a 50% cut in rainfall. For example, a 30% cut in rainfall would impact stored water supply by taking into account the farmers' position, soil characteristics across the basin and monthly rainfall patterns. Table 3 below shows the monthly values of stored water supply considered in the proportional approach and the ones given by the hydrological model for example for farmers v10 and v30. Consider a 30% cut in rainfall in January. The hydrological model estimates a supply of stored water to farmer v10 of 1447.8 m^3, while by using the proportional approach the cut would imply a stored water volume 30% lower than the baseline value at 1266.8 m^3. We can then see that sometimes the proportional approach yields a higher water supply than the hydrological model and vice versa.

To investigate how the impacts differ across the basin, farmers were divided in groups according to their access to stored water. Farmers in groups 1 and 2 receive water from the first reservoir through the channels 1a and 1b respectively (see Fig. 1). Channel 1a has a 50% higher conveyance capacity than channel 1b. Farmers in group 3 withdraw water from Reservoir 2, through channel 2, which is filled with the remaining water from Reservoir 1 after farmers in groups 1 and 2 have used up their stored water. Results can be seen in Table 4 below.

In general, they corroborate the hypothesis that the coarser the timing resolution, the higher the underestimation of the water scarcity impacts on net-revenue. The magnitude of the discrepancy gets more significant in situations of

Table 3
Monthly stored water supply predictions by hydrological (*H*) versus proportional (*P*) approaches from a 30% and 50% cut in rainfall.

Months	Farmers							
	v10				v30			
	30%		50%		30%		50%	
	H[a]	P	H	P	H	P	H	P
January	1447.8	1266.8	1085.8	904.9	2014.6	1762.8	1511.0	1259.1
February	1307.8	1144.4	980.9	817.4	1819.9	1592.4	1364.9	1137.4
March	1448.0	1267.0	1086.0	905.0	2014.9	1763.0	1511.1	1259.3
April	1313.7	1226.1	963.4	875.8	1828.0	1706.1	1340.5	1218.7
May	1267.0	1267.0	905.0	905.0	1763.0	1763.0	1259.3	1259.3
June	1138.5	1226.1	788.2	875.8	1584.3	1706.1	1096.8	1218.7
July	1176.5	1267.0	814.5	905.0	1637.1	1763.0	1133.4	1259.3
August	1176.5	1267.0	814.5	905.0	1637.1	1763.0	1133.4	1259.3
September	1313.7	1226.1	963.4	875.8	1828.0	1706.1	1340.5	1218.7
October	1357.5	1267.0	1086.0	905.0	1888.9	1763.0	1511.1	1259.3
November	1401.3	1226.1	1050.9	875.8	1949.9	1706.1	1462.4	1218.7
December	1448.0	1267.0	1086.0	905.0	2014.9	1763.0	1511.1	1259.3

[a] Values in cubic meters.

Table 4
Regional net-revenue impacts under 30 and 50% cuts in rainfall – hydrological water supply estimates.

Scenarios and temporal resolutions	Regional	Group 1	Group 2	Group 3
30%				
Yearly	−10.5	−7.3	−7.4	−9.0
Seasonal	−11.2	−7.2	−7.8	−13.0
Monthly	−15.8	−7.4	−18.9	−33.6
50%				
Yearly	−36.1	−11.8	−20.2	−28.3
Seasonal	−41.6	−45.2	−29.5	−41.9
Monthly	−53.0	−46.0	−46.5	−64.8

more severe water scarcity. For example, the yearly model predicts a drop of 10.5% in net-revenue in the case of a 30% drop in the rainfall level. Under this scenario, the impact estimates would increase in absolute terms by 0.7% (11.2%–10.5%) and 5.3% had the modeler used a finer timing resolution such as seasonal and monthly respectively. Now, in the event of a more severe drought, as represented by a 50% drop in the rainfall level, the impact estimates would increase by 5.5% in the seasonal model and by 16.9% in monthly model compared to the estimates yielded by the yearly model. This underestimation pattern is also found when we look at the impacts by groups.

The analysis by groups allows us also to see that the impacts of a given cut in rainfall are not uniform across the basin. For example, farmers in group 3 are hit relatively harder. Given that they grow similar crops and use similar input mixes compared to the other farmers in groups 1 and 2, they probably face a higher profit impact due to their geographical position and access to stored water, since they withdraw water from reservoir 2 that is filled with the remaining water from reservoir 1 used first by the more upstream users.

3.1. Measuring the cost of seasonal shifts in rainfall

Several research papers have noted that climate change is likely to shift the seasonality of rainfall as well as its magnitude. Feng et al (2013) conclude that "...increases in rainfall variability were accompanied by shifts in its seasonal magnitude, timing and duration, thus underscoring the importance of analyzing seasonal rainfall regimes in a context that is most relevant to local ecological and social processes." Feng et al in their figure 3, show the changes in monthly rainfall for Parau, Brazil.

Table 5
Yearly net-revenue impacts due to a two-month shift and cuts in rainfall.

Cuts (%)	Monthly model[a]	Monthly model (2 month shift)	Shift cost (%)
0	734.5	677.3	−7.8
10	709.2	607.4	−14.4
20	683.8	573.7	−16.1
30	649.1	527.3	−18.8
40	569.8	483.6	−15.1
50	487.8	443	−9.2
60	425.5	400.1	−6.0
70	370.4	357.9	−3.4

[a] Values in thousands of Brazilian Reais as of 2008.

For the BV region, we simulated a possible two month shift in seasonality as well as a reduction in rainfall. The seasonality change was a shift to earlier rainfall events, with the shifted January rainfall being represented by the current March rainfall measure. Table 5 shows the economic effects of the shift, and of cuts in overall rainfall, by comparing the net-revenue estimates, under the monthly model, with and without the rainfall two-month shift. Under current rainfall levels, the two month shift would result in a loss of 7.8% in net-revenue as the regional yearly net-revenue is reduced from 734.5–677.3. The maximum loss associated with the shift would be under a 30% rainfall cut scenario (-18.8%).

Now, if we compare the results in Table 5 with the ones in Table 1, we can see that on average the yearly hydroeconomic model would underestimate the yearly regional impacts by 7.8% since it yields net return values that are unchanged under a shift scenario. A seasonal model may capture small changes at the seasonal margins but this would not accurately reflect the two rainfall seasons in the BV region. The yearly model would tend also to underestimate the impacts when shifts in rainfall occur simultaneously with rainfall shortages. For example, for a 30% cut in rainfall, the yearly model predictions, under or without the shifts, can be seen in Table 1 since annual results are invariant to the rainfall two-month shift. That is, the annual time scale model would predict a reduction in net-revenue from 734.5–659.9 (a 10.2% drop). The monthly model however would be sensitive to the shift as shown in Table 5 and predict a decrease from 677.3–527.3 (a 22.2% drop) under the shift and a much smaller decrease of 734.5–649.1 (a 11.6% drop) without the shift.These results further emphasize the point raised by Feng et al. that a disaggregated monthly analysis is required to accurately reflect both the changes the levels and the seasonality of rainfall under climate change.

4. Conclusions

This paper shows that the timing resolution of models biases the estimates of the cost of rainfall changes. Using a multiproduct calibrated agricultural production model coupled with a hydrological model, we show that the opportunity costs associated with water availability in the form of rainfall or stored water vary considerably. The variation depends on the timing resolution with which these water supply variables are considered by the modelers. The results show that the coarser the timing resolution, the more the impacts on agricultural income are underestimated. For example, as presented in Table 1, in the event of a 30% cut in rainfall, while the yearly model would predict a 10.2% drop in net-revenue, the seasonal model predicts a drop of 10.4% and the monthly model, 11.6%. And as the cuts get deeper, the differences in the predictions become higher. For example, in the event of a 50% cut in rainfall, the yearly, seasonal and monthly models would predict a drop of 20%, 28% and 34% respectively. Between the yearly and the monthly model, impacts are higher in absolute terms, in the latter by 14%.

The ability of models with finer timing resolutions to reflect the opportunity costs of rainfall and stored water to agriculture is based on the fact that plant water requirements vary across the life span of the plant and also to the time of crop planting and land coverage. For example, in the example described above of farmer v13, in Table 2, the monthly model was able to show that water was needed the most in the month of December, and if the farmer could apply one more unit of water in that month, her profits would increase more than if she applied it in any other month of the agricultural year. This could only be measured because the water supply and the timing of water use were set at the monthly temporal resolution. In summary, since the yearly model assumes that the impact of water scarcity is uniform throughout the year, or in other words that farmers can freely allocate water across the months of the year, water becomes artificially cheaper. This ability to model the monthly water use is therefore essential for the precise estimation of the costs with expected shifts in seasonality due to climate change. This cost is shown to be significant for a two month earlier rain season in this part of Brazil.

These results have clear implications for the study of water scarcity impacts on agricultural income and ultimately on the design of cost-effective public policies that aim to lift up farmers from poverty conditions prevalent in many rural areas of the world that are subject to water scarcity. While the spatial extent of the current empirical example is too small to be scaled up, results do indicate that the timing with respect to climatic variables such as rainfall and water supply, in this case water stored in reservoirs, may significantly influence the precise quantification of water scarcity impacts.

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