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The color of water: The contributions of green and blue water to agricultural productivity in the Western Brazilian Amazon

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ABSTRACT

Deforestation and global climate change are predicted to affect precipitation and agricultural productivity in the Amazon. Anecdotal evidence suggests that farmers are already being affected by changes in the timing and amount of precipitation, but there is little quantitative evidence on the mechanism by which precipitation affects production. This paper uses an innovative application of remote sensing and meteorological data to separate rainfall into green water (soil moisture that contributes to plant water use) and blue water (surface water), to estimate the impact of these water sources on the production and production efficiency of dairy in a mature colonization zone of the Brazilian Amazon. This approach allows us to draw inferences about different pathways through the precipitation-production causal chain and to link changes in precipitation with impacts on farm profits and welfare. We find that production and production efficiency are affected by green and blue water and that reductions in rainfall will have negative impacts that may disproportionally impact the poor. Our methods and results are informative to economists interested in this relatively new application of remote sensing data, to geographers interested in identifying the role of green and blue water in agricultural production, and more generally to researchers interested in the impacts of rainfall and water availability on small-scale producers in the Brazilian Amazon.

1. Introduction

The conversion of tropical forests to agricultural land contributes to climate change by increasing atmospheric carbon dioxide concentrations, increasing surface albedo, and reducing transpiration (Barkhordarian, Saatchi, Behrangi, Loikith, & Mechoso, 2019; Coe, Costa, & Soares-Filho, 2009; Espinoza Villar et al., 2009; Good, Jones, Lowe, Betts, & Gedney, 2013; Panday, Coe, Macedo, Lefebvre, & de Almeida Castanho, 2015). The net effects of land cover change on the availability of water in tropical forest regions are not yet well understood because of complex non-linear interactions that occur between the atmosphere, hydrosphere, and biosphere (Andréassian, 2004; Lacombe et al., 2016; Lima et al., 2014; Wohl et al., 2012). However, reductions in precipitation resulting in a longer dry season have already been observed in southern and eastern Amazonia (Davidson et al., 2012; Khanna, Medvigy, Fueglistaler, & Walko, 2017) and droughts have been predicted to have negative and persistent effects on forests (Saatchi, Asefi-Najafabady, Malhi, Aragão, Anderson, Myneni, & Nemani, 2013), though forest photosynthesis may be resilient to increased atmospheric dryness (Green, Berry, Ciais, Zhang, & Gentine, 2020). Future deforestation may exacerbate dry season length thereby decreasing rainfall (De Sales, Santiago, Biggs, Mullan, Sills, & Monteverde, 2020) and negatively impact agriculture, including beef and dairy production systems that are the predominant land uses in the Amazon.

Poor populations, as defined by relative and absolute poverty, are more likely to be negatively impacted by climate and weather shocks, including drought and the lengthening of the dry season (Balasubramanya & Stifel, 2020). This unequal impact occurs because the poor are positioned to lose a larger fraction of their wealth when weather and climate shocks occur, and because once the shocks have occurred, the poor have less savings and access to

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loans; both of which are often needed for recovery. These disadvantages make the poor more susceptible to poverty-environment traps (Barbier & Hochard, 2018a,b; Carter, Little, Mogues, & Negatu, 2007) and can lead to increases in poverty and reductions in human development (Rodriguez-Oreggia, De La Fuente, De La Torre, & Moreno, 2013). Yet because the income of the poor represents a small portion of national GDP, the impacts of climate change on this population are often largely invisible to government and policy makers (Hallegatte, Fay, & Barbier, 2018).

Precipitation is important for agropastoral systems and in particular, for rain-fed systems that are used by poorer small-scale farmers who cannot afford irrigation and wells. Water serves several important functions in agropastoral systems. "Green water" is soil moisture derived from local rainfall that returns to the atmosphere as evapotranspiration by vegetation and bare soil, and "blue water" is the water found in ponds, streams, and groundwater (Falkenmark & Rockström, 2006). Agriculture is the largest consumer of water in the Brazilian Amazon even though there is a limited use of irrigation (Lathuillière, Coe, Castanho, Graesser, & Johnson, 2018). It is unclear how changes in rainfall will impact agricultural productivity via changes in blue and green water, and whether those changes will disproportionately impact the poor. Green water, used in the production of fodder, is a valuable input for farmers who cannot afford who to buy or store cattle feed. Blue water (as surface water and groundwater) can be used for irrigation, cattle, and domestic activities. Any changes in precipitation are therefore of importance to the productivity of agriculture in deforested regions of the humid tropics, where rainfall has not historically been a limiting factor. Blue and green water consumptive uses are currently estimated to be within sustainable limits in the Brazilian Amazon, but increases in the intensification and/or extensification of agriculture have the potential to threaten the availability of blue water in the dry season (Lathuillière et al., 2018), while increases in pasture productivity (i.e. green water) have the potential to reduce the impacts of cattle production on the water cycle (Lathuillière et al., 2019)

This paper investigates the effects of interannual, and spatial, variability in green and blue water on production and technical efficiency of family-owned dairy farms in a mature colonization zone of the southwestern Brazilian Amazon. This approach allows us to draw inferences about different pathways through the precipitation-production causal chain. More specifically, we provide evidence on the intermediate steps in the causal chain that begin with changes in precipitation (expected as a result of both global climate change and regional deforestation) and end with impacts on farm profits and welfare, thus helping to unpack this complex coupled human-natural system (Balasubramanya & Stifel, 2020; Qiu, Game, Tallis, Olander, Glew, Kagan, & Kalies, 2018). To do this, we use an innovative application of remote sensing data to distinguish between green and blue water to compensate for the lack of property-level rainfall data in our study region. We assume that precipitation alters green and blue water availability and that higher production and higher production efficiency increase welfare, allowing us to focus on testing whether changes in green and blue water availability affect production and production efficiency. We hypothesize that this relationship is moderated by socioeconomic status, such that changes in precipitation could have larger effects on poor households. More specifically, our empirical models examine the impacts of changes in annual and seasonal green and blue water on dairy output by estimating the production and production efficiency of milk as functions of green and blue water in two-way fixed effects models.

Economics research has recently seen an increase in the use of remotely sensed data to analyze a range of behaviors including those related to land use and climate change (Blackman, 2013; Donaldson & Storeygard, 2016). Satellite imagery is collected at regular intervals over extensive geographic areas, and can be used to identify exogenous variation and provide independent verification of household land use. In developing nations, where hydrometeorological data are often limited, these benefits are particularly important (Donaldson & Storeygard, 2016; Henderson, Regan, & Anthony, 2016). This paper uses three proxies for estimating water availability over small geographic regions (Bark, Osgood, Colby, & Halper, 2011) to overcome the low spatial resolution available in station-based data sets (Mendelsohn, 2008). The first is the Enhanced Vegetation Index (EVI), which represents vegetation "greenness", and correlates with both evapotranspiration (Glenn, Nagler, & Huete, 2010) and the water content of vegetation (Payton, Lindsey, Wilson, Ottensmann, & Man, 2008). The second is streamflow estimated at the property level from existing stream discharge data and the delineation of the drainage area supplying each property, which represents "blue" water availability. The third is the amount of aboveground water stored in ponds estimated from classified Landsat data, which represents stored "blue" water. Our methods and results are informative to economists interested in this relatively new application of remote sensing data, to geographers interested in identifying the role of green and blue water in agricultural production, and more generally to researchers interested in the impacts of rainfall and water availability on small-scale producers in the Brazilian Amazon.

Sections 2 and 3 follow and describe the study region and data generated for our analyses. We then outline our empirical models and results in Section 4, and link our results to evidence from a recent pilot program suggesting that supplemental feeding (i.e. providing soy, grass, or corn feed that adds to the pasture grasses available on the farm property) can increase milk production in the face of declining availability of green water in Section 5. The discussion of the combined results follows in Section 6 and we conclude with the main outcomes that we expect can be used to inform policy in Section 7.

2. Study region

The Ouro Preto do Oeste (OPO) region includes six municipalities in the central portion of the state of Rondônia, Brazil (Figure 1) and experiences a tropical monsoonal climate. The average annual temperature is 26 °C with minimal seasonal variation (Beta, 2016). Precipitation averages 2095 mm per year with a dry season from June to August. OPO straddles the watershed divide between the Ji-Parana and Jaru drainage basins with elevations ranging between 100 and 600 m above sea level. Land is predominately used for agriculture and is dominated by cattle pasture with limited annual (e.g. maize, beans, rice and sugarcane) and perennial crops including coffee and cacao (Numata et al., 2003). Crop and pasture systems in OPO are predominantly rainfed while surface water and groundwater are used for cattle and fish production.

OPO was first settled in the late 1960s as a part of a series of legislative acts and decrees collectively known as Operation Amazonia (Moran, 1981). These programs funded infrastructure such as roads and dams and settlements overseen by INCRA (the National Institute of Colonization and Agrarian Reform). Settlement plans included the establishment of urban centers every 30–40 km along federal highways and the allocation of properties around these centers to households migrating from other regions of Brazil (Browder, 1994; Caviglia-Harris & Harris, 2011). Most settlements were laid out on regular grids with rectangular properties of 50 – 100HA along the roads. Settlers were awarded property rights that have been largely uncontested and secure. Migration increased in the 1980s after federal highway BR-364 was paved and financed by the World Bank via the Northwest Brazil Integrated Development Programme (POLONORESTE). Within the Amazon region,

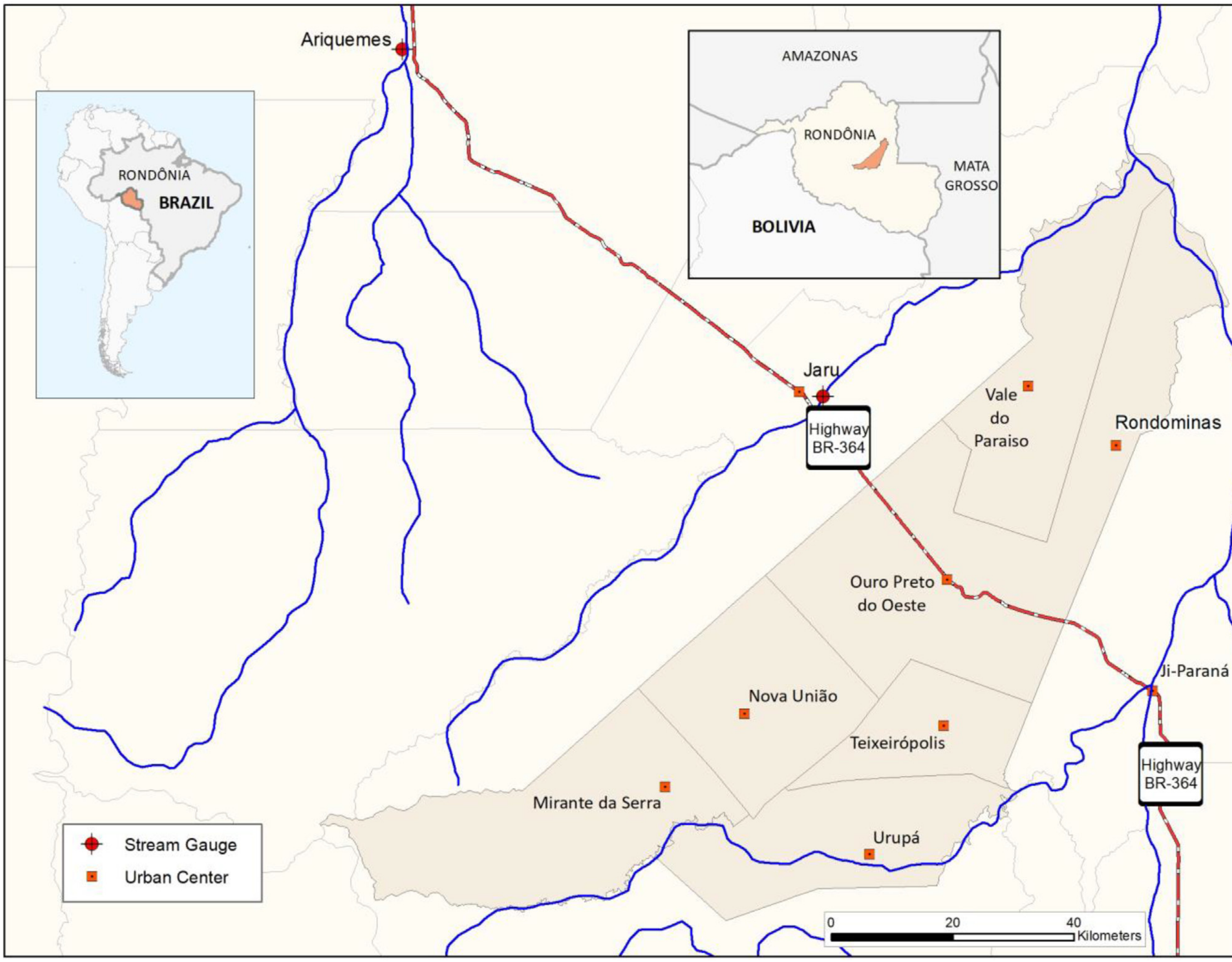

Fig. 1. Ouro Preto do Oeste Study Region The figure outlines the six municipalities in the study region and their urban centers, rivers with steam gauges and federal highway BR-364, which is referenced in the text. The blue lines represent streams at 1:250,000 with the Ariquemes and Jaru stream gauges identified. Brazilian Federal Highway 364 bisects the study municipalities and passes through the largest urban center, Ouro Preto do Oeste. Municipal urban centers and the largest nearby city, Ji-Parana are also identified. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Cattle and Dairy Trends in Study Region, Rondônia, and Comparable Amazonian Municipalities; 1991–2010.

	Cattle (head)	Dairy (head)	Milk (thousands of liters/year)	Cattle (per hectare[4])	Dairy Cattle (per hectare[4])
1991					
Ouro Preto do Oeste[1]	197,914	39,582	24,937	5.35	1.07
Remaining Municipalities in Rondônia[2]	2,367,625	358,648	204,685	4.18	0.62
Settled Amazon[3]	16,670,089	1,369,308	542,165	4.78	0.35
2000					
Ouro Preto do Oeste	574,553	74,167	88,900	1.26	0.15
Remaining Municipalities in Rondônia	3,728,392	277,496	238,493	0.80	0.06
Settled Amazon	28,902,595	1,394,073	857,497	2.52	0.13
2010					
Ouro Preto do Oeste	879,553	204,310	172,036	1.90	0.44
Remaining Municipalities in Rondônia	8,402,948	649,473	469,568	1.39	0.12
Settled Amazon	48,335,661	1,872,260	1,489,393	2.24	0.10

[1]Ouro Preto do Oeste refers to greater Ouro Preto do Oeste, including the six municipalities of Mirante da Serra, Nova União, Ouro Preto do Oeste, Teixeropolis, Urupá, and Vale do Paríso
[2]Includes all municipalities within the state settled prior to 2000 with the exception of the 6 municipalities in greater Ouro Preto do Oeste.
[3]Calculated as the total for all municipalities with INCRA settlements established prior to 2000 with the exception of those in Rondônia.
[4] Per hectare of deforested land.
Sources: IBGE - Pesquisa Pecuária Municipal "Tabela 73 - Efetivo dos rebanhos, por tipo de rebanho (série encerrada)," http://www.sidra.ibge.gov.br/bda/acervo/ accessed January 2016. (Number of head includes cows, calves and bulls. Dairy noted in the last column are a subset of cattle); INPE. 2011. "Projeto Prodes: Monitoramento Da Floresta Amazônica Brasileira Por Satélite." Guamá Belém (PA) Brasil: National Institute for Space Research (INPE). http://www.obt.inpe.br/prodes/sisprodes2000_2010.htm.

Table 2
Descriptive Statistics for Properties and Households (mean; standard deviation in parentheses).

	2000	2005	2009
Production			
Milk harvest, dry season (liters per day)	3.464	2.583	3.488
	(1.188)	(1.909)	(1.723)
Milk harvest, rainy season (liters per day)	4.797	4.141	5.569
	(2.042)	(2.774)	(2.617)
Water			
Blue water flow: dry season stream discharge (meters-cubed per day)	1,044.5	318.8	465.7
	(3143.6)	(998.9)	(1415.0)
Blue water flow: rainy season stream discharge (meters-cubed per day)	14,338.3	11,398.5	8,714.3
	(43152.9)	(35710.4)	(26481.6)
Blue water stock: ponds (hectares)	0.07	0.07	0.16
	(0.24)	(0.22)	(0.29)
Green water: dry season pasture greenness (unitless ranges from 0 to 1; higher = more green)	0.40	0.39	0.39
	(0.04)	(0.034)	(0.03)
Green water: rainy season pasture greenness (unitless ranges from 0 to 1; higher = more green)	0.530	0.516	0.520
	(0.05)	(0.08)	(0.08)
Household and Property Controls			
Average age of the household heads, years	48.67	50.22	51.74
	(11.71)	(13.29)	(13.38)
Average education of the household heads, years	2.483	2.809	3.462
	(1.617)	(2.051)	(2.850)
Soil conditions on lot (1-good, 2-moderate, 3-restricted, 4-unsuitable)	2.121	2.293	2.337
	(0.756)	(0.738)	(0.738)
Distance to the city center, kilometers	35.74	37.86	40.65
	(17.72)	(18.18)	(17.04)
Pasture, hectares	49.24	48.32	42.10
	(29.91)	(37.27)	(36.13)
Income, total from all sources, R$2000	16,281.7	15,709.9	18,123.3
	(14,660.4)	(13,226.8)	(17,755.6)
n	119	194	339

more than 1.2 million migrants were settled as part of these programs (Pacheco, 2009).

The size of cattle - and specifically dairy - herds size has increased rapidly since the early 1990s (Table 1). In OPO, the cattle herd increased by almost 200% between 1991 and 2000, and by another 53% to a herd size of close to 900,000 head by 2010 (Table 1). Milk production increased by 256% between 1991 and 2000, and by 94% from 2000 to 2010, establishing OPO as a dairy industry cluster. Growth was also noted in the number of dairy processing plants in the region, many with daily farmgate pick up every day of the year. There were 11 plants prior to 1996, 14 by 2000 and another 4 added for a total of 18 after 2000. The central municipality in OPO (Ouro Preto do Oeste) and three adjacent municipalities (Urupá, Nova União, and Vale do Paraíso) are among Brazil's top 10 largest dairy producers (SEBRAE 2015). Although dairy production continues to be dominated by smallholder producers in Rondônia, there is evidence of movement toward the large-scale industrial production of milk: professional investment in the dairy industry increased by 20% between 2002 and 2013 while household investments fell by the same amount in the state (SEBRAE 2015).

3. Data

Data used in our estimations integrate household production data (dairy production/head/day), socio-economic characteristics (age and education of the household heads and household wealth), daily rainfall summed by month and season, and proxies for green and blue water (Table 2).

3.1. Household production data

The household survey panel includes data collected in four waves from a stratified random sample of 171 households in 1996 (2% of the 9518 rural properties), 166 in 2000 (2% of the 9785 rural properties), 285 in 2005 (3% of the 10,903 rural properties), and 449 in 2009 (4% of the 10,931 rural properties) for a total of 1071 observations; of these households, 146, 119, 194 and 339 were dairy farmers in 1996, 2000, 2005, and 2009, respectively. The stratified random sampling methodology and survey design were consistent for each of the data collection waves. The sample was expanded in 2005 to include new settlements that had been established in the study region on previous forest reserves and large unoccupied ranches to maintain a representative sample population (Caviglia-Harris, Sills, & Mullan, 2013). The sample was again increased in 2009 following the same procedures (Caviglia-Harris et al., 2012). We refer to 1996 as a reference year but do not include this year in the estimations because the satellite data used to calculate the EVI are only available for the year 2000 and forward.

The survey data provide full information on farm production and purchased inputs, hectares reported in different land uses including forest and pasture, annual crops, perennial crops, measures of wealth including consumer durables, equipment, livestock, and vehicles, reported property values, and a standard set of socio-economic characteristics. Data indicate that once settled in this region, small-farm families have typically remained on the same property throughout the study period (1996–2009), exhibiting a relatively low 5% annual attrition rate (Mullan, Sills, Pattanayak, & Caviglia-Harris, 2018). More precisely, rural populations have increased due to in-fill rather than "hollowing" of the frontier due to turn-over (Caviglia-Harris, Sills, Bell, Harris, Mullan, & Roberts, 2016).

Total (inflation adjusted) income fell from approximately R $16,300 in 2000 to R$15,700 in 2005 and increased to R$18,100 by 2009 (Table 2). We divide total income into agriculture revenue, off-farm labor, government payments and other sources, and find evidence that the 2005 drought impacted the division of these income sources (Table 3). Agricultural revenue declined from an average of 60–80% of total income in the pre-drought study years to<30% of total income during the drought, while off-farm labor increased from 14 to 17% of total income to more 22% likely to compensate for (or as a result of) these losses (see the first four columns of data in Table 3). Milk production was an important source of agricultural income, accounting for more than 50% of the total in

Table 3
Income and Revenue by Category over Time.

	Income and Revenue from all Sources (percent by category)					Agriculture Revenue (percent by category)			
	1996	2000	2005	2009		1996	2000	2005	2009
Agriculture Revenue	73.88	68.49	60.38	61.14	Dairy	55.00	51.06	38.33	52.91
Government Payments	12.51	13.76	17.17	24.35	Livestock	0.00	22.68	36.57	32.10
Off-Farm Income	13.60	17.75	22.44	14.51	Crops	44.74	25.35	24.69	14.96
					Fish and Honey	0.26	0.90	0.40	0.04
Total	99.99	100	99.99	100	Total	100	99.99	99.99	100.01

all years, with the exception of 2005, when this income source fell to<39% of total (Table 3, see last four columns of data).

Mean property size declined between 2000 and 2009 as some households sold portions of their properties, others split properties among children, and still others moved to new properties that were smaller than the original 100 ha distributed during the initial settlement years of 1970–1990. This translates to a reduction in the area of pasture managed by each household from an average of 49 ha in 2000 to 42 ha in 2009 (Table 2). The average household in the region has become older and more educated as in-migration has slowed and access to schooling has increased, household members have remained on their properties (rather than migrate into the forest frontier), and there has been generational turn-over in families. The average age of the household heads increased from 49 to 51 years, while education levels increased from an average of 2.5 years to 3.5 (Table 2). Wealth increased over the survey time period as suggested by the 80% increase in the real value of vehicles owned by the household from approximately R$5400 in 2000 to R$9750 in 2009. The average distance to the OPO urban center for households increased from 36 to 41 km as new properties were settled further from initial settlements along BR-364 (and subsequently added to the survey sample).

Milk production varies and is lower in the dry season and in drought years (Table 4). Production is higher in the rainy season in terms of total quantities (34–62% higher than dry season production depending on year) and per-head production (40–65% higher than dry season production depending on year) and was the lowest during the 2005 drought. Data also suggest the seasonal production efficiency has been improving over time: liters/head/day increase from a dry season average of 2.6 in 1996 to 3.5 in 2009 and a rainy season average of 3.8 in 1996 to 5.6 in 2009 (Table 4).

Household income and wealth vary widely in the six-municipality region enabling for the examination of differences between income strata. We compare production, water, and household data for households in the lowest quartile of the income distribution (who we label as poor) with other households (who we label as non-poor) and present these data in Table 5. Unsurprisingly, our proxy for wealth (the value of vehicles owned) is significantly lower for the poor in each year. However, there are no significant differences in milk production, or blue and green water, for these different groups of farmers, suggesting that any differences in the impact of green and blue water on production on the poor are not due to initial distributional differences. Households in the top three quartiles of the income distribution have older heads of household, are located closer to the city center, and have better soils than poor households (Table 5).

3.2. Blue and green water indices overview

We calculated indices of water availability for each of the properties in the economic survey, including blue water stock (ponds, reservoirs), blue water flow (streamflow) and green water (transpiration of grass, using a greenness index as a proxy). Previous studies of blue and green water in the nearby Amazon state of Mato Grosso (Lathuillière et al. 2018, 2019) calculate a water balance including ET from agricultural and forest land covers, and validate the green and blue water values by comparing with observed stream discharge in a large river basin (170,000 km2). Here, our unit of analysis is not the river basin, but rather the individual farm production unit. We calculate indices of blue water flow (streamflow) for each property separately. Our objective is not to calculate the water balance of each property or of a larger region, but rather to generate indices of blue and green water availability to be considered as factors of production (or inputs) in the econometric models. Lathuillière et al. (2018) also calculated blue and green water consumption using per-unit consumption values, also known as a footprint analysis; here we calculate indices of blue and green water availability, rather than explicitly quantifying blue or green water consumption.[1]

Rainfall data from the National Water Agency (Agencia Nacional de Aguas, http://www.snirh.gov.br/hidroweb/) were used together with streamflow data to define the months of the wet and dry season and to document trends in rainfall for the study years (Figs. 2 and 3). There are only two raingages in our study area, so we did not use rainfall data to estimate any variable describing green or blue water at the property level as used in the economic analysis. Subsequent data on rainfall from a remote sensing product (Climate Hazards Group InfraRed Precipitation with Station data) calibrated and validated with local station data (Mu, Biggs, & De Sales, 2021) show a very low coefficient of variation (CV) in wet season rainfall (mean CV 5%) and somewhat higher variation in the dry season (mean CV 17%); the low variation suggests that rainfall is relatively uniform over the study region for the years of the survey, with more variability in dry seasons and dry years.

3.2.1. Blue water flow: stream discharge

Blue water is the surface or groundwater that is present in streams, surface water bodies, and aquifers that is important for meeting the high drinking water requirements of dairy cattle. Blue water can be present as either a flow or a stock. We proxy blue water flow with a simple model of dry season low flow and wet season baseflow calibrated to stream discharge measurements collected from stream gauges in the study and blue water stock with the total surface area of watering ponds on surveyed properties estimated from remote sensing data.

A proxy for blue water flow (m^3 day^{-1}) was estimated for each property in both dry and rainy seasons by multiplying the specific discharge (m^3 km^{-2} day^{-1}) in a given season by the total drainage area of the three largest streams that drain through the property. Specific discharge for the dry and rainy seasons was calculated from discharge data from two stream gages whose watersheds overlap the study area: the Jamari River at Ariquemes (Station Code 15430000, area 8140 km^2) and Jaru river at Jaru (Station Code 15565000, area 3960 km^2). Dry season discharge was calculated for each year of the survey as the mean of the 10th-percentile flows for that year.[2] Rainy season discharge was calculated as the average baseflow during the rainy season (Fig. 3).[3] According to these estimations, mean dry-season discharge on properties decreased from 1,044 m^3/day in 2000 to 466 m^3/day in 2009 (a 55% decline), and rainy-season discharge decreased from approximately 14,338 m^3/day in 2000 to 8,714 m^3/day in 2009 (a 39% decline) (Table 2).[4,5] Compared to the long-term mean low flow (q_m) over 1981–2015, low flow during the survey years was either above q_m (23–80% above in 1996), similar to q_m (−5 to + 11% in 2000), slightly below q_m (−16 to −47% in 2009), or well below q_m (−57 to −64%, 2005). The 2005 dry year had low flow well below the mean, but had a 3-year recurrence interval (recurrent probability of 32%), sug-

[1] Future work could compare the availability indices with consumptive water uses to compare the balance of water availability and use.

[2] This was calculated using the hydrostats package (Bond 2016) in R statistical software (R Core Team 2017). The 10th percentile flow identifies flows that are exceeded 90% of the time are used here to represent the lowest discharge of each year (Figure 4).

[3] Baseflow was calculated using the EcoHydRology package (Fuka et al. 2014).

[4] These calculations assume that specific discharge (mm/day) is uniform over the study area and with watershed size.

[5] Some of the changes over time are likely due to changes in property size and may be attributed to the inclusion of properties with smaller watersheds in 2009. A balanced panel for 75 properties in both the 2000 and 2019 samples suggest that low flow discharge fell from an average of 1,084 to 690 m^3/day (a 36% decline) in the dry season and from 14,890 to 12,918 m^3/day (13% decline in the rainy season).

Table 4
Milk Production on Properties with Dairy Cows in the Dry and Rainy Seasons; 1996–2009 (mean values; standard deviations in parentheses).

	Dry Season				Rainy Season				Herd Size	
	Milk Harvest (liters/day)	Milk Harvest (liters/head/day)	Milk Price ($2000 reais/ liter)	Milk Revenue ($2000 reais)	Milk Harvest (liters/day)	Milk Harvest (liters/head/day)	Milk Price ($2000 reais/ liter)	Milk Revenue ($2000 reais)	Cattle Herd	Dairy Cows
1996 (n = 146)	42.07	2.567	0.19	1502.2	63.66	3.778	0.19	2273.8	78.53	17.77
	(42.82)	(1.045)	(0.02)	(1568.8)	(68.55)	(1.606)	(0.02)	(2552.1)	(86.65)	(18.57)
2000 (n = 119)	85.39	3.464	0.27	4264.7	113.4	4.797	0.19	3973.5	110.4	25.75
	(76.70)	(1.188)	(0.04)	(4058.5)	(103.0)	(2.042)	(0.05)	(3719.6)	(96.60)	(21.61)
2005 (n = 194)	63.85	2.583	0.25	2897.5	103.6	4.141	0.27	5062.7	124.6	32.13
	(59.26)	(1.909)	(0.04)	(2793.9)	(95.02)	(2.774)	(0.04)	(4723.9)	(111.0)	(29.33)
2009 (n = 339)	72.58	3.488	0.30	4141.7	109.7	5.569	0.23	4716.5	107.7	22.09
	(69.49)	(1.723)	(0.06)	(4301.5)	(92.84)	(2.617)	(0.04)	(4275.7)	(98.57)	(18.55)

Table 5
Descriptive Statistics for Properties and Households Divided by Poverty Category (mean; standard deviation in parentheses).

	2000		2005		2009	
	Non-Poor[1]	Poor	Non-Poor	Poor	Non-Poor	Poor
Production						
Milk harvest, dry season (liters per head per day)	2.567	3.464	2.583	3.488	3.585*	3.226
	(1.045)	(1.188)	(1.909)	(1.723)	(1.272)	(0.974)
Milk harvest, rainy season (liters per head per day)	3.778	4.797	4.141	5.569	4.729	4.931
	(1.606)	(2.042)	(2.774)	(2.617)	(1.962)	(2.210)
Water						
Blue water flow: dry season stream discharge (meters-cubed per day)	1328.1	484.5	408.7*	140.6	470.5	455.9
	(3750.7)	(1131.1)	(1203.5)	(252.2)	(1412.3)	(1426.7)
Blue water flow: rainy season stream discharge (meters-cubed per day)	18230.8	6650.5	14609.9*	5024.9	8805.2	8532.6
	(51487.3)	(15526.5)	(43025.0)	(9015.9)	(26430.8)	(26699.9)
Blue water stock: ponds (hectares)	0.0624	0.0827	0.0733	0.0722	0.178**	0.111
	(0.208)	(0.285)	(0.171)	(0.291)	(0.302)	(0.271)
Green water: dry season pasture greenness (unitless ranges from 0 to 1; higher = more green)	0.399	0.410	0.385	0.391	0.390	0.395
	(0.0356)	(0.0394)	(0.0323)	(0.0374)	(0.0274)	(0.0283)
Green water: rainy season pasture greenness (unitless ranges from 0 to 1; higher = more green)	0.529	0.524	0.512	0.524	0.519	0.527
	(0.0499)	(0.0533)	(0.0778)	(0.0809)	(0.0765)	(0.0794)
Household and Property Controls						
Average age of the household heads, years	50.18***	45.67	52.83***	45.04	54.61***	45.98
	(12.37)	(9.747)	(12.24)	(13.85)	(12.85)	(12.58)
Average education of the household heads, years	2.418	2.612	2.678	3.069	3.279*	3.827
	(1.551)	(1.752)	(2.143)	(1.843)	(3.043)	(2.387)
Soil conditions on lot (1-good, 2-moderate, 3-restricted, 4-unsuitable)	2.039*	2.284	2.168***	2.540	2.264***	2.483
	(0.748)	(0.754)	(0.745)	(0.663)	(0.768)	(0.655)
Distance to the city center, kilometers	32.87***	41.40	34.07***	45.37	37.91***	46.13
	(17.44)	(17.09)	(18.70)	(14.54)	(17.13)	(15.54)
Income, total from all sources, R$2000	21742.1***	5497.4	21208.9***	4796.6	24193.5***	5982.9
	(15276.9)	(1961.4)	(13063.5)	(2086.8)	(18979.8)	(2163.5)
n	79	40	129	65	226	113

*, **, *** indicate *t*-test significance at the 0.05, 0.01 and 0.001 levels, respectively.
[1]We define households in the lowest quartile of the income distribution as poor and include all other households in the non-poor category.

gesting that 2005 was dry but not unusual. The subsequent years, 2006–2007, had significantly lower values of low flow, with recurrence intervals of 12 (2006) and 18 (2007) years, possibly due to lagged and cumulative effects of years of below-average rainfall or increases in the number of impoundments. Our survey data therefore capture years with typical or above average blue water flow, with at least one dry year (2005); the survey data may not capture farmer response to extreme drought conditions like those of 2006–2007.

Validation of our blue water flow estimates is complicated by the lack of stream gage data in the study area and by the practical difficulty of monitoring flow for 400 + properties, including for previous survey years. Our estimates of blue water flow are based on the assumption that specific discharge is uniform over space and watershed size, and that differences in stream flow by property are controlled to a first order by differences in the drainage area of the watersheds that drain through the properties. The contributing area of streams draining to the surveyed properties varies over 6 orders of magnitude, while discharge at the two discharge stations used in the analysis differs from the mean by an average of 9–15% with a maximum of 59% in the year 2000 at the Jaru gauge (Table S1). In addition, the discharge at the two stations is highly correlated (r = 0.90), and the econometric analysis depends more on relative values and correlations than on absolute values. While there may be spatial variations in specific discharge due to local variations in geology, topography, watershed size, soil type, land cover, or rainfall variability, these variations are anticipated to be small compared with the 6-orders of magnitude variation caused by variations in drainage size.[6]

[6] Future efforts could attempt to measure and account for local variations in specific discharge due to topography, land cover, or upstream impoundments.

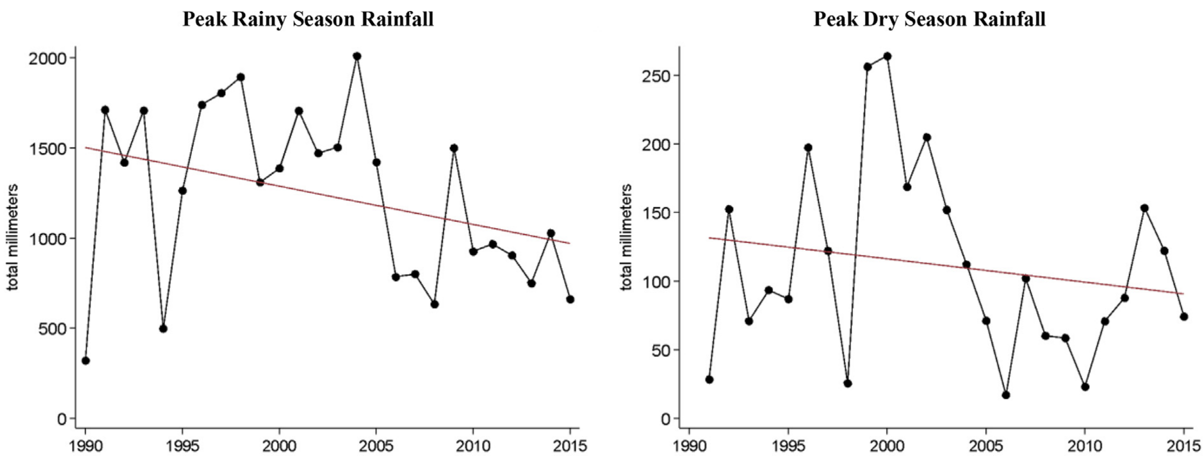

Fig. 2. Rainfall by Peak Season Since 1990. Notes: The peak wet season was defined as the months that had both high rainfall and significant baseflow (January, February and March). The dry season is defined as the three months with the lowest average rainfall (June, July and August). Source: Agencia Nacional de Aguas, http://www.snirh.gov.br/hidroweb/. Correlation coefficient = −0.3429 for the peak rainy season; and = −0.1825 for the peak dry season.

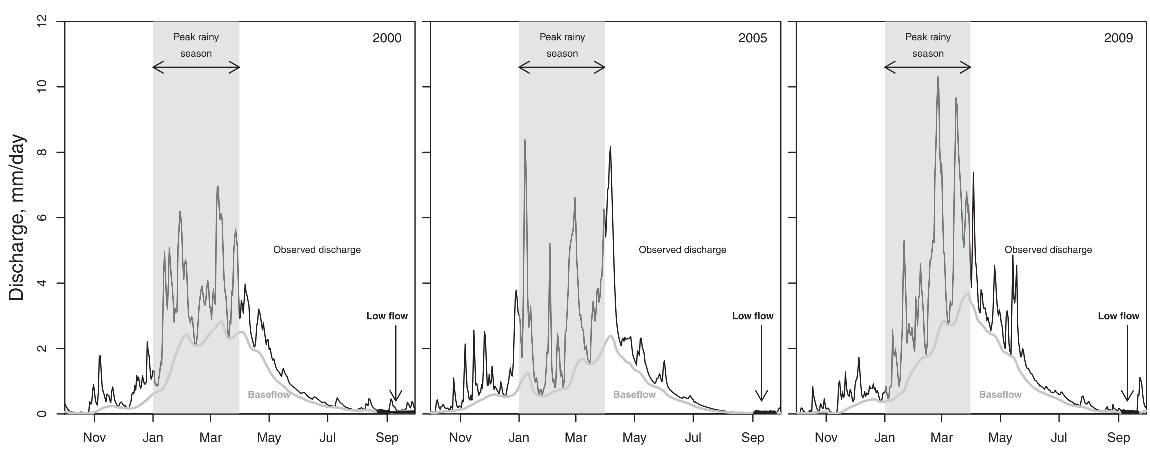

Fig. 3. Observed Discharge, Baseflow and Low Flow for Streams in Study Area. Notes: The peak wet season was defined as the months that had both high rainfall and significant baseflow January, February and March. December often has high rainfall, but stream discharge is typically low in December as much of the rainfall goes to soil moisture and groundwater storage. April has high discharge due to the slow release from storage in soil and groundwater, but April has low rainfall compared with January to March, so the wet season here is defined as January 1 to March 31. Sources: ANA. 2001. HidroWeb – Sistema de Informacoes Hidrologicas (available on-line through the Agencia Nacional de´Aguas, Brasılia, DF, Brasil: http://www.snirh.gov.br/hidroweb/publico/apresentacao.jsf). The stream gage is 15430000, Jamari River at Ariquemes.

3.2.2. Blue water stock: cattle ponds

Cattle ponds in the study region were identified by spectral signature, feature size, and feature location (within pastures) using satellite imagery from 2000, 2005, and 2009. Landsat Thematic Mapper imagery (30 m resolution) was classified by spectral mixture analysis (SMA) where each pixels' fractional percentage of shade, photosynthetic vegetation, non-photosynthetic vegetation, and soil were calculated and aggregated into eight landcover classes based on maximum likelihood: mature forest, secondary forest, pasture, green pasture, burned pasture, water, rock/savanna and urban/bare soil (Roberts et al., 2002). Aquaculture ponds were differentiated from cattle ponds by feature size and location; cattle ponds are often isolated from the stream network and are generally smaller.[7] From these data, we estimate that cattle pond surface area increased from 0.05 ha per property in 2000 to 0.16 ha in 2009 for the households in our sample (Table 2).

3.2.3. Green water: the enhanced vegetation Index (EVI)

Green water is soil moisture that originates as precipitation, infiltrates into the soil, and is then either transpired by plants or evaporates from the soil surface. The productive green water flux can be measured directly by quantifying evapotranspiration (ET) through ground measurements or remote sensing data (Biggs, Marshall, & Messina, 2016).[8] In rainfed systems, ET is often highly correlated with net primary production and above ground biomass. ET can also be estimated indirectly with either vegetation-based or temperature-based algorithms (Biggs, Petropoulos, Velpuri, Marshall, Glenn, Nagler, & Messina, 2015). For example, total green water is operationally estimated by the Moderate Resolution Imaging Spectroradiometer (MODIS) MOD16 product (Mu, Zhao, & Running, 2011). MOD16 is available at 1 km resolution, which is too coarse compared with the size of the properties in the survey, many of which are 1 km or smaller on a side. EVI data from the MOD13Q1 product are available at 250 m resolution and are appro-

[7] Visual analysis of high-resolution visible imagery in Google Earth indicated that pond construction often created soil scars adjacent to water features, for example earthen dams, that were classified as burned pasture and/or water in the classified imagery. Burned pasture pixels were subset to represent water features when feature sizes were<1 km^2 to differentiate pasture disturbance for water retention construction from true large burned pastures.

[8] In rainfed systems, ET correlates strongly with vegetation indices including the normalized difference vegetation index (NDVI) and the Enhanced Vegetation Index (EVI). Such indices are commonly used to model ET, either alone or in combination with ground reference data (Glenn et al., 2010).

priate for estimating greenness in the surveyed properties. Here we use the Enhanced Vegetation Index (EVI) derived from MOD13Q1 as a proxy for ET and the productive green water flux (Table 3).

The mean MOD13Q1 EVI was calculated for the pasture in each property from February 2000 to July 2010.[9] A land cover map for 2010 created from Landsat ™ imagery was used as a mask to calculate mean EVI from pasture alone. While land cover may have changed over 2000–2009, most of the properties in our study area were mostly cleared of forest (mean 84% pasture cover), and 95% of all properties were more than 50% pasture and 70% of properties were more than 80% pasture in 2009. A majority (73%) of properties showed <10% increase in pasture and a large majority (86%) showed <20% increase in pasture between 2000 and 2009. EVI ranges from negative one to one and correlates positively with vegetation cover, biomass, and evapotranspiration (ET) (Glenn et al., 2010). EVI can decline in cleared areas if the amount of woody biomass declines over time (Rufin, Müller, Pflugmacher, & Hostert, 2015), which complicates its use for quantifying pasture condition and transpiration from grass; here we assume that our land use classification effectively masks out secondary forest, and that EVI indicates the greenness and transpiration of pasture grass only, though recent remote sensing analysis suggests that pastures often have scattered shrubs and trees that could impact the EVI value (Mu, Biggs, Stow, & Numata, 2020). The values of EVI for our study period (three peak months in each of the dry and rainy seasons) range from a low of 0.35 in the dry season of 2006 to a high of 0.56 in the rainy season of 2008, with values that are 0.08–0.20 points lower in the dry season as compared to the rainy season. Similar to rainfall, we note a downward trend in these values since 2000, but the rate of change is an order of magnitude lower than for rainfall. More specifically, these values translate into a mean decline of 0.11% per year since 2000 in the rainy season and a mean decline of 0.08% per year since 2000 in the dry season.

The spatial and temporal distribution of green and blue water depends on rainfall, property characteristics, and the size and characteristics of the watersheds of the streams that flow through the properties. For green water, key factors include soil texture, organic matter content and pasture management; including stocking density and vegetation management. Spatial variations in pasture greenness and transpiration may reflect soil nutrient status or overgrazing, and not necessarily moisture availability per se. Our estimates of green water represent consumptive use through transpiration, and not necessarily green water availability alone. However, in the dry season, the pronounced decline in EVI suggests strong soil moisture control on pasture production. The distribution of blue water depends on watershed size, rainfall, soil type, geology, storage capacity on the property, and upstream land use or impoundments. Thus, property-level data on green and blue water allow us to estimate how households respond to spatial and temporal variability in blue water availability and green water consumption. To support our interpretation of estimation results based on panel data from 1996 to 2009, we also draw on data from a pilot program undertaken in 2017 to test possible moderators of the relationship between green and blue water and dairy production. These descriptive data are presented in Section 5 to provide context for our results.

4. Empirical models and results

We estimate the impacts of green and blue water availability on milk production and technological efficiency. We include blue and green water separately because we find that blue and green water are not strongly correlated (likely because pasture greenness, stream discharge and pond excavation are influenced by different geographic and socioeconomic determinants),[10] because they impact production in different ways and through different channels, and because they vary spatially. In both estimations we used fixed effects models that difference out the stable biophysical conditions on the property (i.e. soil type, distance to the urban center and elevation). The sub-sections to follow outline our empirical strategies and present the results from these estimations.

4.1. Production

We first estimate the impact of changes in green and blue water availability on milk production. We use property-level and year fixed effects models to control for unobserved heterogeneity and estimate:

$$M_{jt} = \alpha_j + \beta_1 B_{jt} + \beta_2 G_{jt} + \beta_3 S_{jt} + \varepsilon_{jt} \tag{1}$$

where $M_{jt}$is the daily seasonal milk production (liters/cow) for the dry and rainy seasons, B represents blue water, G is green water, S are the socioeconomic controls for household j and ε_{it} is the error term. The socioeconomic controls include average age and education of the household heads. We also include a dummy variable for poverty status (i.e. those households in the lowest quartile of income) and interaction terms for poverty and blue and green water.

We are concerned about a few potential sources of endogeneity. First, since EVI depends on pasture management as well as rainfall and initial soil conditions, it is possible that farmers who invest more in their property and/or use more inputs have both higher EVI (because they reform pasture, use better grasses, and/or limit stocking density) and higher milk production. We do not find evidence that green water differs between the poor and nonpoor households (i.e. those with and without the resources to invest in pasture management), but do find marginally significant differences in blue water between these households in 2005 and 2009 (Table 5). At the same time, the bivariate correlations between income and green and blue water are all below 0.05[11]. Any remaining endogeneity is partially, but not fully, addressed with the use of property-level fixed effects. We also include a dummy for poverty status and interaction terms with blue and green water to further investigate these differences. Finally, to explore the different impacts of inter-seasonal property-level differences in green and blue water and inter-annual differences in water availability we compare estimation results between models with no fixed effects, property-level fixed effects, year fixed effects, and two-way fixed effects.

We report the panel estimation results separately for the dry and rainy seasons. One takeaway from a comparison of these results (Tables 6 and 7) is that green and blue water increase pro-

[9] MOD13Q1 is the 16-day EVI with a pixel size of 250 m, which is sufficient to calculate EVI over the properties in the study area, which range from 0.05 to 6.4 km^2. The property boundary map was used to extract the EVI value for all pixels in each property. The quality flag information provided in MOD13Q1 was used to exclude pixels affected by cloud contamination (quality flag = 3) or with "marginal data" (flag=2). Only pixels with "good" quality were included. A land use map created from Landsat TM (30m) was used to calculate the fractional cover of pasture, secondary forest, and mature forest in each MODIS pixel. MODIS pixels that had<80% pasture were excluded from the calculation to determine the EVI of pasture. The weighted mean EVI values were calculated for each property by year and season and are used as proxies for green water availability and pasture quality.

[10] The bivariate correlations between EVI, ponds, and stream discharge are between 0.01 and 0.06 in the rainy season and 0.02–0.05 in the dry season. We also ran our panel regression with only green water and only blue water and do not find the significance or size of these coefficients to vary from what is presented in our estimation results.

[11] The bivariate correlations between income EVI, ponds, and stream discharge are 0.0134, 0.0497, 0.0032 respectively in the rainy season and −0.0834, 0.0497, −0.0171 respectively in the dry season.

Table 6
Dry Season Dairy Production (liters/cow/day).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Green Water (EVI)	0.629**	0.753**	0.312	0.432	1.067*	1.352**	1.084*	1.367**
	(0.289)	(0.365)	(0.270)	(0.339)	(0.571)	(0.624)	(0.566)	(0.616)
Blue Water Stock (ponds)	0.106	0.293***	0.0132	0.184**	0.221	0.231	0.153	0.176
	(0.106)	(0.0993)	(0.0964)	(0.0894)	(0.156)	(0.158)	(0.164)	(0.163)
Blue Water Flow (seasonal low flow)	0.0149	0.00544	−0.00351	−0.0114	0.417***	0.448***	0.222	0.309*
	(0.0121)	(0.0146)	(0.0122)	(0.0145)	(0.0731)	(0.0732)	(0.157)	(0.162)
Poor; =1 if the household in lower quartile		−0.296		−0.274		−0.330		−0.319
		(0.567)		(0.521)		(0.962)		(0.961)
Poor*Green Water (EVI)		−0.168		−0.161		−0.462		−0.473
		(0.581)		(0.532)		(0.952)		(0.948)
Poor*Blue Water Stock (ponds)		−0.583***		−0.532***		−0.0509		−0.0338
		(0.220)		(0.200)		(0.399)		(0.402)
Poor*Blue Water Flow (seasonal low flow)		0.0111		0.00440		−0.0771		−0.0794
		(0.0256)		(0.0245)		(0.0531)		(0.0525)
Property-Level Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes
Observations	652	652	652	652	652	652	652	652
Number of panels					425	425	425	425
R-squared	0.026	0.050	0.130	0.154	0.192	0.229	0.197	0.232

Notes: Log-log model. Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Socioeconomic controls include average age and education of the household heads.

Table 7
Wet Season Dairy Production (liters/cow/day).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Green Water (EVI)	0.107	0.102	0.0579	0.0475	0.183	0.188	0.0720	0.0215
	(0.135)	(0.150)	(0.130)	(0.142)	(0.220)	(0.272)	(0.217)	(0.252)
Blue Water – Captured (ponds)	0.159	0.245**	0.0671	0.132	0.251	0.226	0.205	0.180
	(0.0982)	(0.104)	(0.0909)	(0.0987)	(0.212)	(0.175)	(0.197)	(0.149)
Blue Water – Available (seasonal low flow)	−0.0206*	−0.00608	−0.0147	0.00265	−0.572	−0.607	0.229	0.219
	(0.0123)	(0.0150)	(0.0119)	(0.0142)	(0.486)	(0.491)	(0.502)	(0.515)
Poor; =1 if the household in lower quartile		0.320		0.388		0.351		0.345
		(0.302)		(0.292)		(0.489)		(0.487)
Poor*Green Water (EVI)		−0.0263		−0.00664		−0.00153		0.156
		(0.310)		(0.292)		(0.479)		(0.452)
Poor*Blue Water- Captured (ponds)		−0.247		−0.184		0.0577		0.0758
		(0.222)		(0.207)		(0.485)		(0.477)
Poor*Blue Water– Available (seasonal low flow)		−0.0374		−0.0455*		−0.0436		−0.0319
		(0.0271)		(0.0265)		(0.0584)		(0.0582)
Property-Level Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes
Observations	621	621	621	621	621	621	621	621
Number of panels					414	414	414	414
R-squared	0.022	0.028	0.108	0.115	0.025	0.028	0.121	0.123

Notes: Log-log model. Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Socioeconomic controls include average age and education of the household heads.31 observations of the rainy season EVI estimates fell below the reliability criterion and are therefore not include in these estimations.

duction (liters/cow/day) when water is limited (during the dry season), but not otherwise (during the rainy season). We therefore focus on the results for the dry season and do not report further on the rainy season results (Table 7). Looking at the dry season determinants in more detail, we find that green water is positively related to milk production and that this result holds across most of our specifications. More specifically, a 1% increase in EVI, increases milk production anywhere from 0.6 to 1.4% (Table 6). We find evidence that blue water stock and flow (captured and/or the amount available in streams) positively impact milk production, although these results depend on the model specification. We also find that green water is positively related to production in the dry season.

In more detail, Wald tests on the interaction terms for green water in Models 2, 6, and 8 suggest that EVI increases production for the non-poor but not the poor.[12] Wald tests on the interaction terms for blue water stock in Models 2 and 4 suggest blue water stock positively impacts production for the non-poor and negatively impacts the poor.[13] Lastly, Wald tests on the interaction terms for blue water flow in Models 6 and 4 suggest blue water flow positively impacts production for the non-poor and the poor.[14]

We compare our models with and without property and year fixed effects because there is little seasonal variation in rainfall (given the size of our study region), although the division of rainfall between green and blue water does add property-level variation (Table 6). If the property-level variation is not great enough, our identification would be largely driven by the differences between

[12] For example, in Model 2 the combined coefficient on green water and the poor*green water interaction (0.753 – 0.168) is not statistically different from zero (F(1, 642)=1.68; Prob > F= 0.1957), and this is also true for models 4,6 and 8.

[13] For example, in Model 2 the combined coefficient on blue water stock and the poor* blue water stock interaction (0.293 – 0.583) is not statistically different from zero (F(1, 642)=2.17; Prob > F= 0.1409), and in Model 2 the combined coefficient on blue water stock and the poor* blue water stock interaction (0.184 – 0.532) is negative and statistically different from zero (F(1, 640)=3.78; Prob > F= 0.0522).

[14] For example, in Model 6 the combined coefficient on blue water flow and the poor* blue water flow interaction (0.448 – 0.0771) is statistically different from zero F (1, 424)=20.23; Prob > F=0.0000), and in Model 8 the combined coefficient on blue water flow and the poor* blue water flow interaction (0.309 – 0.0794) is not statistically different from zero (F(1,424)=1.98; Prob > F=0.1602).

just three time periods and largely reflect the impact of the 2005 drought. What we find is that the impact of green water does not vary across these specifications and is significant when year and property level fixed effects are included. The impact of blue water does, however get smaller and/or less significant when year fixed effects are included suggesting that blue water reduction in dry years and in the dry season may impact all but the poorest uniformly.

4.2. Production efficiency

The production approach above assumes technical efficiency. This is a strong assumption for a developing region with incomplete markets and other market failures (Bravo-Ureta & Pinheiro, 1993), especially among migrants to a new biophysical region such as a tropical forest frontier. In this case, technical inefficiency arises when given the chosen inputs, output is lower than the maximum (Greene, 2008). An alternative is the stochastic frontier (SF) model, which defines the output of the most efficient firms as the production frontier, and then uses this frontier to estimate the degree of inefficiency (Chiona, Kalinda, & Tembo, 2014). From a statistical point of view, the regression model is characterized by a composite error term in which the classical idiosyncratic disturbance is included with a one-sided disturbance representing the inefficiency (Cross, Färe, Grosskopf, & Weber, 2013). In other words, the error term of the production frontier model consists of a random error and an inefficiency term:

$$Q_{ij} = \exp(X_{ij}\beta + \varepsilon_{ij}) = \exp(X_{ij}\beta + V_{ij} + U_{ij});\ \ \varepsilon_{ij} = V_{ij} + U_{ij}$$

where Q_{ij} is the observed scalar output of product i for the jth household, X_{ij} is a vector of inputs, β is a vector of parameters to be estimated, exp is the exponential function, V_i is the disturbance term, assumed to be independent and normally distributed, and U_{ij} is a non-negative random variable associated with the technical inefficiency in production, assumed to be independently distributed. U_{ij} can be represented as

$$U_{ij} = Z_{ij}\delta + W_{ij}$$

where Z_{ij} is a vector of variables that impact efficiency, δ is a vector of parameters to be estimated and W_{ij} is the random variable defining the truncation of the normal distribution. Technical efficiency is defined as the ratio of observed output (Q_{ij}) and the frontier output ($Q_{ij}{}^*$):

$$Q_{ij/}\ Q_{ij}{}^* = \exp\ (X_{ij}\beta\ +\ V_{ij}\ +\ U_{ij});\ \varepsilon_{ij}\ =\ V_{ij}\ +\ U_{ij} \qquad (4)$$

Next, we use a stochastic frontier (SF) model to estimate the efficiency of milk production (liters/cow/day) by household in the study region, which like other developing regions is likely to be populated by producers who operate below the production frontier (i.e. operate inefficiently). Climate variables are not traditionally included in these models (Bravo-Ureta & Pinheiro, 1993), but more recently biophysical indicators have been tested (Ekbom, Alem, & Sterner, 2013). Our hypothesis suggests that water availability has the potential to explain some of the variability in efficiency. We analyze the determinants of efficiency using a translog functional form and include the same controls as above. If we assume that the production function takes on the Cobb-Douglas log-linear form and drop the output subscripts, the estimation can be written as:

$$lnlnM_{jt} = \alpha + \beta_1 lnB_{jt} + \beta_2 lnG_{jt} + \beta_3 lnS_{jt} + \upsilon_{jt} - \mu_{jt} \qquad (5)$$

where M_{jt} is the seasonal milk production for the dry and rainy seasons, B represents blue water, G is green water, S includes the socioeconomic controls for household j. v_{jt} is the disturbance term assumed to be independent and normally distributed, and u_{jt} is a non-negative random variable associated with the technical inefficiency.

We again report the panel estimation results separately for the dry and rainy seasons. One takeaway from a comparison of these results (Table 8) is that green and blue water increase production (liters/cow/day) when water is limited (during the dry season), but not otherwise (and during the rainy season). We therefore focus on the results for the dry season and do not report further on the rainy season results. Looking at the dry season determinants in more detail, we find that green water is positively related to milk production but that this result does not hold when year fixed effects are included but rather only when the property-level fixed effects are included. More specifically, for these models a 1% increase in EVI, increases milk production efficiency anywhere

Table 8
Stochastic Frontier Estimations of Production Efficiency (liters/cow/day).

	Dry Season				Rainy Season			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Green Water (EVI)	0.715**	0.341	0.874**	0.524	0.114	0.0617	0.108	0.0549
	(0.284)	(0.268)	(0.340)	(0.320)	(0.128)	(0.124)	(0.149)	(0.142)
Blue Water - Captured (ponds)	0.122	0.0215	0.245**	0.148	0.148	0.0641	0.209**	0.121
	(0.107)	(0.102)	(0.100)	(0.0911)	(0.104)	(0.0952)	(0.0979)	(0.0938)
Blue Water – Available (seasonal low flow)	0.0223*	−0.000712	0.0150	−0.00784	−0.0167	−0.0134	−0.00109	0.00309
	(0.0121)	(0.0119)	(0.0142)	(0.0139)	(0.0126)	(0.0120)	(0.0148)	(0.0138)
Poor; =1 if the household in lower quartile			−0.383	−0.441			0.335	0.359
			(0.546)	(0.510)			(0.298)	(0.288)
Poor*Green Water (EVI)			−0.277	−0.340			−0.0195	−0.0133
			(0.559)	(0.520)			(0.296)	(0.278)
Poor*Blue Water- Captured (ponds)			−0.495*	−0.484**			−0.191	−0.168
			(0.254)	(0.222)			(0.250)	(0.224)
Poor*Blue Water– Available(seasonal low flow)			0.00424	0.00265			−0.0393	−0.0419
			(0.0240)	(0.0232)			(0.0269)	(0.0268)
Property-Level Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Technical Efficiency	0.73	0.76	0.74	0.77	0.76	0.79	0.77	0.80
Observations	652	652	652	652	621	621	621	621
Number of panels	425	425	425	425	414	414	414	414
Wald (full model)	19.11	82.19	35.02	112.1	10.79	53.29	15.59	60.03

Notes: Log-log model. Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Socioeconomic controls include average age and education of the household heads and wealth (as measured by the value of vehicles owned).

Table 9
Daily On-farm Dairy Production (Data from 2017 Pilot Study Rolim de Moura, Rondônia).

	Dry Season (liters/cow/day)	Rainy Season (liters/cow/day)
Pilot extension program		
mean	12.07	8.71
95% confidence interval	12.01–12.14	8.42–9.00
Average dairy farmer		
mean	4.40	6.25
95% confidence interval	3.59–5.22	5.33–7.18

Notes: Pilot extension mean based on four months of daily seasonal milk production in 2017. Average dairy farmer mean based on survey data from 54 households.

from 0.7 to 0.8% (Table 8). We also find evidence that blue water (captured and/or the amount available in streams) positively impacts milk production, but again these results do not hold when year fixed effects are included.

We also include a poverty dummy variable for poor to determine if there are differences in efficiency between these groups (Models 3, 4) and do find that poor households are significantly less efficient in the dry season through the interaction term between poverty and blue water stock. This suggests that although the availability of green and blue water (and rainfall) do not differ for poor and non-poor households, the impact of rainfall shocks (i.e. dry season and droughts) may translate into relatively greater negative impacts in production efficiency of poor households.

5. Pilot program: investments in blue and green water

Our regression results suggest that green and blue water have a direct effect on production and production efficiency. This suggests that the availability of forage (i.e. productive green pasture) and the supply of water for drinking may serve as limiting factors for milk production in the dry season. During the time period of this study, there was not much investment in reducing or mitigating green water scarcity, as farmers did not have the ability to provide supplemental feed to cattle, plant pasture seed or invest in irrigation. However, these results suggest that farmers could benefit from investments to prevent or mitigate the effects of scarcity in green water (cattle feed) and blue water (by damming streams and creating watering ponds). A recent pilot program launched in 2017 in a similar dairy production region, Rolim de Moura, Rondônia (located 260 km southeast of Ouro Preto do Oeste) supports this conclusion.

Daily data collected from a farmer enrolled in a pilot extension program designed to test the impact of supplemental feed are compared to survey data from 54 households that produce milk in the same municipality and in the same year (Table 9). From these comparisons, milk production is significantly higher in the dry (174%) and rainy (39%) seasons for the farmer in the feed extension program. As expected, the mean production improvement (from the use of supplemental feed) per cow per day is greater in the dry season (7.67 L higher per day) in comparison to the rainy season (2.46 L higher per day). Taken with our regression results, these findings suggest that providing feed can be an important way to counter the impacts of a longer dry season in this part of the Amazon. However, because the provision of feed for cattle has implications for lower income households who can rarely afford the input, these conclusions suggest climate adaptation will be more difficult for this income strata unless programs specifically target the poor.

6. Conclusion

Increased drought occurrence and changes in precipitation have been observed and widely reported as signs of climate change in the Brazilian Amazon (Davidson et al., 2012; Hayhoe, Neill, Porder, McHorney, LeFebvre, Coe, Elsenbeer, & Krusche, 2011) including in Rondônia (Tomasella et al., 2008). Yet, relatively little is known about the impacts of climate change on agricultural production in the region, including how those impacts vary by income level (Perez-Mendez, Roibas, & Wall, 2019). To address this gap in the literature, we use innovative proxies for water availability with panel data from a time period that included a severe drought (in 2005) to estimate how changing climate and water availability could affect production efficiency. Specifically, we estimate production functions and stochastic frontier models that distinguish between the "green water" captured by plants from soil moisture and the "blue water" present in ponds and streams. We find that production is affected by both green and blue water. We also find the availability of water–in both blue and green forms–is important to technical efficiency. While it is possible that farmers could adapt to water scarcity by increasing efficiency, in fact, we find the opposite: efficiency is positively correlated with both green water (as proxied by EVI) and blue water (as proxied by low flow in the streams) in the dry season. While both effects are statistically significant, the effect of EVI is much larger: in the dry season, a 1% decrease in EVI decreases production efficiency by approximately 1%, while a 1% decrease in stream low flow reduces efficiency by approximately 0.03%. To put these numbers in perspective: the average rainfall in the peak dry season months in the 2000s was 121 mm. This fell to an average of 89 mm in 2010–2015. This is a 26% decline in the average rainfall during these peak dry season months, which could translate to similar reductions in green and blue water.

Our results confirm that green water, as measured by EVI, has a consistent positive effect on the productivity and efficiency of pasture-based dairy systems. This suggests that research and extension efforts should seek to mitigate the negative effects of the expected increasing scarcity of green water. Supplemental feeding is one strategy supported by evidence we provide from a pilot study. Only 17% of the households in our sample provided feed in 2009, suggesting potential for improvement, but at an unknown cost (because we do not have information on the costs of supplemental feeding).

We also find evidence that future reductions in rainfall may have a greater negative impact on the poorest households in the region. In particular, we find this relationship for blue water stock to be telling. Unlike green water, households invested in the creation of ponds in the study time period, and these investments positively impacted the non-poor but had no impact on the poor. This suggests that investments in blue--and possibly green--water (expected as the dry season increases in length) may not be an effective adaptation strategy for the poorest households. Although the availability of green water (and rainfall) do not differ for poor and non-poor households (see the descriptive statistics, Table 5), rainfall shocks (i.e. dry seasons and droughts) translate into relatively greater negative impacts on the production and production efficiency of poor households. Again, these results point to an unequal impact of climate and weather shocks on the relatively poor in this region.

Amazonian farmers may find new ways to adapt to water scarcity that are not represented in our sample or models. These will not necessarily be in the agricultural sector: our survey data show that off-farm labor increased in the drought year (2005), at least partially compensating for the reduction in dairy income. The share of income earned from agriculture declined from an average of 60–80% of income in the pre-drought study years to <30% during the drought, while off-farm labor increased from 10 to 20% of total income to almost 60% of income in the drought year. Even so, not all households can easily exit agriculture. Farmers who are relatively poor and/or have less access to urban labor opportunities will likely find the transition difficult. For this reason, policy makers should invest in research and education about effective adaptive strategies (such as supplemental feeding) for agriculture to address expected future water shortages in the seasonally-dry tropics while simultaneously addressing potential impacts on poverty.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.worlddev.2021.105607.

References

Andréassian, V. (2004). Waters and forests: From historical controversy to scientific debate. *Journal of Hydrology, 291*(1–2), 1–27. https://doi.org/10.1016/j.jhydrol.2003.12.015.

Balasubramanya, Soumya, and David Stifel. (2020). "Viewpoint: Water, Agriculture and Poverty in an Era of Climate Change: Why Do We Know So Little?" Food Policy 93 (May).

Barbier, E. B., & Hochard, J. P. (2018a). The impacts of climate change on the poor in disadvantaged regions. *Review of Environmental Economics and Policy, 12*(1), 26–47.

Barbier, E. B., & Hochard, J. P. (2018b). Poverty, rural population distribution and climate change. *Environment and Development Economics, 23*(3), 234–256.

Bark, R. H., Osgood, D. E., Colby, B. G., & Halper, E. B. (2011). How do homebuyers value different types of green space?. *Journal of Agricultural and Resource Economics, 36*(2), 395–415.

Barkhordarian, A., Saatchi, S. S., Behrangi, A., Loikith, P. C., & Mechoso, C. R. (2019). A recent systematic increase in vapor pressure deficit over tropical South America. *Scientific Reports, 9*(1), 1–12. https://doi.org/10.1038/s41598-019-51857-8.

Biggs, Trent, George P. Petropoulos, Naga Manohar Velpuri, Michael Marshall, Edward P. Glenn, Pamela L. Nagler, and Alex Messina. (2015). "Remote Sensing of Actual Evapotranspiration from Cropland: Chapter 3." https://pubs.er.usgs.gov/publication/70176490.

Biggs, T. W., Marshall, M., & Messina, A. (2016). Mapping daily and seasonal evapotranspiration from irrigated crops using global climate grids and satellite imagery: Automation and methods comparison. *Water Resources Research, 52*(9), 7311–7326. https://doi.org/10.1002/2016WR019107.

Blackman, A. (2013). Evaluating forest conservation policies in developing countries using remote sensing data: An introduction and practical guide. *Forest Policy and Economics, 34*(September), 1–16. https://doi.org/10.1016/j.forpol.2013.04.006.

Bravo-Ureta, B. E., & Pinheiro, A. E. (1993). Efficiency analysis of developing country agriculture: A review of the frontier function literature | Agricultural and resource economics review | Cambridge core. *Agricultural and Resource Economics Review, 22*(1), 88–101.

Browder, J. O. (1994). Surviving in Rondônia: The Dynamics of Colonist Farming Strategies in Brazil's Northwest Frontier. *Studies in Comparative International Development (SCID), 29*(3), 45–69.

Carter, M. R., Little, P. D., Mogues, T., & Negatu, W. (2007). Poverty traps and natural disasters in Ethiopia and Honduras. *World Development, 35*(5), 835–856.

Caviglia-Harris, Jill, Erin Sills, Andrew Bell, Daniel Harris, Katrina Mullan, and Dar Roberts. 2016. "Busting the Boom–Bust Pattern of Development in the Brazilian Amazon." World Development 79 (Supplement C): 82–96. DOI:10.1016/j.worlddev.2015.10.040.

Caviglia-Harris, J., Hall, S., Mulllan, K., Macintyre, C., Bauch, S. C., Harris, D., et al. (2012). Improving household surveys through computer-assisted data collection: Use of touch-screen laptops in challenging environments. *Field Methods, 24*(1), 74–94. https://doi.org/10.1177/1525822X11399704.

Caviglia-Harris, J., & Harris, D. (2011). The impact of settlement design on tropical deforestation rates and resulting land cover patterns. *Agricultural and Resource Economics Review, 40*(3), 451–470.

Caviglia-Harris, J., Sills, E. O., & Mullan, K. (2013). Migration and mobility on the amazon frontier. *Population and Environment, 34*(3), 338–369. https://doi.org/10.1007/s11111-012-0169-1.

Chiona, S., Kalinda, T., & Tembo, G. (2014). Stochastic frontier analysis of the technical efficiency of smallholder maize farmers in Central Province, Zambia. *Journal of Agricultural Science, 6*(10), 108. https://doi.org/10.5539/jas.v6n10p108.

Coe, M. T., Costa, M. H., & Soares-Filho, B. S. (2009). The influence of historical and potential future deforestation on the stream flow of the amazon river – Land surface processes and atmospheric feedbacks. *Journal of Hydrology, 369*(1), 165–174. https://doi.org/10.1016/j.jhydrol.2009.02.043.

Cross, R., Färe, R., Grosskopf, S., & Weber, W. L. (2013). Valuing vineyards: A directional distance function approach. *Journal of Wine Economics, 8*(1), 69–82. https://doi.org/10.1017/jwe.2013.5.

Davidson, E. A., de Araújo, A. C., Artaxo, P., Balch, J. K., Brown, I. F., Bustamante, M. M. C., et al. (2012). The Amazon Basin in transition. *Nature, 481*(7381), 321–328.

De Sales, Fernando de, Thais Santiago, Trent Wade Biggs, Katrina Mullan, Erin O. Sills, and Corrie Monteverde. 2020. "Impacts of Protected Area Deforestation on Dry-Season Regional Climate in the Brazilian Amazon." Journal of Geophysical Research: Atmospheres 125 (16): e2020JD033048. DOI:10.1029/2020JD033048.

Donaldson, D., & Storeygard, A. (2016). The view from above: Applications of satellite data in economics. *Journal of Economic Perspectives, 30*(4), 171–198. https://doi.org/10.1257/jep.30.4.171.

Ekbom, A., Alem, Y., & Sterner, T. (2013). Integrating soil science into agricultural production frontiers. *Environment and Development Economics, 18*(3), 291–308. https://doi.org/10.1017/S1355770X13000089.

Espinoza Villar, J. C., Ronchail, J., Guyot, J. L., Cochonneau, G., Naziano, F., Lavado, W., et al. (2009). Spatio-temporal rainfall variability in the amazon basin Countries (Brazil, Peru, Bolivia, Colombia, and Ecuador). *International Journal of Climatology, 29*(11), 1574–1594. https://doi.org/10.1002/joc.v29:1110.1002/joc.1791.

Falkenmark, M., & Rockström, J. (2006). The new blue and green water paradigm: Breaking new ground for water resources planning and management. *Journal of Water Resources Planning and Management, 132*(3), 129–132. https://doi.org/10.1061/(ASCE)0733-9496(2006)132:3(129).

Glenn, E. P., Nagler, P. L., & Huete, A. R. (2010). Vegetation index methods for estimating evapotranspiration by remote sensing. *Surveys in Geophysics, 31*(6), 531–555. https://doi.org/10.1007/s10712-010-9102-2.

Good, P., Jones, C., Lowe, J., Betts, R., & Gedney, N. (2013). Comparing tropical forest projections from two generations of hadley centre earth system models, HadGEM2-ES and HadCM3LC. *Journal of Climate, 26*(2), 495–511. https://doi.org/10.1175/JCLI-D-11-00366.1.

Green, J. K., Berry, J., Ciais, P., Zhang, Y., & Gentine, P. (2020). Amazon rainforest photosynthesis increases in response to atmospheric dryness. *Science Advances, 6*(47), eabb7232. https://doi.org/10.1126/sciadv.abb7232.

Greene, W. H. (2008). *Econometric Approach to Efficiency Analysis*. Oxford U.K: xford Univerity Press.

Hallegatte, S., Fay, M., & Barbier, E. B. (2018). Poverty and climate change: Introduction. *Environment and Development Economics, 23*(3), 217–233.
Hayhoe, S.J., C. Neill, S. Porder, R. McHorney, P. LeFebvre, M.T. Coe, H. Elsenbeer, and A.V. Krusche. (2011). ''Conversion to Soy on the Amazonian Agricultural Frontier Increases Streamflow without Affecting Stormflow Dynamics.'' Global Change Biology.
Henderson, J. Vernon, Tanner Regan, and Anthony J. Venables. (2016). ''Building the City: Sunk Capital, Sequencing, and Institutional Frictions.'' 11211. CEPR Discussion Papers. C.E.P.R. Discussion Papers. https://ideas.repec.org/p/cpr/ceprdp/11211.html.
Khanna, J., Medvigy, D., Fueglistaler, S., & Walko, R. (2017). Regional dry-season climate changes due to three decades of Amazonian deforestation. *Nature Climate Change, 7*(3), 200–204. https://doi.org/10.1038/nclimate3226.
Lacombe, G., Ribolzi, O., de Rouw, A., Pierret, A., Latsachak, K., Silvera, N., et al. (2016). Contradictory hydrological impacts of afforestation in the humid tropics evidenced by long-term field monitoring and simulation modelling. *Hydrology and Earth System Sciences, 20*(7), 2691–2704. https://doi.org/10.5194/hess-20-2691-2016.
Lathuillière, M. J., Coe, M. T., Castanho, A., Graesser, J., & Johnson, M. S. (2018). Evaluating water use for agricultural intensification in Southern Amazonia using the water footprint sustainability assessment. *Water, 10*(4), 349. https://doi.org/10.3390/w10040349.
Lathuillière, M. J., Solvik, K., Macedo, M. N., Graesser, J., Miranda, E. J., Couto, E. G., et al. (2019). Cattle production in Southern Amazonia: Implications for land and water management. *Environmental Research Letters, 14*(11), 114025. https://doi.org/10.1088/1748-9326/ab30a7.
Lima, L. S., Coe, M. T., Soares Filho, B. S., Cuadra, S. V., Dias, L. C. P., Costa, M. H., et al. (2014). Feedbacks between deforestation, climate, and hydrology in the Southwestern Amazon: Implications for the provision of ecosystem services. *Landscape Ecology, 29*(2), 261–274. https://doi.org/10.1007/s10980-013-9962-1.
Mendelsohn, R. (2008). The impact of climate change on agriculture in developing countries. *Journal of Natural Resources Policy Research, 1*(1), 5–19. https://doi.org/10.1080/19390450802495882.
Moran, E. F. (1981). *Developing the Amazon*. Bloomington: Indiana University Press.
Mu, Y. e., Biggs, T., & De Sales, F. (2021). Forests mitigate drought in an agricultural region of the Brazilian Amazon: Atmospheric moisture tracking to identify critical source areas. *Geophysical Research Letters, 48*(February). https://doi.org/10.1029/2020GL091380.
Mu, Y. e., Biggs, T., Stow, D., & Numata, I. (2020). Mapping heterogeneous forest-pasture mosaics in the Brazilian Amazon using a spectral vegetation variability index, band transformations and random forest classification. *International Journal of Remote Sensing, 41*(September), 8682–8692. https://doi.org/10.1080/2150704X.2020.1802529.
Mu, Q., Zhao, M., & Running, S. W. (2011). Improvements to a MODIS global terrestrial evapotranspiration algorithm. *Remote Sensing of Environment, 115*(8), 1781–1800. https://doi.org/10.1016/j.rse.2011.02.019.
Mullan, Katrina, Erin Sills, Subhrendu K. Pattanayak, and Jill Caviglia-Harris. 2017. ''Converting Forests to Farms: The Economic Benefits of Clearing Forests in Agricultural Settlements in the Amazon.'' Environmental and Resource Economics, June, 1–29. DOI:10.1007/s10640-017-0164-1.
Numata, I., Soares, J. V., Roberts, D. A., Leonidas, F. C., Chadwick, O. A., & Batista, G. T. (2003). Relationships among Soil fertility dynamics and remotely sensed measures across pasture chronosequences in Rondônia, Brazil. *Remote Sensing of Environment, 87*(4), 446–455. https://doi.org/10.1016/j.rse.2002.07.001.
Pacheco, P. (2009). Agrarian Reform in the Brazilian Amazon: Its Implications for land distribution and deforestation. *World Development, The Limits of State-Led Land Reform, 37*(8), 1337–1347. https://doi.org/10.1016/j.worlddev.2008.08.019.
Panday, P. K., Coe, M. T., Macedo, M. N., Lefebvre, P., & de Almeida Castanho, A. D. (2015). Deforestation offsets water balance changes due to climate variability in the Xingu River in Eastern Amazonia. *Journal of Hydrology, 523*(April), 822–829. https://doi.org/10.1016/j.jhydrol.2015.02.018.
Payton, S., Lindsey, G., Wilson, J., Ottensmann, J. R., & Man, J. (2008). Valuing the benefits of the urban forest: A spatial hedonic approach. *Journal of Environmental Planning and Management, 51*(6), 717–736. https://doi.org/10.1080/09640560802423509.
Perez-Mendez, J. A., Roibas, D., & Wall, A. (2019). The influence of weather conditions on dairy production. *Agricultural Economics, 50*(2), 165–175. https://doi.org/10.1111/agec.2019.50.issue-210.1111/agec.12474.
Qiu, Jiangxiao, Edward T Game, Heather Tallis, Lydia P Olander, Louise Glew, James S Kagan, Elizabeth L Kalies, et al. 2018. ''Evidence-Based Causal Chains for Linking Health, Development, and Conservation Actions.'' Bioscience 68 (3): 182–93. DOI:10.1093/biosci/bix167.
Roberts, D. A., Numata, I., Holmes, K., Batista, G., Krug, T., Monteiro, A., et al. (2002). Large Area Mapping of Land-Cover Change in Rondônia Using Multitemporal Spectral Mixture Analysis and Decision Tree Classifiers. *Journal of Geophysical Research, 107*(D20), 8073.
Rodriguez-Oreggia, E., De La Fuente, A., De La Torre, R., & Moreno, H. A. (2013). Natural disasters, human development and poverty at the municipal level in Mexico. *Journal of Development Studies, 49*(3), 442–455. https://doi.org/10.1080/00220388.2012.700398.
Rufin, P., Müller, H., Pflugmacher, D., & Hostert, P. (2015). Land use intensity trajectories on Amazonian pastures derived from Landsat time series. *International Journal of Applied Earth Observation and Geoinformation, 41* (September), 1–10. https://doi.org/10.1016/j.jag.2015.04.010.
Saatchi, Sassan, Salvi Asefi-Najafabady, Yadvinder Malhi, Luiz E. O. C. Aragão, Liana O. Anderson, Ranga B. Myneni, and Ramakrishna Nemani. 2013. ''Persistent Effects of a Severe Drought on Amazonian Forest Canopy.'' Proceedings of the National Academy of Sciences 110 (2): 565–70. DOI:10.1073/pnas.1204651110.
SEBRAE. 2015. ''Diagnóstico Do Agronegócio Do Leite e Derivados Do Estado de Rondônia. Porto Velho, 2015.'' Rondônia. Porto Velho: SEBRAE. Serviço de Apoio às Micro e Pequenas Empresas em Rondônia.
Tomasella, J., Hodnett, M. G., Cuartas, L. A., Nobre, A. D., Waterloo, M. J., & Oliveira, S. M. (2008). The Water Balance of an Amazonian Micro-Catchment: The effect of interannual variability of rainfall on hydrological behaviour. *Hydrological Processes, 22*(13), 2133–2147. https://doi.org/10.1002/(ISSN)1099-108510.1002/hyp.v22:1310.1002/hyp.6813.
WeatherSpark Beta. 2016. 2016. https://weatherspark.com/averages/33475/Porto-Velho-Rondonia-Brazil.
Wohl, E., Barros, A., Brunsell, N., Chappell, N. A., Coe, M., Giambelluca, T., et al. (2012). The hydrology of the humid tropics. *Nature Climate Change, 2*(9), 655–662. https://doi.org/10.1038/nclimate1556.