The economic potential for rainfed agrivoltaics in groundwater stressed regions

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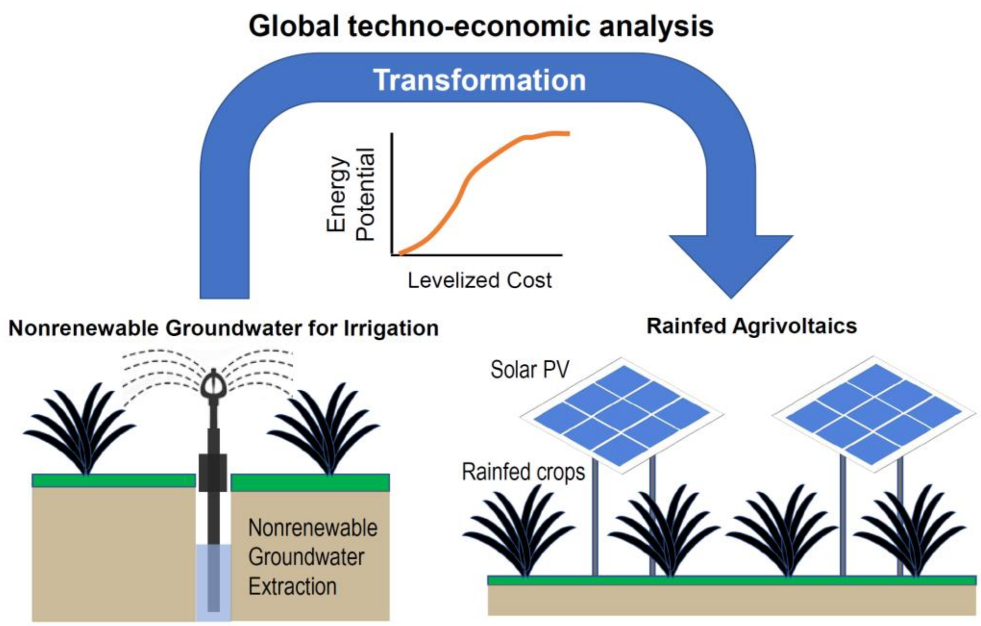
Abstract

Agrivoltaics co-locate crops with solar photovoltaics (PV) to provide sustainability benefits across land, energy and water systems. Policies supporting a switch from irrigated farming to rainfed, grid-connected agrivoltaics in regions experiencing groundwater stress can mitigate both groundwater depletion and CO_2 from electricity generation. Here, hydrology, crop, PV and financial models are integrated to assess the economic potential for rainfed agrivoltaics in groundwater stressed regions. The analysis reveals 11.2-37.6 PWh/yr of power generation potential, equivalent to 40-135% of the global electricity supply in 2018. Almost 90% of groundwater depletion in 2010 (~150 km^3) occurred where the levelized cost for grid-connected rainfed agrivoltaic generation are 50-100 USD/MWh. Potential revenue losses following the switch from irrigated to rainfed crops represents 0-34% of the levelized generation cost. Future cost-benefit analysis must value the avoided groundwater stress from the perspective of long-term freshwater availability.



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Introduction

Solar photovoltaics (PV) are mature low-carbon energy solutions with enough resource and technological potential to fully support global energy demand[1]. Recent analysis of pathways to achieve the Paris climate goal estimates that 0.24-1.55 trillion USD/yr of investment into similar renewable energies is needed to decarbonize electricity by 2050[2]. PV costs are competitive with fossil fuel generation[3], and system operators are increasingly experienced with high penetrations of solar energy[4]. How to prioritize project development and siting to maximize societal benefits remains an open research question.

Groundwater stress is concurrent to the climate change challenge, and impacting an estimated 2 billion people[5]. Policies designed to conserve groundwater may restrict irrigation, reducing crop yields or shifting crops elsewhere[6]. These pressures could reduce agricultural jobs with detrimental impacts to local communities if the training to pursue alternative livelihoods locally is not supported[7]. Conversely, maintaining irrigation deliveries under groundwater conservation could lead to expansion of wastewater recycling and desalination, with the energy footprint making it more difficult and costly to reduce CO_2 emissions[8].

Integrated policies developed from a systems perspective leverage resource synergies that achieve benefits for multiple goals[9]. An integrated approach can reduce the costs of policy implementation when compared to situations where each policy is pursued on its own[10]. Livelihood shifting is an unexplored policy integration lever for groundwater and renewable energy transformations that could balance job impacts across the economy, enabling workers from impacted sectors to secure the income they need for a decent living.

In this context, agrivoltaics represent an attractive solution for reducing water use and energy-related CO_2 emissions by co-locating rainfed crops with utility-scale PV generation[11,12]. Farmers offset investment costs and diversify their income stream through zero-interest loans combined with power purchasing agreements from the utility. Field research demonstrates co-location of PV has limited impact on yields for many high value crop varieties[13,14], and previous analysis indicates there are favorable operational conditions and massive resource potential on croplands globally[12]. Yet, there are no previous analyses quantifying the potential for rainfed agrivoltaics to contribute to the groundwater and climate policy agendas at global-scales.

In this paper, we fill this knowledge gap by addressing the following research question: what are the potential economic costs of switching from irrigated farming to rainfed agrivoltaics in groundwater stressed regions when accounting for the geospatial distribution of solar resources, existing infrastructure and crop yield impacts? The theory of change in the analysis is that future investments into solar energy under the Paris Agreement can be translated into financing for utility-scale PV generation that is owned and operated by farmers in groundwater stressed regions. PV investments configured in this way would bring both reductions in CO_2 from fossil power generation and unsustainable groundwater extractions from irrigation. For example, the Clean Development Mechanism (CDM) is an international CO_2 trading framework where high-income countries invest in low-cost renewable energy projects in developing regions and account for the emission reductions within their own national emissions inventory[15]. Similar financing if reframed from an integrated water-energy-land perspective could enable farmers to switch from unsustainable groundwater irrigation to harvesting rainfed crops and solar energy in support of food, climate and groundwater sustainability goals.

Materials & Methods

The steps in the geospatial analysis are depicted in Figure 1. Groundwater stressed areas are identified using outputs from the global hydrological model PCR-GLOBWB[16]. This framework is modeling the water balance in half degree grid-cells that include vertically stacked layers representative of the land surface and soil column at a daily time-scale. Multi-sector human water withdrawals and return flows interact with the soil moisture calculations to estimate groundwater stress. We assume grid cells are groundwater stressed where non-renewable groundwater extraction is used in the model to fulfill the water demands and depletion occurs[17]. The analysis considers the complete switching of groundwater stressed irrigated area to rainfed area (i.e., no irrigation). Irrigated area within each groundwater stressed grid cell is delineated by intersecting it with a global map of irrigated areas[18].

For benchmarking the results, the analysis compares PV with wind power technology. Twenty-five (25) years of sequential hourly PV and wind power production data are generated at each groundwater stressed location using calibrated resource potential and power plant performance models[19,20]. The resource data are based on the MERRA-2 re-analysis of satellite measurements and calibration to performance data in Europe. The data has known over-biases in Europe (~10% on average), with additional uncertainties expected outside of Europe. These over-biases suggest that estimates in this paper could be overly optimistic. The power plant simulations consider generic utility-scale systems of 1 MW capacity. Siting density assumptions (i.e., the intensity of land use per unit of installed capacity) translate the performance simulations into gross power generation and land use at each location.

The production time-series are combined with average technology investment and operational costs to estimate the total levelized costs of agrivoltaic energy (LCOE) at each groundwater stressed location. The LCOE represents the unit cost of electricity generated and is calculated with the following equation[29]:

$$LCOE = \frac{CAPEX + \sum_{t=1}^{N} OPEX_t \cdot (1 + WACN)^{-t}}{\sum_{t=1}^{N} ELEC_t \cdot (1 + WACR)^{-t}} \qquad (1)$$

where *CAPEX* and *OPEX* are the capital and operational expenditures respectively, *WACR* is the real weighted average cost of capital (with inflation) and *WACN* is the nominal value (without inflation), and *ELEC* is the electricity supplied by the project in a given year *t* and over its lifetime *N*. Electricity supply is quantified from the hourly power plant simulations. Depreciation rates are used to scale power generation yields in future years[29,30]. Grid-connection costs are included in the CAPEX and calculated using either OpenStreetMap[22] or the urban areas from Global Human Settlement Layer (GHSL) for 2019[21]. The datasets are compared to find the minimum distance to each groundwater stressed location. Grid extension costs are expressed per unit capacity and distance to provide a site-specific investment multiplier for the CAPEX input to the LCOE calculation. Groundwater stressed locations with grid expansion distances greater than 200 km are excluded from the analysis due to high investment costs. Country risk premiums are used to estimate weighted average cost of capital for discounting future cash flows and assuming a risk-free premium of 3.1% [26,29,31]. Economies-of-scale are not included in the calculations.

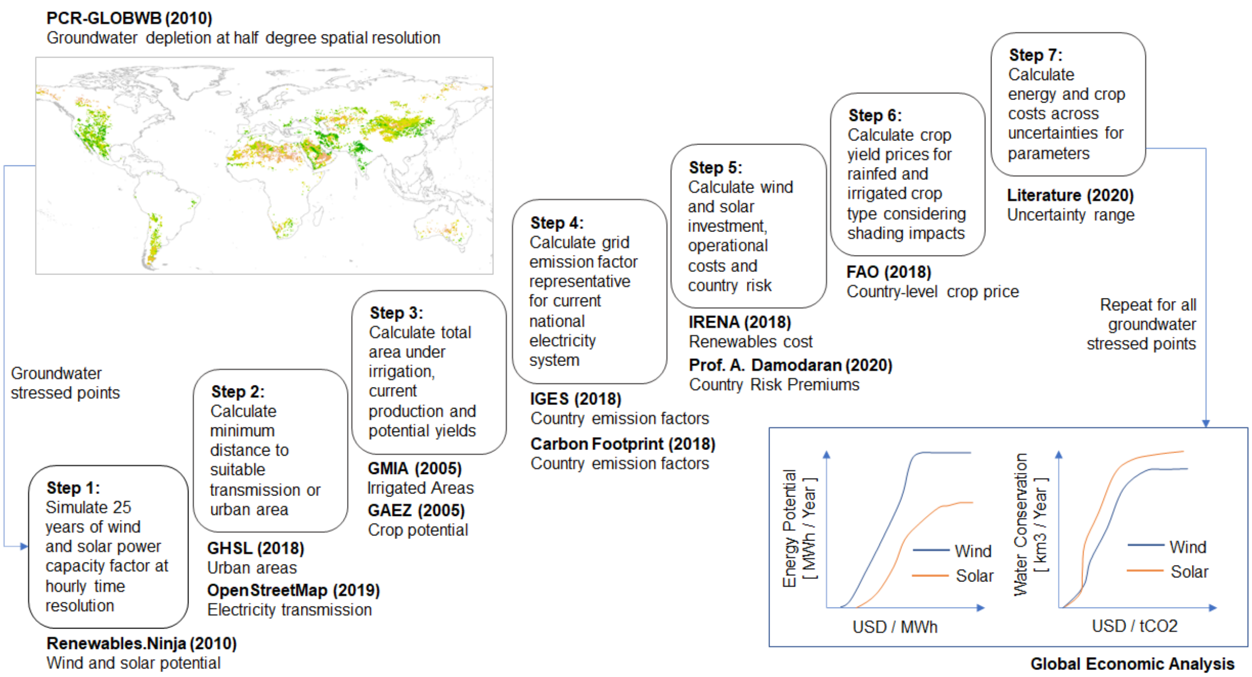

Figure 1: Spatially-explicit approach for calculating agrivoltaic economic potential in groundwater stressed regions. Groundwater stressed locations are estimated following the analysis of groundwater depletion in Wada et al. (2014)[16]. Datasets input to each calculation step are indicated with the most recent year reported in the dataset. Data sources are: Renewables.Ninja[19,20]; Global Human Settlement Layer (GHSL)[21], OpenStreetMap[22], Global Map of Irrigated Areas (GMIA)[18], Global Agro-ecological Zones (GAEZ)[23]; Institute for Global Environment Strategies (IGES)[24]; Carbon Footprint[25]; International Renewable Energy Agency (IRENA)[3]; A. Damodaran[26]; and United Nations' Food and Agriculture Organization (FAO)[27]. Polygons from the Global Administrative Areas Database (GADM) are used to categorize the groundwater stressed points by country[28]. An open-source online repository stores the R programming script performing the geospatial analysis steps (https:/github.com/scparkinson/gw_renewables).

Uncertainties are reflected using a range of cost and performance assumptions (Table 1). For example, PV panel shading helps protect crops prone to heat stress, leading to a net increase in crop yields[13,32]. Conversely, for other crops, yields vary proportionately with shading level[33,34]. Panel density in turn impacts power generation potential. Half-spacing typical in agrivoltaic operations reduces the power density per unit area compared with a conventional PV plant.

Parameter	Unit	Range	Source(s)
1 MW Solar PV			
Investment	USD/kW	1210 (796, 2745)	3
Operations & Maintenance	USD/kW-yr	15 (11, 24)	35
Panel density[1]	MW/km^2	15 (10, 30)	36
Depreciation[2]	% / year	0.5 (0.2, 0.9)	29
Lifetime	Years	25 (20, 30)	35
1 MW Wind Turbine			
Investment	USD/kW	1499 (1174, 2439)	3
Operations & Maintenance	USD/kW-yr	48 (11, 150)	35
Turbine density	MW/km^2	5 (2.5, 6)	37
Depreciation[2]	% / year	1.6 (0.5, 1.8)	30
Lifetime	Years	25 (20, 30)	35
Grid Connection[3]			
Investment	USD/kW·km	3.7 (1.1, 5.3)	38,39
Crop Yield Change[4]			
Wheat	%	-13 (-27, 0)	11
Rice	%	-38 (-67, -19)	34
Pulses	%	-13 (-27, 0)	Assumed
Maize	%	-12 (-20, 0)	33,34
Fodder	%	-12 (-20, 0)	Assumed
Sugarcane	%	-38 (-67, -19)	Assumed
Fruit	%	0 (-20, +40)	13,32
Vegetables	%	0 (-20, +20)	13,14
Cotton	%	0 (-20, +40)	32

[1] Average is half panel density on unoccupied land.
[2] Power production yield depreciation due to device degradation.
[3] Operational costs for grid extensions excluded due to lack of data.
[4] Change in yields from crop shading (included for solar PV).

Table 1: Cost and performance assumptions for the analysis.

Following the approach described by Gernaat et al. (2017)[40], the LCOE incorporates the cost of agricultural land loss caused by switching from irrigated to rainfed operations. The difference in land value (irrigated minus rainfed) is added to OPEX in equation (1). The crop-type that maximizes land value is selected for the difference calculation. A land value map with 5 arc minute spatial resolution is generated based on the potential agricultural yields calculated with the Global Agro-Ecological Zones (GAEZ) model[23]. The analysis considers eight crop-types: wheat, rice, maize, pulses, cotton, sugarcane, fruit and vegetables. Historical national crop price ranges over the past 5 years are obtained from FAOSTAT[27], and mapped to the crop-types considered for GAEZ. Crop prices are held constant in future years, and averages are used where data is missing.

The CO_2 emissions impact of PV development at each water stressed location is further estimated using the United Nations' ACM0002 baseline methodology for CDM projects[15]. The avoided CO_2 emissions from the displaced grid generation are initially quantified by multiplying the average annual agrivoltaic generation by the corresponding national grid CO_2 emission factor[24,25]. The CO_2 price required to pay for the agrivoltaic CAPEX and OPEX is then estimated by dividing the discounted lifecycle system costs by the avoided CO_2. It is important to emphasize the simplifications, including the exclusion of future cost reductions projected for solar PV technology[29], revenue from electricity pricing, and the impacts from power system flexibility and dispatch strategy. For example, solar PV might be used preferentially to offset the most carbon-intensive generating units in a utilities' fleet, making the average grid emission factors utilized overly pessimistic. Additional energy storage technologies and approaches may also be needed in some locations to aid in grid-integration, particularly at high PV penetrations[4].

Results and Discussion

Results of the global analysis are summarized as economic supply curves for electricity generation potential, avoided CO_2 and groundwater depletion (Figure 2). Globally, 11.2-37.6 PWh/yr of agrivoltaic generation potential is found to exist on groundwater stressed irrigated area, equivalent to 40-135 % of global electricity generation in 2018. An estimated 150 km^3 of groundwater depletion would be displaced from the switch to rainfed operations (~90% of the global total in 2010). The average levelized costs for agrivoltaic systems, accounting for power production and crop yield impacts, are 50-100 USD/MWh (Figure 2a). The equivalent avoided grid CO_2 costs are 75-200 USD/tCO_2 (Figure 2b). These results compare well with recent pilot project analysis in Germany[41].

Solar PV potential exceeds wind potential in most locations, with global wind potential in groundwater stressed regions ranging from between 2.7-8.4 PWh per year (Figure 2a). Under half-spacing typical in agrivoltaic operations[14,42], PV continues to provide more power density per unit area than wind turbines. The extreme performance scenarios show that wind and solar PV potential are similar if the cost and density assumptions for PV are less optimistic. The analysis identifies more than 1.3 PWh of wind power potential that is less expensive than solar PV under average performance assumptions in Table 1. Additional uncertainties exist due to e.g., the use of reanalysis data, future prices and system integration barriers.

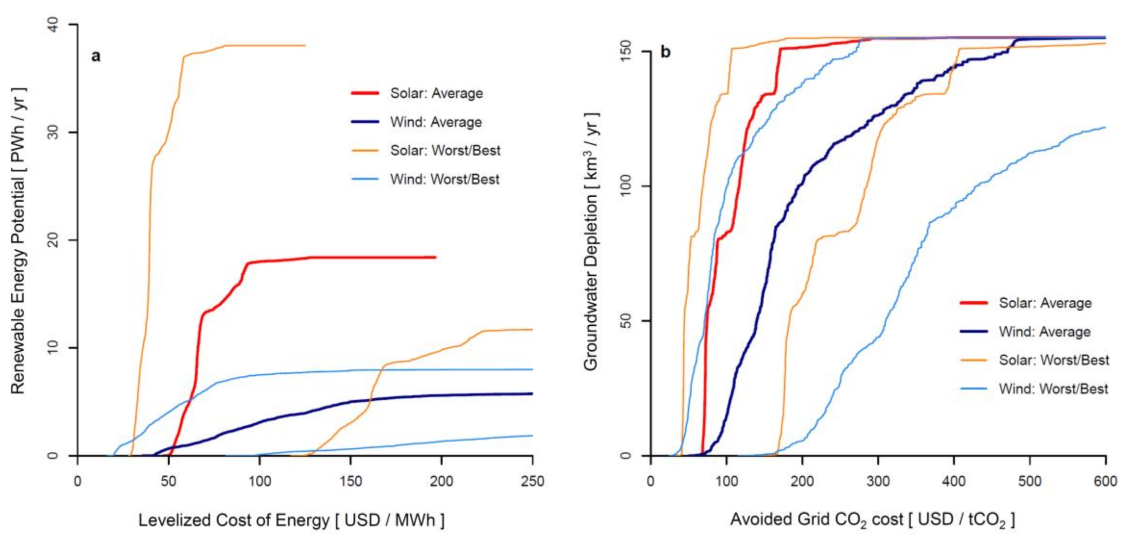

Figure 2: Global economic supply curves for agrivoltaic systems in groundwater stressed regions and comparison to equivalent wind operations. a. cumulative renewable electricity generating potential across the distribution of levelized costs; and b. cumulative groundwater depletion across the distribution of avoided grid CO_2 costs. The uncertainty range is obtained from calculating the potentials under the worst/best combinations of the parameters in Table 1.

Co-location of PV and the switch to rainfed operations impacts crop yield potential. The quantified economic impact of the reduced crop yield represented on average 6 % of the LCOE (ranging from 0-34 %). Crop shifting to varieties benefitting from panel shading did not lead to net increases in crop revenue. Crop-types maximizing yield revenues can differ for irrigated and rainfed operations. This leads to a presumptive switch in crop-type under agrivoltaic transformation. Switching leads to an unintuitive gain in the yield potential for the rainfed crop-type that is offset by the reduction in yield potential for the irrigated crop-type present prior to switching. At a country-level, largest impacts of PV co-location on the revenue generation potential of farmers occurs for vegetable crops (Table 2). The result is driven by the high prices offered for vegetable crops within national and international markets relative to other crops such as wheat, rice or maize. We find that India and Iran with the most groundwater depletion within economic distance to existing infrastructure (Table 2) also have the most to lose in terms of rice yield potential: an important staple in local diets. However, yield losses across all crop types are relatively small compared to overall national production rates, and could likely be recovered economically through additional crop shifting and imports[43].

In terms of avoided CO_2 costs (Table 2), projects in India are estimated to be more economical than in Iran because India has a combination of lower investment risk (determined by the weighted average cost of capital) and its electricity grid has a higher CO_2 emissions intensity (determined by the national grid emission factor). Understanding these differences across regions helps identify where investments bring the largest impacts on both CO_2 and groundwater. However, it is important to emphasize the grid dispatch strategy might focus PV integration on the displacement of the most CO_2-intensive generating source (e.g., coal), leading to similar avoided emissions intensities across countries. In this situation, the location specific financial risk, crop yield and solar resource indicators would continue driving levelized cost heterogeneities across groundwater stressed regions.

Existing policies need tweaking to take advantage of the multi-faceted benefits agrivoltaics offer. Project financing must take an integrated view and consider the influence of PV development on water resources. For example, there are concerns in groundwater stressed areas of South Asia that subsidized expansion of PV could lead to increased groundwater stress due to reduced electricity costs for groundwater pumping[44]. PV subsidies in similarly groundwater stressed irrigated areas should be focused on promoting agrivoltaics and include financing to cover crop yield impacts from the switch to rainfed operations. This paper has demonstrated the massive untapped potential to generate solar power on groundwater stressed irrigated area, and the relatively minor impacts of panel shading and crop yield losses from the switch to rainfed operations.

The switch to rainfed operations liberates irrigation deliveries, which can be allocated to groundwater flows that sustain some perennial rivers[45]. Yet, rainfed operations miss opportunities for managed aquifer recharge through intelligent irrigation[46]. Future cost-benefit analysis of agrivoltaic systems must include a hydro-economic assessment of avoided groundwater use and opportunities for conjunctive management with surface water resources. These interactions are complex but may have an important influence on agrivoltaic economics, particularly where liberated irrigation deliveries help to avoid investments in unconventional freshwater supply options (e.g., desalination)[8].

Other uncertainties unaccounted for in this work include the influence of farm size and how cooperation across farms can achieve economies-of-scale. These partnerships might be appealing in developing regions where farmers may lack sufficient land area or investment financing for utility-scale power generation[47]. Importantly, the analysis did not consider the costs of power system integration, which may present barriers to widespread PV deployment due to its impacts on system reserve requirements[4]. Smart control of on-farm electricity uses may provide a leverage for demand response that supports system integration. Diversification of on-farm revenue in agrivoltaic systems and the interplay with technological learning and climate resilience represent other economic benefits requiring future research. Importantly, there continue to be major PV technology innovations that could halve the CAPEX in the next 10 years[29], with implications for the levelized cost calculations. Finally, the analysis did not consider the corresponding energy and emissions impacts from shifts in on-farm machinery and the land-based emissions from different crops[48], or the influence of climate change and future crop prices[6].

Future research is needed to address these research gaps, requiring multi-sector modeling tools that consider the co-dependent transformations in water, energy and land systems. The multi-dimensional supply curves and framework presented in this paper support the integration of agrivoltaics into long-term planning models used by decision-makers.

Country	GWD[1] [km^3]	CO_2 Price[2] [USD / tCO_2]	Solar[3] [TWh / yr]	Wind [TWh / yr]	Wheat [kton-DW / yr]	Rice [kton-DW / yr]	Cotton [kton-DW / yr]	Pulses [kton-DW / yr]	Maize [kton-DW / yr]	Fruit [kton-DW / yr]	Vegetables [kton-DW / yr]
India	54.07	73 (44,178)	5605 (3475,11708)	1421 (665,1987)	0 (0,0)	-39.16 (-0.16,-144.83)	3.56 (3.16,3.4)	0.32 (0.09,0)	45.76 (17.79,120.02)	0 (0,0.72)	-94.92 (-161.16,0)
Iran	23.86	127 (79,301)	1766 (1095,3689)	486 (228,680)	3.25 (1.00,9.06)	-45.54 (-45.31,-45.97)	0 (0,0)	3.64 (1.05,3.95)	0 (0,0.77)	0 (0,0)	0.1 (0.04,1.69)
USA	18.16	116 (68,290)	2871 (1780,5997)	1196 (560,1673)	1.17 (0.84,1.83)	0 (0,0)	0 (0,0)	-0.03 (-0.01,-0.19)	0 (0,0)	0 (0,0.17)	-86.22 (-91.09,-81.5)
Pakistan	16.63	166 (103,396)	1554 (964,3246)	380 (178,531)	0 (0,0)	-10.88 (-10.88,0)	0 (0,0)	0.08 (0,0.38)	0 (0,0)	0 (0,0)	-41.39 (-42.24,-30.09)
China	13.44	82 (48,203)	3121 (1935,6521)	1187 (555,1659)	-0.01 (-0.01,0.01)	0 (0,0)	0.02 (0.02,0.09)	-16.19 (-20.13,-14.61)	-0.37 (-0.37,-1.94)	0 (0,0)	0 (0,0.01)
S. Arabia	11.03	85 (50,210)	329 (204,688)	114 (53,159)	0 (0,0)	-0.38 (-0.38,0)	0 (0,0)	0 (0,0)	0 (-0.22,0)	0 (-0.08,0)	-9.38 (-9.53,-9.08)
Mexico	6.36	115 (68,283)	792 (491,1654)	216 (101,301)	0.02 (0.02,0.03)	0 (0,0)	0.02 (0.01,0.06)	0 (0,0.35)	0.65 (0,0.76)	0 (0,0)	-19.18 (-20.7,-16.83)
Libya	1.72	86 (52,208)	79 (49,164)	33 (15,46)	0 (0,0)	0 (0,0)	0 (0,0)	0.08 (0,0.18)	0 (0,0)	-0.98 (-0.98,0)	-2.62 (-2.67,-0.71)
UAE	1.40	99 (58,246)	49 (30,102)	13 (6,18)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	-1.48 (-1.48,-1.48)
Russia	0.99	257 (153,627)	103 (64,215)	58 (27,81)	0 (0,0)	-1.62 (-2.74,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0.15 (1.43,-1.66)
Turkey	0.98	282 (172,677)	169 (105,354)	46 (22,65)	0.08 (0.12,0)	0 (-0.9,0)	0 (0,0)	-0.06 (-0.18,0)	0 (0,0)	0 (0,0)	-3.35 (-3.76,-2.86)
Uzbekistan	0.77	117 (69,286)	255 (158,533)	95 (44,133)	0.01 (0.01,0.02)	-0.18 (-0.18,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	-7.88 (-8.17,-7.44)
Argentina	0.56	212 (132,494)	111 (69,232)	45 (21,63)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0.15)	-3.61 (-3.87,-3.31)
S. Africa	0.48	66 (39,161)	101 (62,210)	29 (14,40)	0 (0,0)	0 (0,0)	0 (0,0)	0.03 (0.01,0.08)	0 (-0.62,0)	0 (0,0.25)	-3.04 (-3.25,-1.95)
Egypt	0.46	150 (93,359)	122 (76,255)	38 (18,53)	0 (0,0)	0 (0,0)	0 (0,0)	0.06 (0.04,0.06)	-0.11 (-0.05,-0.11)	-2.49 (-2.49,-2.49)	0 (-0.05,0)
Spain	0.43	239 (142,588)	172 (107,360)	59 (28,83)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	-5.19 (-5.95,-4.42)
Morocco	0.37	101 (61,246)	92 (57,192)	26 (12,36)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	-1.17 (-1.3,-0.91)	0.12 (0.1,0.14)
Yemen	0.36	185 (117,427)	179 (111,373)	33 (15,46)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	-3 (-2.11,-3.07)	-1.57 (-1.66,-1.53)	0 (-0.63,0)
Australia	0.32	73 (42,180)	100 (62,209)	47 (22,66)	0 (0,0)	0 (0,0)	0.01 (0,0.06)	0 (0,0)	0 (0,0)	0.14 (0,0.89)	-4.51 (-4.94,-4.15)
Mauritania	0.27	123 (75,294)	15 (10,32)	7 (3,10)	0 (0,0)	0 (0,0)	0 (0,0.01)	0 (0,0)	0 (0,0)	0 (0,-0.08)	-0.46 (-0.46,-0.28)
Kazakhstan	0.25	128 (76,311)	89 (55,186)	37 (17,51)	0 (0,0)	-0.13 (-0.11,0)	0 (0.01,0)	0 (0,0)	-2.72 (-2.76,-0.46)	0 (0,0)	-0.06 (-0.26,-1.8)
Romania	0.21	215 (129,527)	185 (115,386)	84 (39,117)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	-3.39 (-4.53,-2.25)
Algeria	0.21	143 (89,339)	47 (29,98)	17 (8,24)	0.07 (0.06,0.17)	0 (0,0)	0 (0,0)	0 (0,0)	-0.15 (-0.15,0)	0.05 (0.04,0.07)	-1.66 (-1.87,-1.68)
Brazil	0.20	375 (226,910)	25 (16,53)	12 (6,17)	0 (0,0)	0 (0,0)	0 (0,0)	0.01 (0,0.03)	0 (0,0)	0 (0,0.01)	-0.5 (-0.54,-0.44)
Italy	0.18	228 (137,558)	20 (12,41)	9 (4,12)	0 (0,0)	0 (0,0)	0 (0,0)	0.13 (0,0.17)	0 (0,0)	0 (0,-0.11)	-1.11 (-1.11,0)
Israel	0.13	78 (46,194)	16 (10,34)	3 (2,5)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	-0.55 (-0.59,-0.52)
Peru	0.13	108 (63,264)	28 (17,58)	5 (2,6)	0 (0,0)	0 (0,0)	0 (0,0)	-0.01 (-0.01,-0.01)	0 (0,0)	-0.5 (-0.5,-0.5)	0 (0,0)
Ukraine	0.12	208 (130,492)	76 (47,158)	43 (20,61)	0 (0,0)	0 (-2.1,0)	0 (0,0)	0 (0,0)	0 (-0.01,0)	0 (0,0)	-1.08 (0,-1.42)
Iraq	0.10	155 (95,363)	12 (7,25)	5 (2,7)	0 (0,0.09)	-0.27 (-0.33,0)	0 (0,0)	0.03 (0.02,0.03)	0 (0,0)	0 (0,0)	-0.05 (-0.31,0.04)
Senegal	0.10	125 (76,303)	13 (8,27)	6 (3,8)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	-0.42 (-0.42,-0.42)
Qatar	0.09	87 (52,217)	3 (2,6)	1 (0,1)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	-0.1 (-0.1,-0.1)	0 (0,0)	0 (0,0)
Tunisia	0.08	159 (98,381)	26 (16,53)	11 (5,16)	0 (0,0)	0 (0,0)	-0.06 (-0.09,0.01)	0.06 (0,0.16)	-1.18(-1.18,0)	0.09 (0.15,0.26)	-0.4 (-0.4,0)
Kyrgyzstan	0.08	144 (88,342)	46 (29,97)	8 (4,11)	0 (0,0)	-0.18 (-0.18,0)	0 (0,0)	0 (0,-0.05)	0 (0,0)	0 (0,0)	-0.07 (-0.46,0.21)
Canada	0.07	483 (282,1203)	23 (14,48)	15 (7,21)	0.03 (0,0.03)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	-0.18 (-0.21,-0.11)
Bolivia	0.06	114 (68,273)	8 (5,16)	2 (1,2)	-0.01 (-0.01,-0.02)	0 (0,0)	0 (0,0)	-0.01 (0,-0.01)	0 (0,0)	0 (-0.02,0)	0 (0,0.03)
Bulgaria	0.06	169 (102,416)	73 (45,152)	23 (11,32)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	-0.86 (-1.37,-0.36)
Venezuela	0.05	350 (224,799)	5 (3,10)	2 (1,3)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0.09 (0.05,0.11)	0 (0,0)	-0.03 (-0.04,-0.02)
Chad	0.05	121 (73,289)	2 (2,5)	1 (1,2)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	0 (0,0)	-0.08 (-0.08,-0.08)
Mongolia	0.04	98 (59,228)	9 (6,19)	3 (2,5)	0 (0,0)	0 (0,0)	0 (0,0)	-0.03 (-0.04,-0.03)	0 (0,0)	0 (0,0)	-0.01 (-0.01,0)
Oman	0.03	102 (61,247)	4 (3,9)	1 (0,1)	0 (-0.02,0)	0 (0,0)	0 (0,0)	0 (0,0)	-0.14 (-0.14,0)	0 (0,0)	0 (-0.06,0)

[1] GWD = Annual groundwater depletion that is classified within economic distance (200 km) to existing transmission or urban areas.
[2] Levelized price per unit of CO_2 emissions mitigated from the national electricity systems by the agrivoltaic project.
[3] Averages presented with the minimum and maximum from the uncertainty analysis included in brackets.
[4] Green shading indicates net gains in yield; orange shading indicates net losses in yield.
Note: The analysis finds negligible impacts to sugarcane when aggregated and the entries are excluded.

Table 2: Solar PV and wind potential, CO_2 mitigation costs and impacts on maximum crop yield potentials for the top 40 countries ranked by groundwater stress.

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Associated Content

The open source R programming code used for the analysis is available online at: https:/github.com/scparkinson/gw_renewables.

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