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Water Stress and Productivity: An Empirical Analysis of Trends and Drivers

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Key Points:
- Only 29 out of 179 countries show a statistically significant decrease in water stress
- At a national scale, increasing productivity is the explanation for the highest variation in water stress through time within a country
- When looking across all countries, GDP and precipitation are associated with variations in water stress

Supporting Information:
- Supporting Information S1

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Abstract Water scarcity is a global risk that could arguably be mitigated by using water more efficiently, that is, increasing water's productivity. However, the effects of water productivity on water stress have not been empirically tested or validated across countries. Evidence from other natural resource sectors suggests that improving productivity may, in fact, lead to "rebound" effects that exacerbate resource exploitation. An econometric analysis is used to evaluate the relationship between water stress and productivity at the country level. A 1.0% increase in productivity is associated with a 0.81% decrease in water stress through time within a country, on average, and accounts for 75% of the variance of water stress. This suggests that targeting improvements in productivity have the ability to lower water stress. Analysis of trends in stress and productivity demonstrates that several developed countries are starting to exhibit decreasing trends in stress. Conversely, stress is low in developing countries, but rising. Productivity is generally increasing across all countries. Fixed effects panel regressions demonstrate that population, cultivated land, and political stability are also related to a variance in stress within a country. Differences in gross domestic product and precipitation explain variations in stress when looking across countries. The results of this analysis show that as a country develops, water stress is initially likely to increase. Increasing water productivity, which typically occurs later in a country's development pathway, is linked to decreasing stress, so water stress has the potential to be mitigated if a "productivity transition" were to take place sooner.

1. Introduction

Water scarcity is a lack of water or the inability to meet human, economic, and environmental needs for water (Damkjaer & Taylor, 2017). It is estimated that more than 4 billion people face blue water scarcity at least 1 month a year, with scarcity occurring if withdrawals exceed availability (Mekonnen & Hoekstra, 2016). This statistic is a metric of water stress, as it measures the amount of water used versus the available amount. By capturing the stress placed on the resource, it is possible to highlight areas of water scarcity. In the coming decades, scarcity is expected to increase in locations such as continental Europe, the Middle East and North Africa (MENA), regions of the American Southwest, and central Asia (Wada & Bierkens, 2014).

Policymakers have several options when attempting to assuage water scarcity. There is the option of increasing the supply by incorporating desalinization, new reservoirs, or facilities to treat water for reuse. In addition, policies may be adopted to reduce demand for water. This could include shifting away from water intensive agriculture in favor of virtual water imports (Kummu et al., 2017) or implementing other policies such as regulating water withdrawals, pricing mechanisms, and enhancing the efficiency of water use (Dilling et al., 2019). It has been found that an increase in efficiency can lead to a rise in productivity (Playán & Mateos, 2006). There is some confusion within the literature as to the difference between efficiency and productivity. We attempt to disentangle this below, but essentially, efficiency is a measure of utilized input relative to total input, while productivity is the ratio of output to total input.

One aim of policy instruments that target efficiency and productivity could be to reduce overall water usage. Many authors imply that one might expect a negative relationship between water stress and efficiency or productivity (Khair et al., 2019; Mekonnen & Hoekstra, 2016; Scheierling & Treguer, 2016). For example, Khair et al. (2019) suggest "that competition for scarce resources will lead to greater efficiency." However, there have been few studies that empirically test this relationship. A 2017 article asserted that "improvements in water productivity would reduce the requirement for additional freshwater by an estimated 16% against a business as usual baseline" (Unver et al., 2017). However, the same article goes on to question this by saying, "improvements in water productivity do not necessarily mean more water for others … farmers might use the water they save due to increased efficiency to expand production" (Unver et al., 2017). Zheng et al. (2018) showed that by increasing water productivity (yield/m^3), water usage went down. There have also been studies that look at specific subsectors of water usage and how their efficiency or productivity affects scarcity. For example, Porkka et al. (2016) studied changes in green-blue water scarcity and found that "by 2009 the same food supply could be produced with half of the water it took a century earlier." This gives evidence that productivity (in terms of agricultural yield) has increased. In Wada et al. (2016), the authors compare three global water models and focus specifically on domestic and industrial water usage projections. The results show an increase in domestic and industrial water usage by 2050, but the actual estimates are sensitive to underlying assumptions regarding socioeconomic drivers such as economic growth (Wada et al., 2016). They also find that the industrial estimates vary across models partially due to the differences in projections of efficiency improvements (Wada et al., 2016). So it is understood in these global models that variations in efficiency have the ability to alter future industrial water usage.

As documented in the energy literature, increasing efficiency or productivity may result in a "rebound effect," meaning that overall resource use does not reduce as much as anticipated (Jekins et al., 2011; Sorrell, 2009). The exact strength of this rebound effect is debated and likely varies by case (Greening et al., 2000). There have been several studies on the rebound effect in the water literature with a specific focus on the relationship of withdrawals to efficiency, but none of a global nature. Pfeiffer and Lin (2014) found an increase in groundwater withdrawal after efficiency measures were put in place in Kansas. Freire-González (2019) found a minor rebound effect in his analysis of Spain. Given both the potential for a rebound effect and the possible benefits that could be achieved by increasing water efficiency and productivity, it is essential to obtain more empirical evidence of the extent to which increasing productivity leads to lower water stress.

Many different methods have been proposed for measuring stress and productivity. They have been grouped as the UN Sustainable Development Goals (SDG) Target 6.4: "water use and scarcity" (UN-Water, 2019). For this analysis, we use the equations associated with SDG Target 6.4. Before we empirically test the relationship between productivity and stress, we first take a more in-depth look and water stress and productivity. Water stress, in terms of SDG indicator 6.4.2, is readily reported on (FAO Aquastat, 2019; World Bank Databank, 2019). It has been mapped with country-level mapping showing higher water stress in western countries along with MENA and Asia (FAO, 2018a). The most recent UN summary report on SDG 6.4.2 found that water stress "increased for most countries in the world" but "that it had decreased in 44 countries half of which are in Europe" (FAO, 2018a). This report did not map trends or analyze if trends were significant. Little work has been done on SDG indicator 6.4.1, as it develops a new calculation for water-use efficiency. The most recent UN report only listed the most recent value for each country (FAO and UN-Water, 2018). A recent article by Giupponi et al. (2018) estimated water-use efficiency using the same equations, but only for South and South-East Asia from 1980 to 2100. Thus, this new metric, which we believe is a better measure of water productivity, as discussed below, has yet to be created in a time series for all countries. Therefore, a global trend analysis of this metric has yet to be developed.

In addition to water productivity, several other variables have the potential to affect water stress. These include socioeconomic drivers such as population growth and a country's wealth (Fant et al., 2016), as well as physical drivers such as climate (Le Blanc & Perez, 2008; Wada & Bierkens, 2014). These variables, among others, are included in our exploratory analysis to control for their effect and to understand their impact on water stress. Several studies have been done in this regard. When looking across potential drivers of increased water stress, Fant et al. (2016) find that socioeconomic drivers are more important than the climate in the future of water scarcity. Veldkamp et al. (2015) find that hydro-climatic variability contributes to the variation in global water scarcity in the short term, whereas socioeconomic drivers become more important after 6 to 10 years.

Ultimately, we aim to answer three main research questions: (1) Are there significant trends in water productivity and water stress? (2) What is the relationship between water productivity and water stress? (3) What are the main drivers of water stress? Significant trends in water productivity and water stress have yet to be mapped. In this paper, we use an econometric analysis to verify whether or not a relationship between water stress and water productivity is present. It is important to note that even though we may find a relationship between stress and productivity, there may be multiple mechanisms that lead to a relationship. Playán and Mateos (2006) indicate that productivity can be increased by incorporating high-value crops, increased yield, or reduced water application. So even though productivity is rising, it does not necessarily mean that withdrawals are decreasing. We then continue our econometric analysis to look at how multiple variables affect stress. This is, therefore, also novel since this combination of productivity and drivers of stress has yet to be studied. Ultimately, this research aims to understand the water productivity and water stress metrics better, how they interact, and what drives stress. The results of this research can affect policymakers since they can take this evidence into account when evaluating the implementation of policies to improve productivity based on its relationship with water stress.

Before going further, it is important to have an understanding of the concepts used in this analysis due to their ambiguity. This includes water stress, water efficiency, water productivity, and what we consider a driver. Next, we discuss how water stress and productivity were calculated and describe the methods used to analyze trends and relationships. The results are then presented and discussed, followed by concluding remarks.

2. A Review of Metrics

2.1. Water Stress

Water stress measures the amount of water withdrawn relative to the amount of water available. It essentially captures the pressure on a water resource and is one way to measure water scarcity. There are at least 150 indicators of water scarcity (Damkjaer & Taylor, 2017). Several review articles specifically highlight the evolution of these indicators (Brown & Matlock, 2011; Chenoweth, 2008; Damkjaer & Taylor, 2017). These review articles list the Falkenmark indicator that measures the amount of renewable freshwater per capita, as the first water scarcity indicator (Brown & Matlock, 2011; Chenoweth, 2008; Damkjaer & Taylor, 2017). Many metrics have been created since with the literature expanding in two different directions; one toward the human development side (Ohlsson, 2000; Sullivan, 2002) and the other toward a more physical measurement (Chaves & Alipaz, 2007; Raskin et al., 1997). On the physical side, the "use-to-resource ratio" was a precursor for the water stress metric that is widely used today (Raskin et al., 1997). This indicator looks at the withdrawals compared to the total amount of renewable supply, and a country is highly stressed if they are using more than 40% of their renewable water (Raskin et al., 1997). This indicator has been adapted in several different metrics, such as the watershed sustainability index (Chaves & Alipaz, 2007).

Given the number of water scarcity metrics available, there is little consensus as to which is best. Particular articles have chosen to focus on what is lacking from current metrics or what an ideal measurement should include. Wada and Bierkens (2014) listed items missing from current indicators: nonrenewable water usage, lack of environmental flows, and foresight into future water needs. Vanham et al. (2018) set out seven criteria for a holistic water stress metric to measure water stress: (1) gross versus net water use; (2) environmental flows; (3) temporal scale saying the finer, the better; (4) spatial scale meaning the finer, the better; (5) surface and groundwater use; (6) alternative water sources; and (7) water storage or reuse.

It is useful to compare the SDG indicator 6.4.2 to these criteria. This SDG indicator is titled "water stress," and its purpose is to "ensure sustainable withdrawal and supply of freshwater to address water scarcity" (FAO, 2018c). This indicator meets several of the above criteria: it incorporates water usage across sectors, environmental flow needs, and includes both renewable surface and groundwater usage. However, the SDG indicator fails to capture nonrenewable water use, alternative water use, and water storage values. There is also an issue with the quantity and quality of water resource data available to measure and monitor the indicator at the national scale. Nevertheless, this indicator is widely reported in country-level statistics (FAO Aquastat, 2019; World Bank Databank, 2019) and will, therefore, be used in our analysis.

2.2. Water Productivity and Water Efficiency

Water productivity and water efficiency are both system performance metrics that are often used interchangeably. In an article focused on a review of water productivity, 55 of the 59 articles assessed also mentioned efficiency (Clement, 2013). Efficiency can be thought of as getting the most out of each unit of input. It is typically a unitless quantity or represented by a percentage. Productivity can be thought of as getting the greatest value for your work, so typically has units of output per unit input. These basic system definitions have not translated fully to water resources, so in the water literature, a variety of sometimes inconsistent definitions and measurements are found. For example, Lankford (2013) deems irrigation efficiency as the ratio of "beneficial water consumption to total water withdrawals (m^3/m^3 or %)." He calls productivity, a form of "dimensional efficiency" that measures "economic output per input (USD/m^3)." Lankford (2013) distinguishes between dimensionless efficiency, which is typically referred to as "efficiency" and a dimensional efficiency called "productivity." He also classifies them both as performance metrics. Even with these definitions, water efficiency and water productivity are still measured in many different ways.

In the biological sciences, water-use efficiency is typically defined as gross primary production over evapotranspiration (Sun et al., 2016, 2018; Xue et al., 2015). Essentially, this is how well a plant and or leaf utilizes the water available to it. Pereira et al. (2012) discuss how efficiency is typically considered the beneficial water used versus the water applied in percentage terms. This water-use efficiency is dimensionless. These metrics refer to efficiency in terms of the amount of water used for a task compared to the total amount of water supplied for the task. Van Halsema and Vincent (2012) cite a similar explanation as Lankford (2013) but show that this is more of an engineering term for efficiency. Finally, there are cases where water-use efficiency is defined in terms of dollars per water used ($/$m^3$) (Long & Pijanowski, 2017), that is, in terms that are closer to the conventional definition of productivity.

Water productivity is referred to as crop yields per water use or dollars generated per water used (Molden et al., 2010). The first type of productivity is typically referred to as physical or agricultural water productivity (Molden et al., 2010). Agricultural water productivity is regarded as an indicator of farm water management, but its usefulness is debated (Wichelns, 2014). The second type of productivity is most often referred to as economic water productivity and refers to the amount of value in monetary terms that is gained from the water used (Molden et al., 2010). Economic water productivity can either use total gross domestic product (GDP), gross value added (GVA), or be broken down by sectors, that is, agriculture, industry, or services. As a quick note, GVA measures the amount of output (USD) of a good minus the input(s) used to produce it (World Bank Databank, 2019). GDP is the total GVA plus taxes and minus subsidies (World Bank Databank, 2019). Currently, the total economic water productivity, in terms of GDP, is the only productivity or efficiency metric reported on the country scale. It can be found in the World Bank's Databank, and the data are available back to 1960. However, it becomes increasingly intermittent the further back one looks. Select studies have mentioned that water productivity is a better metric to report on than efficiency, since it implies an incentive for users such as farmers, with the incentive being higher profit or yields, and also that it is easier to target and measure across scales (Unver et al., 2017). Additional authors agree, citing the suitability of productivity rather than efficiency since efficiency is hard to account for at larger scales (Molden, 1997; Van Halsema & Vincent, 2012).

The creation of SDG indicator 6.4.1 has further complicated matters by defining water-use efficiency as the amount of GVA gained from water withdrawals by sector (FAO, 2018b). The units are in (USD/m^3). This, therefore, is closer to previous definitions of economic productivity. The UN website for the indicator explains,

> "The indicator differs from water productivity as it does not consider the productivity of the water used in a given activity as an input to production, or even better the marginal productivity of the extra dose. Instead, this indicator will show how much the growth of the economy is linked to the exploitation of natural water resources, indicating the decoupling of economic growth from water use. In other terms, if the value added (VA) produced by the economy doubles, how much will the water use increase?" (FAO, 2018b)

This indicator makes methodological strides in calculating the monetary value gained from water because it is broken down by economic sectors and factors in the proportion of water used by each respective sector. Thus, it has the potential to offset high productivity values from countries that have a large service sector GVA but only use a small proportion of their water budget on services. This helps to give a more accurate depiction of total economic water productivity. However, based on the discussion above, we argue that it is an indicator of productivity rather than efficiency. Pereira et al. (2012) explicitly state that "water use efficiency should only be used to measure the water performance of plants and crops, irrigated or non-irrigated, to product assimilates, biomass and/or harvestable yield." Ultimately, SDG 6.4.1 is a measure of output (USD) over input (m^3), which is the definition of productivity. Hence, the remainder of this article will refer to SDG 6.4.1 as a measure of water productivity.

2.3. Drivers

A driver is an item that can affect the state of a system or its performance. For example, as population increases (driver), water stress (system performance) may increase due to more demand for water, even if per capita consumption remains the same. Drivers give us an idea of what is happening within the overall system and indicate where it might be headed in the future. Social-ecological system theory highlights four "settings" that have the potential to influence an social-ecological system, and we adopt these four settings as our categories of drivers: social, economic, political, and environmental (Ostrom, 2009). We selected a primary indicator for each category based on the second-tier variables in Table 1 of Ostrom's (2009) framing: S2, S1, S3, and ECO1. GDP was used as a proxy of economic development corresponding to the (S2) variable and population as an indicator for demographic change corresponding to (S1). Temperature and precipitation indicate changing climate patterns (ECO1). In Ostrom's (2009) framing, (S3) is categorized as political stability. The Fragile States Index is a comprehensive indicator and a top choice to measure stability since it measures state vulnerability across 12 metrics (The Fund for Peace, 2019). However, data reporting on this indicator only began in 2006, and this would detrimentally affect the size of our time series. The political stability indicator from the World Bank World Governance Indicators was ultimately chosen as a proxy. The World Governance Indicators measures governance across six separate categories, and political stability was selected since it is closest in meaning to the (S3) variable set out in Ostrom's (2009) framing, as well as being the main indicator out of the six that specializes in government stability (World Bank, 2019). Finally, we add one additional driver regarding the amount of agriculture within a country, the percent of cultivated land, since it consumes a large part of a country's water budget. As of 2012, 99 out of 159 countries (62%) had agricultural water usage that accounted for over 50% of their total usage (Liu et al., 2016; FAO Aquastat, 2019). The amount of cultivated land is used as a proxy for the actual amount of land irrigated, as the later has substantial data gaps. In this instance, cultivated land includes both arable and permanent crops, which include annual and perennial crops (FAO Aquastat, 2019).

Previous studies have already analyzed several of these relationships. It has been found that population growth increases water stress (Chenoweth, 2008; Mekonnen & Hoekstra, 2016). Fant et al. (2016) find that population and GDP both have the ability to increase stress. Studies show that as precipitation goes down, stress will increase in sub-Saharan African (Le Blanc & Perez, 2008), and higher temperatures are found to increase water stress (Wada & Bierkens, 2014). One dimension that has not been studied as readily is the effect of governance and political stability on water stress. However, there is ample literature that cites the importance of good governance and strong institutions for water security (Gupta et al., 2013; Klümper et al., 2017; Pahl-Wostl et al., 2013). In terms of agriculture and water stress, Mancosu et al. (2015) find that several already stressed basins are expected to have increased water stress due to increasing crop irrigation demands.

3. Methods

The research design employed in this study was an exploratory empirical analysis done through panel regressions and does not attempt to discern causation. Panel regressions can also be referred to as longitudinal regressions and allow for the added insight of changes through time, whereas ordinary least squares (OLS) regression does not. A panel analysis allows us to account for changes both within a country (how stress changes over time for each country) and across countries (how stress differs by country) through time. To the best of our knowledge, this is the first econometric study of water stress and water productivity. For the analysis, we have a strongly balanced panel with data gaps, which are discussed below. It is also a short panel since N (number of countries) is greater than T (time steps).

3.1. Data

Data were collected from secondary sources for all countries (Table 1). The first five variables in Table 1 were used to calculate water stress and water productivity (see section 2.2.) and were, therefore, not included in any of the regression models. The last six variables in Table 1 were considered drivers and used in specific

Table 1
Main Data and Their Sources

Variable	Unit	Years available	Source
Data for calculations			
Water withdrawals[a] (total and by sector)	m^3	1973–2012 (5-year time step), 2013	Liu et al., 2016; FAO Aquastat, 2019; USGS, 2019
Total renewable freshwater	m^3	1958–2017 (5-year time step)	FAO Aquastat, 2019
Environmental flow require	m^3	1958–2017 (5-year time step)	IWMI via FAO Aquastat, 2019
Proportion of irrigated land[a]	ratio	1958–2017 (5-year time step)	FAO Aquastat, 2019
Gross value added by sector (Ag, industry, and services)	constant 2010 US$	1960–2017	World Bank Databank, 2019
Drivers			
Population	inhabitants	1960–2017	World Bank Databank, 2019
GDP	constant 2010 US$	1960–2017	World Bank Databank, 2019
Cultivated land	%	1958–2017 (5-year time step)	FAO Aquastat, 2019
Avg yearly precipitation	mm	1950–2015	CRU TS v 4.02 from Harris et al., 2014
Avg yearly temperature	°C	1950–2015	CRU TS v 4.02 from Harris et al., 2014
Political stability	Adjusted Scale (0–100)	1996–2018	World Bank, 2019

[a]Have large data gaps that were accounted for through interpolation, extrapolation, and inverse distance weighting.

regression models. All data listed in Table 1 have been compiled and are publicly available (Doeffinger & Hall, 2019).

The first limiting factor in this study was the water withdrawal data. FAO Aquastat currently reports this data in 5-year windows, broken down into the agricultural, domestic, and municipal sectors. These 5-year windows start with 1958–1962 and run through to 2013–2017. The data entered for each country can be listed for any of the years within the 5-year window, so this creates gaps and inconsistencies within the withdrawal data. A study in 2016 generated a new water withdrawal data set reporting data across countries on a 5-year time step from 1973 to 2012 and then 2013 (Liu et al., 2016). The data set created by Liu et al. (2016) was created through interpolation and inverse distance weighting to fill in gaps from the FAO Aquastat data and has been used in this study for the calculations of water stress and water productivity. It was cross referenced with the current FAO database to update any new data entries. Based on these updates, adjustments in interpolations and extrapolations were made.

The second limiting factor for this analysis was the political stability indicator used as a proxy indicator for the political driver category. Since this metric was not created until 1996, it limited our study to five time steps (1997, 2002, 2007, 2012, and 2013). In the beginning, these data were only collected every 2 years. So data for 1997 were linearly interpreted from the 1996 and 1998 data points. The data were normalized to a 0–100 scale.

A third limiting factor was the list of countries that varied across sources and many countries that contained missing data. Countries were removed from the sample for the following reasons: no water withdrawal data available, missing data for two or more drivers, and South Sudan was removed due to its formation in 2011. The resulting panel data set used in this study contains values for a maximum of 179 countries, with data gaps being present. These gaps can be better understood by looking at the summary statistics in Tables 2 through 4. Table 2 lists the descriptive statistics for the six drivers. Population and GDP are both right skewed, so the log transform was used to normalize them.

3.2. Calculating Metrics

Water stress and water productivity were calculated values based on the first five variables of Table 1. Water stress is currently reported in FAO Aquastat (2019) but was calculated for this study based on the water withdrawal data from Liu et al. (2016). This creates a more complete water stress data set. In addition, a time series of water productivity based on SDG 6.4.1 was generated for the majority of countries for the first time.

3.2.1. Water Stress

Water stress was calculated using equation 1 as provided by UN SDG 6.4.2 (FAO, 2018c).

Table 2
Descriptive Statistics for Drivers

	Mean	Median	*SD*	Min	Max	No. of countries	No. of obs
Population (inhabitants)	3.68E+07	8.18E+06	1.35E+08	4.38E+04	1.36E+09	179	893
GDP (Constant 2010 USD)	3.43E+11	2.61E+10	1.29E+12	1.25E+08	1.58E+13	175	867
Cultivated land (%)	17.83	13.86	14.93	0.04	64.60	179	888
Precipitation (mm)	96.62	83.19	68.11	2.8	331.94	178	890
Temperature (°C)	19.29	22.80	8.15	−4.9	29.00	178	890
Political stability (0–100)	62.52	64.33	19.90	0	100	179	892

$$WS = \frac{TWW}{TRWR - Env} * 100, \tag{1}$$

where
WS = water stress (%)
TWW = total freshwater withdrawal (not including desalinization or reuse; m^3)
TRWR = total renewable freshwater resources (m^3)
Env = environmental water requirements (m^3)

The total water withdrawal does not include water from desalinization or water that has been reused. Nonrenewable abstraction is included in water withdrawals such as groundwater usage, but not in the overall water availability. This results in countries having over 100% water stress. The total renewable freshwater has not changed in the FAO Aquastat database between 1958 and 2017. So the water stress metric does not account for interannual variability in renewable freshwater. The descriptive statistics water stress can be seen in Table 3. Water stress is skewed to the right, so it is log transformed for the analysis. Water stress also exhibits large between and within country variance—with the largest being between countries.

3.2.2. Water Productivity

Water productivity was first calculated based on the formula set out by the UN for SDG 6.4.1 (FAO, 2018b) and seen in equations 2–6. Water productivity "wp" is substituted for water use efficiency "we" in equations 2–6 and thus differs in terminology from the UN calculation (FAO, 2018b).

$$WP = A_{wp} \times P_A + M_{wp} \times P_M + S_{wp} \times P_s, \tag{2}$$

where
WP = water productivity
A_{wp} = irrigated agriculture water productivity (USD/m^3)
P_A = proportion of water used by the agricultural sector over the total use
M_{wp} = mining and quarrying; manufacturing; electricity, gas steam, and air conditioning supply; and constructions (MIMEC) water productivity (USD/m^3)
P_M = proportion of water used by the MIMEC sector over the total use
S_{wp} = services water productivity (USD/m^3)
P_s = proportion of water used by the service sector over the total use

Table 3
Descriptive Statistics for Water Stress

	Water stress (%)
Mean	75.97
Median	8.48
SD	371.35
Min	0.01
Max	5,157.78
Between variance	349.09
Within variance	123.99
Number of countries	179
Number of observations	886

$$A_{wp} = \frac{GVA_a \times (1 - C_r)}{V_a}, \tag{3}$$

where
GVA_a = gross value added by agriculture (excluding river and marine fisheries and forestry; USD)
C_r = proportion of agricultural GVA produced by rainfed agriculture
V_a = volume of water used by the agricultural sector (m^3)

Table 4
Descriptive Statistics for Water Productivity Metrics

	Productivity ($/m^3)	Productivity_no_CR ($/m^3)	WB_Productivity ($/m^3)
Mean	29.66	37.02	52.54
Median	11.09	14.08	17.21
SD	56.66	84.54	115.73
Min	0.14	0.14	0.19
Max	644.14	1,163.46	1,307.62
Between variance	78.29	96.32	108.84
Within variance	7.75	22.12	38.44
Number of countries	149	166	175
Number of observations	475	729	857

$$C_r = \frac{1}{1 + \left(\frac{A_i}{(1 - A_i)^{*}.375}\right)}, \tag{4}$$

where
A_i = proportion of irrigated land on the total cultivated land, in decimals
.375 = generic default ratio between rain and irrigated yields

$$M_{wp} = \frac{GVA_m}{V_m}, \tag{5}$$

where
GVA_m = gross value added by MIMEC (including energy; USD)
V_m = volume of water used by MIMEC (including energy; m^3)

$$S_{wp} = \frac{GVA_s}{V_s}, \tag{6}$$

where
GVA_s = gross value added by services (USD)
V_s = volume of water used by the service sector (m^3)

While the UN (FAO, 2018b) relates specifically to agriculture (GVA_a), global data typically report forestry and fisheries in the same sector as agriculture, but the UN calculation calls for these subsectors to be excluded from the calculation. Alternative methods were considered to disaggregate agriculture from fisheries and forestry, such as a global input-output model (Lenzen et al., 2012). Past studies have listed the World Bank as the primary data source for all GVA data (FAO and UN-Water, 2018; Giupponi et al., 2018). However, GVA data for the industrial and service sectors from the global input-output model did not match World Bank estimates. So we chose to obtain our GVA data from the World Bank to remain consistent in our calculations, even though fisheries and forestry are included in the overall agriculture GVA.

There was an additional issue with calculating irrigated agricultural water productivity (A_{wp}) since irrigation data at the country level are intermittent. Again, additional sources were considered, including satellite data. The World Bank data on irrigated agriculture land were evaluated since it was used in other studies (FAO and UN-Water, 2018; Giupponi et al., 2018). However, we chose to use data from FAO since it better aligned with the definition laid out by FAO and UN-Water (2018). These data were limited, so interpolation was used, and extrapolation was also used on countries with three or more data points. It is also important to note that the final agricultural water productivity value includes water from desalinization and water reuse, as these are included in sector withdrawal values from FAO Aquastat (2019).

Ultimately, three versions of water productivity were calculated, and their summary statistics can be seen in Table 4. The first water productivity metric calculated is based on equations 2–6 and is simply referred to as Productivity in Table 4. The second metric calculated is referred to as Productivity_no_CR, and it excluded equation 4 and removed Cr from equation 3, thus no longer taking into account the amount of irrigated agriculture. Stated another way, Productivity_no_CR includes the GVA from both rainfed and irrigated agriculture. We then calculated a productivity metric based on the World Bank definition of water productivity, which is simply GDP divided by total water withdrawals. This is listed as WB_Productivity in Table 4.

These additional metrics were calculated due to limited irrigation data resulting in a low number of observations for the analysis. Moving forward, we chose to use the Productivity_no_CR value as a proxy for water productivity. This metric gives us more accuracy than the World Bank productivity measure. Productivity_no_CR accounts for the fraction of water used by each sector, thus lowering the potential for total water productivity to be skewed by a high service sector GVA. The productivity_no_CR metric also gave us more observations to work with than the full productivity metric from generated from equations 2–6.

Table 4 shows that the data for all metrics are skewed right. Therefore, the log transformation was used. In addition, Table 4 shows that productivity varies both between countries (between variance) and within each country (within variance)—the largest variance occurring between countries.

3.3. Trend Analyses

OLS regression was used for trend detection rather than nonparametric tests such as Mann Kendall. This is based on the characterization of our sample, since there are only five time steps and several countries oscillate between increasing and decreasing stress. Nonparametric tests tend to underperform in the presence of cyclical trends or small sample sizes (Helsel & Hirsch, 2002; Hess et al., 2001). Additionally, OLS was chosen over generalized least squares regression with AR errors, since there is no expected autocorrelation within the water stress or water productivity metrics given that they are a short time series and lack seasonality. A *t* test for the difference was not used due to it being a small time series. Using OLS, we sought to determine the presence of a significant trend in both water stress and water productivity metrics. Equation 7 shows the model used to estimate a trend in water stress. A similar model was used for water productivity. The results were then mapped.

$$Y_i = \beta_0 + \beta_1 X_1 + \varepsilon_i, \tag{7}$$

where

Y_i is the dependent variable, that is, water stress,
β_0 is the y intercept,
β_1 is the slope or coefficient,
X_1 is the independent variable (time), and
ε_i is the error term.

3.4. Panel Regressions

We first used the panel data set to explore if water productivity had any influence on water stress. The benefit of the panel data set is that it compounds the effects of each cross section through time. Panels show how changes in the independent variable(s) affect the dependent variable not just in one instance but also over several instances. The panel regression models used were based on country fixed effects and time fixed effects. The fixed effects account for the change in the dependent variable based on individual country features, whereas the time fixed effects account for any factors that occurred during the time period that could have similarly affected all countries (Khan et al., 2017). We tested for the need to include time fixed effects within the models, and it was needed in some cases and not in others. To remain consistent, we chose to include time fixed effects in all models. In addition to fixed effects models, there are also random effects models. Random effects are typically used if estimating effects on a population from a random sample of data (Khan et al., 2017).

Various diagnostic tests were run to determine the validity of each model. We used the Breusch-Pagan Lagrange multiplier to test whether there are any effects present within the country(s) or whether a simple OLS regression would be more appropriate. Each model showed the presence of fixed effects, so fixed effects and random effects regressions were used. However, OLS regressions were also run for all models based on equation 7. These multiple regression types allow us to show the strength of the fixed or random effects. The test for serial correlation, a unit root, and cross-sectional dependence could not be run due to gaps in the data. The test for a unit root and cross-sectional dependence were deemed unnecessary since we are using a short panel ($N > T$). All models showed the presence of heteroscedasticity. The clustered robust standard error approach was used for all models to correct the heteroscedasticity and the potential of serial correlation. It is important to note that we found no presence of multicollinearity within these models. All had a mean variance inflator factor below 3.0.

The first regression model focused solely on the relationship between water productivity and water stress. The model specification can be seen in equation 8, which is similar to a model used by Khan et al. (2017).

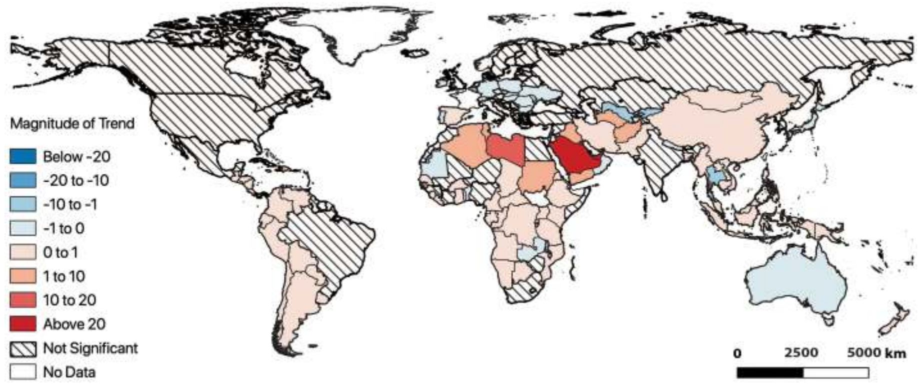

Figure 1. Map of significant trends in water stress from 1997 to 2013.

We first ran the regression for all countries. The panel regression differs from the standard OLS model in equation 7, by adding in the fixed effects (a_i) and time fixed effects (ρ_t). We then looked at the outcome based on different income levels: high, upper middle, low middle, and low. The country income levels are from the World Bank (2018), and changes over the period are included. OLS, fixed effect, and random effect regressions were run in all cases. A Hausman test was performed after each regression to indicate which model was more appropriate: fixed effects or random effects, and the fixed effects model was deemed appropriate in this case.

$$Y_{it} = \beta X_{it} + a_i + \rho_t + \varepsilon_{it}, \tag{8}$$

where

1. Y_{it} represents the dependent variable (water stress) for the ith country during the year t,
2. β is the coefficient for the independent variable (water productivity),
3. X_{it} represents the independent variable (water productivity) the ith country in year t,
4. a_i is the country fixed effect,
5. ρ_t is the time fixed effect, and
6. ε_{it} is the error term.

We then ran several regression models exploring possible relationships between water stress and its potential drivers. The first model included all potential drivers of water stress, including water productivity. The second model we created included all potential drivers, excluding water productivity, in order to determine the overall effect of the additional drivers. We then proceeded to create additional models based on a backward stepwise elimination method. Essentially, drivers that were not statistically significant were removed from the analysis. We ran OLS, fixed effects, and random effects regressions in all cases. Based on the Hausman test, the fixed effects regressions were more appropriate in all cases; thus, we only report the results of the OLS and fixed effect regressions.

4. Results and Discussion

4.1. Trends

Figure 1 shows the trends in water stress from 1997 to 2013. Trends shown are those significant to a p value <0.05. Several developed countries show a decline in water stress while developing countries show an increase. Most notably, countries in Eastern Europe and Australia exhibit this trend. Countries in Latin America, Africa, the Middle East, and Southeast Asia are generally showing an increase in water stress. The largest increases can be found in Saudi Arabia and Kuwait, where the highest declines are seen in Belgium, Uzbekistan, Kyrgyzstan, and Thailand. A few of the trends might not be as meaningful such as the increase in water stress in Argentina, Columbia, and Venezuela since these countries have relatively low values of water stress.

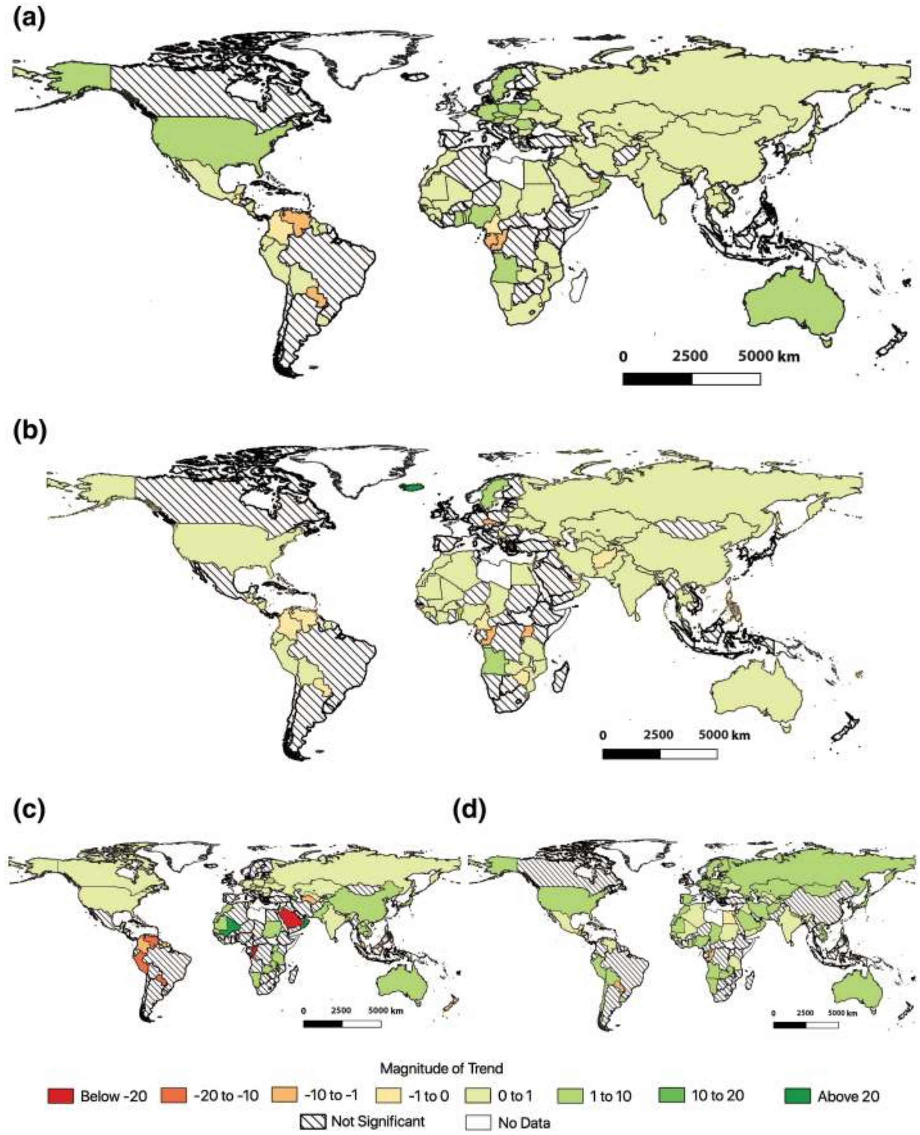

Figure 2. Map of significant trends in water productivity from 1997 to 2013: (a) total water productivity, (b) agricultural water productivity, (c) industrial water productivity, and (d) services water productivity.

We find a total of 29 countries with a significant negative trend in water stress, with close to half coming from Western and Eastern European countries. Nineteen of the countries with a decreasing trend are categorized as high or upper-middle-income countries. This finding is in contrast to the 44 countries the UN reported on with half coming from Western countries (FAO, 2018a). It is, therefore, crucial to continue to measure this trend, to accurately determine if developed countries are indeed decreasing water usage and when as this could inform policymaking for developing countries.

Figure 2 shows the trends in water productivity from 1997 to 2013. The figure includes total water productivity as well as agricultural, industrial, and services productivity trends. Total water productivity trends were first mapped for a p value <0.05, with only 28 countries showing a significant trend. To highlight the possible existence of trends in water productivity, the presented results show a p value <0.1 in all cases. In this first study to map global water productivity trends, we find that all categories of water productivity are generally increasing, as seen in Figure 2. The largest increases in total water productivity can be found in Eastern Europe, Australia, and the United States.

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Table 5
Regression Results for Water Stress Versus Water Productivity

	Global		High income		Upper middle		Lower middle		Low	
	OLS	Fixed	OLS	Fixed	OLS	Fixed	OLS	Fixed	OLS	Fixed
Coefficient	−0.23***	−0.81***	−0.51**	−0.96***	−0.68***	−0.85***	−0.98***	−0.92***	−0.96***	−0.69***
Robust errors[a]	0.05	0.05	0.2	0.08	0.16	0.11	0.10	0.04	0.07	0.10
R2	0.03	0.75	0.04	0.81	0.12	0.82	0.32	0.94	0.46	0.71
No. of countries		166		47		60		79		64
Avg. no. of tears		4.4		3.1		2.7		2.7		3.3

Note. Each column represents a different model specification, that is, high-income countries versus low-income countries. The top row shows whether OLS or fixed effects regressions were used. The dependent variable is the natural log of water stress. The independent variable is the natural log of Productivity_no_Cr.
[a]Robust errors for OLS regressions and clustered robust errors for fixed effects regressions. ***$p < 0.01$. **$p < 0.05$.

However, several countries are experiencing a decline in total productivity: Belize, Cameroon, Colombia, El Salvador, Eswatini, Guatemala, Gabon, Guinea-Bissau, Paraguay, The Republic of the Congo, Timor-Leste, UAE, and Venezuela. Countries such as Columbia, Guinea-Bissau, and Venezuela have had massive increases in their industrial water withdrawals and show a decline in industrial productivity, as seen in Figure 2c. Cameroon and the UAE have had large increases in their agricultural withdrawals and show a decline in their agricultural water productivity, as seen in Figure 2b. The rest of the countries have either significant withdrawal increases or a mix of withdrawal increase coupled with declining GVA, which could be causing the decline in total productivity.

The water service productivity metric shows 88 countries having a statistically significant trend, with 78 countries showing an increasing trend. Industrial productivity has trends increasing for 47 out of 64 statistically significant countries, and agricultural productivity has 45 out of 74 countries with a rising trend. As far as trends in agriculture, Porkka et al. (2016) found that water requirements needed to generate a referenced food yield decreased in East Asia, North America, Western Europe, and Southeast Asia. We show similar findings in Figure 2b. However, Porkka et al. (2016) found increasing water requirements for food in Northern Africa, Southern Africa, and the Middle East. We do find a few instances of decreasing agricultural productivity in Africa, but we find that the majority of countries in Africa and the Middle East either show no trend or show an increase in agricultural productivity. There are two main reasons for the differences in these findings. First, Porkka et al. (2016) used a longer time period of analysis 1901–2009 and would thus have a better opportunity of discovering long-term trends. Second, the measures of productivity are different. This study focused on productivity in terms of ($\$/m^3$), whereas Porkka et al. (2016) focused on yield. Our measure is tied to value added and is thus subject to commodity prices. So even though yield may decrease, a crop could have a high and or rising commodity price, which would result in a rise in productivity in terms of ($\$/m^3$).

It may appear that the services water productivity is driving the overall total water productivity trend, but it is important to remember the calculation for total water productivity factors in the proportion of water used by each sector. Thus, since services water use is typically low, the overall effect of the services water productivity is mitigated within the total productivity calculation. Ultimately, for the majority of countries that exhibit a statistically significant trend, all productivity metrics are rising. However, some countries are experiencing an increase in productivity even though they see an increase in withdrawals. An example of this is China, which has seen a rise of total water productivity from $\$3.4/m^3$ to $\$13/m^3$. However, China's water withdrawals have increased from 525 to 598 billion cubic meters. This example illustrates the importance of investigating the reason behind a change in productivity. We see here that an increase in productivity does not necessarily amount to a decrease in overall withdrawals.

4.2. Water Stress and Water Productivity

Results for the panel regressions of water stress and water productivity can be found in Table 5. The global model was run for all available countries (166). Based on the Hausman test, the fixed effects model is more appropriate here (Prob > $chi^2 = 0.00$). Reading through the global fixed effects result, if water productivity increases by 1%, we would expect stress to decrease by 0.81%. This example of a 1% difference is one instance from the log-log relationship identified in the regressions. For example, a 10% increase in productivity would result in an 8.1% decrease in stress. A 10% increase in productivity would be going from $10/m^3 to $11/m^3. The coefficient remains similar across all models, as does the negative relationship. This robust relationship is in contrast to evidence against the usefulness of productivity found in more localized case studies (Wichelns, 2014). Lankford (2013) also suggested that there could be adverse side effects to increased productivity, such as a rebound effect. Given that the relationship remained negative both across the OLS and fixed effects regressions as well as globally and the four different economic levels, the results robustly support the negative relationship for the sample and time steps used here. For a comparison of how these results change based on the other two productivity metrics found in Table 4, please see the supporting information.

We found a much higher variation of water stress to water productivity within a country through time compared to between countries. This relationship can be seen by looking at the R^2 values for the fixed effects regression versus the OLS regressions. All models showed this relationship. The OLS shows variance between countries or how water stress differs by country, while the fixed effect regressions show the variance within a country or how stress changes over time for each country. For example, the global model explains that 75% of the variance in water stress within countries is attributed to productivity. However, only 3% of the variation in water stress between countries can be attributed to productivity. The largest variance within countries can be found in lower-middle income countries at 94%. These findings show that productivity does not explain why Zambia may have less water stress than the United Kingdom. However, if we were looking at how water stress has changed within Zambia, we could expect that as their productivity increases, there, in turn, would be a decrease in water stress. This validates the negative relationship and allows policymakers to understand that by targeting productivity, they could have the potential to lessen water stress (assuming that this effect dominates over the impact of stress on productivity).

4.3. Water Stress and Drivers

This analysis shows how drivers are related to water stress and is based on a backward stepwise removal process across five separate models. These model results can be found in Table 6. Model (1) incorporates all drivers, including water productivity. Model (1) accounts for 62% of the variance in water stress between countries, but 96% of the variation within countries. The results show a positive statistically significant relationship between water stress and GDP and the percent of cultivated land, and a negative association with population and productivity for the OLS version. It also shows a positive relationship with temperature and a negative relationship with precipitation, as was expected (Le Blanc & Perez, 2008; Wada & Bierkens, 2014). As for the fixed effects results, water stress exhibits statistically significant relationships with productivity, GDP, and temperature.

We remove water productivity in Model (2) in order to determine the effects of the remaining drivers. Model (2) accounts for 41% of the variance in water stress between countries. However, the variance within countries now drops to 27%, solidifying the impact water productivity has on the stress within a country. As far as the OLS results for Model (2), the nature and significance remain the same as Model (1). For the fixed effects results of Model (2), GDP is now no longer significant. This indicates a form of overlap between productivity and GDP, which could be explained by the inclusion of a country's wealth in its productivity calculation.

Models (3)–(5) were generated by removing drivers that showed low statistical significance based primarily on the fixed effects regression results. In Model (3), GDP is removed due to its lack of statistical significance in the fixed effects regression results in Model (2). Model (3) accounts for 31% of the variation in stress between countries and 27% of the variance in water stress within countries. Model (3) fixed effects results show a statistically significant relationship between water stress and population, cultivated land, political stability, temperature, and precipitation. However, precipitation is not as significant as the other three drivers, so it is removed in Model (4). Once precipitation is removed from the analysis, the variance between countries drops to only 5%, highlighting its importance. Finally, temperature is removed in Model (5), since it is not significant in the OLS regression. When excluding temperature in Model (5), the OLS and fixed effects R^2 values change by only 1%.

There are several interesting results from these findings. There is a negative relationship between population and water stress in the OLS regressions for both Models (1) and (2). Once GDP is removed from the analysis, the relationship turns positive. A possible reason for this could be due to the large water stress values found

Table 6
Regression Results for Water Stress Versus Potential Drivers

Variables	Model 1 OLS	Model 1 Fixed	Model 2 OLS	Model 2 Fixed	Model 3 OLS	Model 3 Fixed	Model 4 OLS	Model 4 Fixed	Model 5 OLS	Model 5 Fixed
lnProductivity	−0.92*** [0.04]	−0.97*** [0.02]								
lnGDP	1.23*** [0.05]	0.98*** [0.04]	0.63*** [0.05]	0.05 [0.11]						
lnPopulation	−1.23*** [0.06]	0.06 [0.07]	−0.56*** [0.06]	0.91*** [0.17]	0.12*** [0.04]	0.89*** [0.15]	0.21*** [0.04]	0.88*** [0.15]	0.21*** [0.03]	0.92*** [0.16]
Cultivated land	0.04*** [0.00]	−0.00 [0.00]	0.03*** [0.00]	0.01** [0.01]	0.02*** [0.00]	0.01** [0.01]	0.01** [0.00]	0.01** [0.01]	0.01*** [0.00]	0.01* [0.01]
Political stability	−0.00 [0.00]	0.00 [0.00]	−0.01** [0.00]	0.01** [0.00]	0.02*** [0.00]	0.00** [0.00]	0.01** [0.00]	0.00** [0.00]	0.01*** [0.00]	0.01*** [0.00]
Temperature	0.09*** [0.01]	−0.02*** [0.01]	0.07*** [0.01]	−0.08** [0.03]	0.05*** [0.01]	−0.08*** [0.03]	−0.00 [0.01]	−0.08*** [0.03]		
Precipitation	−0.02*** [0.00]	−0.00 [0.00]	−0.02*** [0.00]	0.00* [0.00]	−0.02*** [0.00]	0.00* [0.00]				
R^2 overall[a]	0.62	0.96	0.41	0.27	0.31	0.27	0.05	0.27	0.04	0.26

Each column represents a different model specification. The analysis was conducted using backward stepwise elimination. Productivity was removed first to determine the overall effects of the additional variables. Following this, insignificant variables were removed based on the fixed effects regression results. The top row shows whether OLS or fixed effects regressions were used. The dependent variable is the natural log of water stress. Values in [] show robust errors for OLS regressions and clustered robust errors for fixed effects regressions.
[a]R^2 value for OLS regressions is the "overall R^2" value. R^2 for fixed effects regressions is the "within R^2" value. *$p < 0.1$. **$p < 0.05$. ***$p < 0.01$.

in MENA, such as Bahrain, Israel, Kuwait, Oman, Qatar, United Arab Emirates, and also Singapore. Each of these countries has a relatively high GDP, coupled with a lower population. The reason why these countries could sway the relationship in the OLS regression and not the fixed effects is due to the OLS looking at all values as a single cross section of data. So essentially, each of these countries is represented five times within the OLS regression model. It is important to note that the positive relationship between stress and population that we had expected is seen across all models for the fixed effects regressions.

We find a positive and statistically significant relationship between temperature and water stress in the OLS version of Models (1) – (3). This corroborates a finding that an "increase in irrigation water consumption is primarily driven by rising regional temperature" (Wada & Bierkens, 2014). However, the fixed effect regressions across all models show a negative relationship. When Models (1)–(4) were run across subregions, the only two regions to exhibit this similar relationship were found in Eastern Europe and Latin America. Specific Eastern European countries, such as Belarus, Bulgaria, the Czech Republic, Hungary, Moldova, Poland, Romania, Russia, Slovakia, and Ukraine, were found to have some decline in water stress between 1997 and 2013, coupled with a decrease in average temperature (albeit a small one). This seems to have influenced the relationship between temperature and water stress in the fixed effect regression models. This could potentially be improved by adding more data points in order to generate a longer time series.

We found several statistically significant relationships between the drivers and water stress in terms of both the variation in stress between countries but also within a country. The main drivers in this analysis that are related to variation in water stress by country are a combination of productivity, GDP, population, percent of cultivated land, temperature, and precipitation. This is based on the OLS findings in Model (1) found in Table 6. However, we found that water productivity only accounts for 3% of the variation in water stress based on the OLS findings in the global model found in Table 5. Based on Models (4) and (5) found in Table 6, we also find that the combination of population, cultivated land, temperature, and political stability result in only a 4 to 5% variation in water stress. Thus, based on our model specifications, we can reasonably say that the variation in water stress across countries is associated with GDP and precipitation. We also see that some developing countries are exhibiting an increase in water stress, whereas 19 high or upper-middle-income countries are starting to show signs of decreasing stress (Figure 1). Adding this to our finding of the positive association of GDP with stress across countries might suggest the presence of a Kuznets curve. However, studies that have previously looked at water usage and income have yet to definitively prove its existence (Duarte et al., 2013).

Across time, within a country, precipitation does not play as large of a role, while GDP also becomes insignificant when water productivity is removed from the model. This leaves population as a principal driver of the variation in water stress within a country. We negate temperature here since the variation in water stress does not change with its removal in Model (5) found in Table 6. There is also a statistically significant relationship between water stress and cultivated land as well as political stability in Models (3)–(5) found in Table 6. This shows an increase in cultivated land and an increase in political stability are related to an increase in stress. The positive relationship between stress and cultivated land was expected (Mancosu et al., 2015). However, the positive relationship with political stability is in contrast to our initial hypothesis. This could be explained since countries with higher GDP may be associated with higher political stability, even though we tested for collinearity between these two drivers.

4.4. Limitations

Conducting analysis on the scale reported in this paper has been challenging because of several data limitations. FAO Aquastat (2019) provides time series data on country level water resource availability, water withdrawals, environmental flow requirements, irrigation, and several other water resource categories. However, data are only reported on 5-year time steps and becomes increasingly intermittent the further back one goes in time. Currently, around half of the countries in FAO Aquastat (2019) have data on whether water withdrawals come from surface or groundwater. However, no data are reported on sectoral water usage in regard to whether or not water is withdrawn from surface or groundwater sources. This would be a useful analysis as it could show whether groundwater reserves or surface water is bearing the brunt of water stress, and how it varies by sector. Water quality is another important factor that would be useful to factor in but was excluded due to limited data. Poor water quality limits the amount of water available for use. Thus, water stress values may actually be higher than reported. Quality could also affect stress and productivity based on the intended use; that is, water for irrigation is held to a different standard than drinking water (U.S. Department of Agriculture, 2011). Hot spots of water stress based on water quality issues could occur due to increasing salinization, such as in coastal Bangladesh (Chen & Mueller, 2018; Vineis et al., 2011).

Because the analysis has been done using national data, subnational spatial heterogeneity has not been analyzed, though it can be significant, particularly in large countries. For example, there are several hot spots of water stress in the United States, such as the American Southwest, where groundwater is relied on more heavily (Wada & Bierkens, 2014). However, the overall water stress value for the United States may be relatively low due to areas such as the Northeast that have low water stress (Wada & Bierkens, 2014). The same holds true for water productivity, which is likely to have spatial ambiguities such as reliance on irrigated agriculture.

The results of some of the regressions to identify the effect of drivers raised questions about plausible mechanisms, such as the negative relationship between water stress and population in the OLS Models (1) and (2) found in Table 6. A negative relationship between temperature and stress was identified across the fixed effects models in Table 6. These show the limitations of the given models and their sensitivity to abnormal conditions, such as a decrease in temperature and an increase in stress found in some Eastern European countries. Certain drought conditions may also have a nonlinear effect with water stress, as at a certain point, agriculture may no longer be viable, and irrigation water needs could decline or be curtailed, which occasionally happens in the United States (Stubbs, 2016). Thus, these models could be greatly improved by adding more time steps, gathering new and updated information on all metrics, and incorporating multiple scales of analysis. In addition, global water models such as those reviewed in Wada et al. (2016) separate their analyses into the subsectors of water usage: domestic, industrial, and agricultural. This offers a more nuanced approach to understanding the specific drivers and mechanisms for each of these subsectors instead of total water usage and or total water stress. Moving forward, it would be useful to conduct analyses looking at what drives water stress in these three water usage sectors and how productivity has the ability to assuage each sector's stress.

Finally, there are some concerns around the usefulness of the productivity indicator and its ability to help alleviate water scarcity conditions (Lankford, 2013; Wichelns, 2014). Clement (2013) also warns of the unintended consequences of increasing productivity, mentioning that switching to more productive crops could price poorer farmers out of the market. This same argument was made by Boelens and Vos (2012), who warn of applying normative productivity and efficiency ideals on countries because it might harm the poor. It is also important to note that the primary rationale behind increasing water productivity could be for profit rather than a reduction in water usage. This is also subject to spatial heterogeneity.

5. Conclusions

We found that water stress is increasing in developing countries such as Latin American and Africa as well as countries in the Middle East. However, we only found evidence of 29 countries out of 179 with a significant decreasing trend, which is in contrast to 44 countries found to show a decrease in a recent report (FAO, 2018a). Water productivity was found to be generally increasing worldwide, with a few notable exceptions in South American and Africa. On the whole, we expect that as a country becomes more developed (i.e., its GDP rises), it will become more productive in its use of water. We are now able to understand whether or not a country's rising water productivity is solely related to the growing economy, or if it is due to a growing economy and a decline in water usage. This key piece of information is essential since the panel regression analysis showed an overall negative relationship between water stress and water productivity. This relationship is based on global data that is imperfect, but the negative relationship across both OLS and fixed effect regression models for five different cases (global and four economic tiers) strengthens the case that a negative relationship is present. These results give substantive evidence to implement policies targeted to increase productivity to lower water stress and overall water scarcity.

We also find that water productivity plays a far greater role in water stress within a country than differentiating between levels of stress across countries. This research intuits that the leading cause of water stress between countries is based more on a country's climate, in terms of precipitation, and development stage. However, productivity plays a much higher role in the change in water stress within a country, giving strength to the argument that productivity should be a policy target to reduce stress. In addition to productivity, we find that population, cultivated land, and political stability are related to water stress levels within a country.

Overall this study gives evidence to the intuition that improving productivity can decrease water stress. As more reliable data and metrics become available, additional studies should be conducted to explore the relationship and causality of not only water productivity and water stress across the three primary sectors but also water efficiency. There is also a need to understand how and what types of efficiency techniques to incorporate to increase productivity and lower stress and how the effects of these techniques can promote sustainable use of water resources. An example of this could be to study the specific drivers of each subproductivity metric, that is, agriculture, industry, and services, to target specific mechanisms to enhance productivity. As water scarcity becomes more frequent due to climate change and increased pressure from anthropogenic forces, it becomes even more imperative to understand how to implement these performance metrics to obtain the greatest reduction in water scarcity.

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