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data-descriptor

Keywords:

Posted Date: October 6th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11000717/v1>

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Additional Declarations: No competing interests reported.

Daily evaporation from 23 irrigated and rainfed crops worldwide from 2000 to 2025

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7 **Abstract**

8 **Growing agricultural water use, driven by cropland expansion and a warm-**
9 **ing climate, has substantially altered the Earth's hydrological cycle. Despite**
10 **its importance, accurate estimation of crop evaporation at a global scale**
11 **remains an outstanding scientific challenge. Here, we introduce CropET, a**
12 **global dataset of daily evaporation from 23 irrigated and rainfed crops at 5**
13 **arc-minute spatial resolution for the years 2000–2025. The dataset is de-**
14 **veloped by combining a FAO-56-based model with recent developments in**
15 **dynamic crop mapping, satellite-derived precipitation, and reference evap-**
16 **oration based on atmospheric reanalysis. Our dataset compares favorably**

17 **with existing products with a global crop evaporation estimate of 5,531 km³**
18 **against 5,868 km³ from WATNEEDS for the year 2000. It also shows a me-**
19 **dian correlation of 0.77 and Kling-Gupta Efficiency of 0.64 when validated**
20 **against 10 eddy covariance sites. Given its explicit representation of tempo-**
21 **ral variability in crop areas and observation-based climate inputs, CropET**
22 **will enable a wide range of applications, including benchmarking Earth sys-**
23 **tem models, assessing irrigation withdrawals, and quantifying how agricul-**
24 **tural expansion has reshaped regional water and energy budgets.**

25 **Background & Summary**

26 Human modification of the Earth's land surface¹ has impacted every component
27 of its hydrological cycle², from streamflow in major rivers³ to water stored in the
28 aquifers⁴. Land evaporation, one of the largest outgoing fluxes in the global water
29 balance⁵, is no exception, with evaporation from crops representing the primary
30 anthropogenic contribution to it. Two main reasons have driven changes in crop
31 evaporation (referred to as just 'ET' henceforth) in the first quarter of the 21st cen-
32 tury. First, growing demand for food due to population and economic growth⁶
33 has led to significant expansion of both rainfed and irrigated agriculture across
34 the globe⁷. Between 2003 and 2019, cropped land area has increased by ~9%

most prominently in South America and Africa⁸. For example, area cultivated with soybean crop has doubled in the last twenty years at considerable cost to natural ecosystems, such as the Amazon rainforests^{9,10}. Second, rising carbon dioxide (CO₂) and the associated warming of the Earth's climate has fundamentally changed how crops use water and respond to environmental stressors¹¹. Crops behave similar to natural vegetation, with increasing CO₂ expected to enhance water use efficiency¹² and thus productivity of plants¹³. On the other hand, higher vapor pressure deficit¹⁴ (VPD), soil water stress¹⁵, and heat extremes¹⁶ might favor biomass declines. The positive impacts of CO₂ on different varieties of crops is apparent in free-air CO₂ enrichment (FACE) experiments, where reduction in both stomatal conductance and ET are observed along with higher yields^{17,18}. The detrimental effects of warming are also clearly visible with productivity declines in major crops of China being attributed to increasing VPD, and high sensitivity of crop yields to dry and hot extremes observed across the globe^{19–22}. As a consequence of the warming-driven drying of the Earth's surface²³, much of the agricultural expansion in recent years is driven by irrigated crops in predominantly water-stressed regions²⁴. The concurrent expansion of irrigated agriculture and global warming, therefore, makes it crucial to accurately quantify their nonlinear impacts on crop ET at high spatial and temporal resolution.

54 Several datasets provide observation-based estimates of global terrestrial
55 ET at daily timescales. A few examples include FLUXCOM²⁵, PT-JPL²⁶, GLEAM⁵,
56 PML²⁷, all of which utilize Earth observations to constrain semi-empirical ET mod-
57 els. However, very few, and none of the aforementioned datasets, explicitly esti-
58 mate ET from either rainfed or irrigated crops. While recent efforts such as the
59 OpenET²⁸ initiative represent a significant step forward in this regard by provid-
60 ing crop ET at very high spatial and temporal resolution, they do not yet generate
61 crop-specific estimates. A different class of datasets follow the Food and Agri-
62 culture Organization Irrigation and Drainage Paper Number 56²⁹ (FAO-56) to esti-
63 mate reference crop ET using the Penman-Monteith equation. Here, crop-specific
64 phenological and water stress coefficients are used to scale the reference poten-
65 tial ET to actual values. Such models, e.g., WATNEEDS³⁰, CropGBWater³¹, and
66 WaterCROP³², are parametrically parsimonious and computationally efficient, and
67 hence widely used to compute crop-specific blue and green crop water require-
68 ments at global scales. Recently, physically based crop models based on FAO's
69 AquaCrop have also been applied to estimate global crop ET³³. However, the res-
70 olution of these datasets is typically monthly and the potential of such algorithms
71 to generate daily estimates of crop ET has not been fully leveraged.

72 Irrespective of the algorithm employed, global crop ET data products are

hindered by the lack of accurate, spatially-distributed crop maps (harvested and growing areas) and associated phenological calendars. Most datasets rely on monthly irrigated and rainfed cropping areas (MIRCA2000) maps, which provide static crop distributions and calendars for the year 2000³⁴. Hence, currently available datasets do not account for the time-varying impact of agricultural expansion on crop ET. Some studies have addressed this limitation by using dynamic crop distribution data from the Spatial Production Allocation Model³⁵ (SPAM) which provides maps for the years 2000–2020 in five year intervals^{31,33}. However, unlike MIRCA2000, SPAM does not provide crop calendars which are essential for robust estimation of crop ET at daily to seasonal timescales. The recent availability of MIRCA-OS³⁶ – which provides spatially-explicit cropping areas for 23 crop classes for the years 2000, 2005, 2010, 2015, and 2020 – provides an ideal opportunity to capture the effects of agricultural expansion on ET at a global scale. Importantly, MIRCA-OS also provides spatially-explicit crop calendars enabling seasonally-consistent estimation of crop ET.

Here, we present CropET, a 5 arc-minute (0.0833° , $\sim 9.3\text{km}$ at the equator) daily crop ET dataset that spans the years 2000–2025 and the following 23 rainfed and irrigated crop classes: Rice, Wheat, Maize, Others (perennial), Soybeans, Others (annual), Fodder, Sugarcane, Pulses, Oil Palm, Cotton, Sorghum,

92 Barley, Cassava, Millet, Groundnuts, Rapeseed, Coffee, Sunflower, Cocoa, Pota-
93 toes, Sugar beet, and Rye. CropET is based on a FAO56-type model which has
94 been extensively used for global and regional studies of both rainfed and irrigated
95 crop water use^{37–40}. The model is forced with precipitation from the Multi-Source
96 Weighted Ensemble Precipitation (MSWEP) v2.8⁴¹ dataset and reference poten-
97 tial ET from the hPET⁴² data product derived from ERA5⁴³ atmospheric reanal-
98 ysis. Furthermore, the model is constrained by time-varying cropping areas and
99 calendars from MIRCA-OS³⁶ and soil parameters from the Harmonized World Soil
100 Database (HWSD) v2⁴⁴. The dataset is validated against the WATNEEDS³⁰ crop
101 water use dataset for the year 2000 and eddy covariance measurements from 10
102 sites within the FLUXNET⁴⁵ network. The CropET dataset can reliably capture the
103 impact of both climate change and agricultural expansion on crop ET at a global
104 scale and at daily timescales, while providing a valuable resource for agricultural
105 water management, food security assessment, global hydrological modeling, and
106 the evaluation of agricultural impacts on regional water-energy dynamics.

107 **Methods**

108 **Preparation of input datasets** All input datasets mentioned above, both climate
109 and land surface variables, were bilinearly interpolated to a global 5 arc-minute

110 spatial grid. No other processing step was applied to the datasets, with the
111 exception of the MIRCA-OS cropping areas and calendars. The preprocessing
112 steps applied to the MIRCA-OS dataset are described below. MIRCA-OS³⁶ re-
113 ports cropping areas and calendars for 23 crop classes in five years, 2000, 2005,
114 2010, 2015, and 2020, treating the irrigated and rainfed cultivation of each crop
115 separately. Areas are provided as gridded monthly growing areas and annual har-
116 vested areas, while the calendars report the planting maturity months of each crop
117 within the administrative units of a country. Crops grown in more than one cycle
118 per year, such as rice and wheat, are reported as separate sub-seasons, each
119 with its own area and calendar. Monthly cropping and annual harvested areas
120 are provided for 23 crop classes. We rasterized these administrative boundaries
121 and assigned the respective cropping areas and calendar information to grid cells.
122 For every combination of grid cell and crop class, we assigned the planting and
123 maturity months of the record with the largest growing area within the unit. The
124 area value was then taken from the gridded annual harvested area and distributed
125 among sub-seasons in proportion to their reported growing area, which conserves
126 the harvested area of each crop in every grid cell.

127 Because MIRCA-OS is limited to five years, we interpolated the areas and
128 calendars to a continuous annual series spanning 2000–2025. The years 2000,

129 2005, 2010, 2015, and 2020 were retained unchanged. In the intervening years,
130 the harvested area and crop calendar of each crop class and sub-season were
131 interpolated linearly between the years for which information is available. The
132 years 2021–2025 were held at the 2020 areas and calendars, as MIRCA-OS pro-
133 vides no basis for extrapolating cropland beyond the year 2020. Furthermore, crop
134 coefficients are estimated for each subseason and defined according to the four
135 growth stages described in FAO-56²⁹, namely initial, development, mid-season,
136 and late season. However, as relative durations of each growth stage vary with
137 climate, we regionalized the duration and crop coefficients using a six-class agro-
138 climatic zone map (tropical, subtropical with summer rainfall, subtropical with win-
139 ter rainfall, temperate oceanic, temperate continental, and boreal to arctic). This
140 regionalization^{39,46} is done such that timing and length of every season follow the
141 local MIRCA-OS calendar while the partitioning among stages and the values of
142 the crop coefficients follow the climate zone of the grid cell.

143 Two of the 23 classes, Others (annual) and Others (perennial), aggregate
144 crop classes that MIRCA-OS does not resolve individually, so their composition
145 varies between administrative units and no crop-specific coefficients could be de-
146 fined for them. Therefore, we assigned generic values uniformly across the globe:
147 Others (annual) takes the crop coefficients and rooting depth of fodder grasses

148 and Others (perennial) those of cocoa, as a representative evergreen tree crop.
 149 Together these two classes account for 16% of the global harvested area and 18%
 150 of the evaporation reported here. They are retained for completeness and for con-
 151 sistency with the MIRCA-OS crop classification. Thus, the evaporation attributed
 152 to them should be used cautiously.

153 **Crop evaporation model** CropET solves a daily soil water balance independently
 154 at each grid cell, and for each crop and sub-season^{37,38}. Each solution is driven
 155 by the cropping calendar assigned to that grid cell, so the model state advances
 156 continuously through the record rather than being restarted at each season. Con-
 157 sidering S as a single growing cycle of length L_S days and j as the day counted
 158 from planting, the cumulative ET over the cycle is $E_{c,S} = \sum_{j=1}^{L_S} E_c(j)$, where the
 159 daily crop ET is calculated based on the of FAO-56²⁹ equation,

$$E_c(j) = K_c(j) K_s(j) E_0(j). \quad (1)$$

160 Here E_0 (in mm d^{-1}) is the reference potential ET taken from hPET⁴², K_c is
 161 the crop development coefficient, and K_s is the water stress coefficient. The grow-
 162 ing cycle runs from the first day of the planting month to the last day of the maturity

163 month reported by MIRCA-OS, and cycles whose maturity month precedes their
 164 planting month are carried across the turn of the year, so that a crop planted in
 165 autumn is driven by the forcing of the year in which it actually matures.

166 Each cycle is divided into the four FAO-56 development stages, of lengths
 167 l_1 to l_4 days, obtained as fractions p_{st} of the growing cycle length, $l_{st} = \lfloor p_{st} L_S \rfloor$.
 168 The crop coefficient is held constant within the initial and mid-season stages and
 169 varies linearly in between,

$$K_c(j) = \begin{cases} K_{c,ini} & j < l_1 \\ K_{c,ini} + \frac{j - l_1}{l_2} (K_{c,mid} - K_{c,ini}) & l_1 \leq j < l_1 + l_2 \\ K_{c,mid} & l_1 + l_2 \leq j < l_1 + l_2 + l_3 \\ K_{c,mid} + \frac{j - l_1 - l_2 - l_3}{l_4} (K_{c,end} - K_{c,mid}) & j \geq l_1 + l_2 + l_3. \end{cases} \quad (2)$$

170 The three coefficients $K_{c,ini}$, $K_{c,mid}$ and $K_{c,end}$ and the stage fractions p_{st} are
 171 regionalized as described in the previous section⁴⁶.

172 The water available to the crop is the total available water in the root zone,
 173 $TAW(j) = AWC \cdot Z_r(j)$, where AWC [mm m⁻¹] is the available water content

174 of the soil, taken from the Harmonized World Soil Database v2⁴⁴, and Z_r [m] is
 175 the root depth. Roots are assumed to occupy one fifth of their maximum depth at
 176 planting and to deepen linearly until the end of the development stage, after which
 177 they remain at their crop-specific maximum $Z_{r,max}$,

$$Z_r(j) = \begin{cases} Z_{r,max} \left(0.2 + 0.8 \frac{j}{l_1 + l_2} \right) & j < l_1 + l_2 \\ Z_{r,max} & j \geq l_1 + l_2. \end{cases} \quad (3)$$

178 The crop is assumed to draw water without restriction until the readily avail-
 179 able fraction $RAW(j) = \rho TAW(j)$ has been depleted, where the depletion frac-
 180 tion ρ is crop specific and constant through the cycle. Both $Z_{r,max}$ and ρ are taken
 181 from FAO-56²⁹.

182 The state variable of the soil water balance is the root zone depletion D
 183 (mm), i.e., the water deficit relative to field capacity. Precipitation P , obtained from
 184 MSWEP v2.8⁴¹, is applied at the start of each day,

$$D_m(j) = \max \{ D_e(j-1) - P(j), 0 \}, \quad (4)$$

185 where the subscripts m and e denote the value before and after the daily
 186 evaporative loss. Water in excess of field capacity is removed as surface runoff,
 187 and neither deep percolation nor capillary rise is represented. For rainfed crops
 188 the stress coefficient is

$$K_s(j) = \min \left\{ 1, \max \left\{ 0, \frac{TAW(j) - D_m(j)}{TAW(j) - RAW(j)} \right\} \right\}, \quad (5)$$

189 so that ET proceeds at its potential rate while the depletion remains within
 190 RAW and declines linearly once the crop enters stress. For irrigated crops the
 191 stress coefficient is fixed at 1.0 and the daily irrigation volume I_j is determined,
 192 assuming that the crop experiences no water stress,

$$I(j) = \max \{ K_c(j)E_0(j) + D_m(j) - RAW(j), 0 \}. \quad (6)$$

193 No assumption is made about the irrigation technique or its efficiency, so I
 194 represents the net irrigation requirement at the field. The depletion carried to the
 195 following day is then

$$D_e(j) = D_m(j) + E_c(j) - I(j), \quad (7)$$

196 with $I = 0$ for rainfed crops. Outside the growing cycle the depletion is reset
 197 at each time step to a value of zero for rainfed crops and equal to the precipitation
 198 of the day for irrigated crops.

199 ET is partitioned into a green component sustained by precipitation and a
 200 blue component sustained by irrigation. All ET from rainfed crops is green. For
 201 irrigated crops the blue component is the irrigation water that evaporates on the
 202 day it is applied, $E_b(j) = \min \{I(j), E_c(j)\}$, with irrigation water in excess of the
 203 evaporative demand entering the soil storage, while the green component is the
 204 remainder, $E_g(j) = E_c(j) - E_b(j)$.

205 Two adjustments are made for rice. The depletion is set to zero on the first
 206 day of the cycle, representing the saturation of the root zone that precedes sowing
 207 or transplanting, and irrigated rice receives a further 200 mm per unit area to
 208 account for the water used in puddling the field⁴⁷. This volume is distributed evenly
 209 across the days of the cycle and is added to the reported total and blue ET without
 210 entering the water balance, since it is consumed in field preparation rather than

211 transpired by the crop.

212 The soil state is initialised by repeating the year 2000 three times before
213 the simulation record begins, and the depletion, together with the progress of any
214 cycle in course on 1 January, is then carried forward from one year to the next
215 for the whole of 2000–2025 period. The model returns daily, monthly and annual
216 total, green and blue ET, separately for every crop class, sub-season and water
217 supply system. We note that bare soil evaporation is not explicitly modelled.

218 **Data Records**

219 The CropET dataset amounts to approximately 737 GB. The dataset is freely
220 available under a MIT licence and is hosted on Google Drive. The instructions
221 to download them are given in the Zenodo repository at [https://doi.org/10.](https://doi.org/10.5281/zenodo.XXXXXXXX)
222 [5281/zenodo.XXXXXXXX](https://doi.org/10.5281/zenodo.XXXXXXXX). For a detailed description of the dataset, including its
223 specifications and version history, we refer readers to the same repository. The
224 period covered by CropET is currently 2000–2025 at daily temporal resolution and
225 5 arc-minute spatial resolution.

226 ET is reported separately for each crop class, each water source (irrigated
227 or rainfed), and each growing cycle within a year. Most of the 23 crop classes

228 are grown in a single cycle per year, while rice is reported in up to three cycles
229 and wheat in up to two. The following three variables are available for each of
230 these combinations: (a) total crop evaporation (E , mm day^{-1}), (b) green crop
231 evaporation (E_{green} , mm day^{-1}), and (c) blue crop evaporation (E_{blue} , mm day^{-1}).
232 ET from rainfed crops is only green by definition, and therefore E_{green} and E_{blue}
233 are provided for irrigated crops only.

234 **Structure of the dataset** Data is organized into netCDF files, with one file per
235 variable per combination of crop class, water source (irrigated and rainfed), and
236 each growing cycle (described above) per year. Each daily file contains a 3D array
237 with dimensions $n \times 2160 \times 4320$, where n is the number of days in the respective
238 year, 2160 is the number of grid cells in the latitudinal dimension, and 4320 is
239 the number of grid cells in the longitudinal dimension. The first record in each file
240 corresponds to January 1st of that year, and the first grid cell is centered at latitude
241 -89.96° and longitude -179.96° . In addition to daily data, netCDF files containing
242 monthly (dimensions $12 \times 2160 \times 4320$) and annual (dimensions 2160×4320) totals
243 are also available. Values are cumulated over the corresponding period, so that
244 the units are mm day^{-1} , mm month^{-1} and mm year^{-1} for daily, monthly and annual
245 files, respectively.

246 These datasets are stored on the server in the following directory structure:
247 <CROP>/<TEMPORAL_RESOLUTION>/<SYSTEM>/<VARIABLE>/, where <CROP>
248 refers to one of the 23 crop classes, <TEMPORAL_RESOLUTION> indicates the
249 temporal aggregation level ('daily', 'monthly', or 'yearly'), <SYSTEM> refers to ei-
250 ther 'Irrigated' or 'Rainfed', and <VARIABLE> refers to 'ET', 'GreenET', or 'BlueET'.

251 Files follow this naming convention: <CROP>_<SYSTEM><CYCLE>_<VARIABLE>_
252 <PERIOD>_<YEAR>.nc, where <SYSTEM> is 'IR' for irrigated or 'RF' for rainfed
253 cultivation, <CYCLE> is the number of the growing cycle and is written directly af-
254 ter the system without a separator, <PERIOD> is 'daily', 'monthly' or 'annual', and
255 <YEAR> is the four-digit year. For example, a file containing daily blue evaporation
256 from the second irrigated rice cycle for 2015 would be named: Rice/daily/
257 Irrigated/BlueET/Rice_IR2_BlueET_daily_2015.nc, and a file contain-
258 ing monthly ET from the first rainfed wheat cycle for 2003 would be named: Wheat/
259 monthly/Rainfed/ET/Wheat_RF1_ET_monthly_2003.nc.

260 **Technical Validation**

261 In this section, we first describe the spatial, temporal, and crop-specific patterns
262 of ET from the CropET dataset. We show how rainfed and irrigated crops differ

263 spatially and temporally. Additionally, we decompose ET into its blue and green
264 water components, and show how they vary for different crops. Then, we validate
265 our global ET estimates with the widely used WATNEEDS dataset³⁰ for the year
266 2000 and against *in situ* observations of ET from eddy covariance towers within
267 the FLUXNET⁴⁵ network in sites with predominantly crop land cover. All results
268 presented here are based on the years 2000–2020, as the crop areas for years
269 2021–2025 are based on the 2020 crop area. Consequently, the uncertainty in
270 crop ET induced by the use of static crop areas cannot be reliably quantified for
271 the final five years of the dataset.

272 **Spatial and temporal patterns of global crop evaporation** The spatial distribu-
273 tion of total crop ET (Figure 1a) averaged over 2000–2020 shows that the high-
274 est values are concentrated in regions with highly intensive agriculture such as
275 the Indo-Gangetic Plain, eastern China, Southeast Asia, the U.S. Midwest, the
276 southeastern parts of South America, and the Central Vally in the U.S. The latitu-
277 dinal profile peaks near 25°N, where irrigated crops account for a large share of
278 the total, while rainfed crops dominate at all other latitudes, with a secondary
279 maximum near 30°S. When decomposed into its rainfed and irrigated compo-
280 nents(Figure S1), we see that rainfed ET is distributed across all cultivated re-
281 gions, whereas irrigated ET is concentrated between 20°N and 40°N. This band

holds most of the global area equipped for irrigation²⁴, and the partitioning into green and blue components follows the same patterns, with blue ET peaking sharply between 20°N and 35°N (Figure S2). Aggregated by crop class (Figure 1b), rice (1,030 km³ yr⁻¹), wheat (970 km³ yr⁻¹), and maize (800 km³ yr⁻¹) are the largest contributors, together accounting for 40% of global crop ET. Rice exhibits the largest blue water component in both absolute and relative terms, consistent with its concentration in irrigated South and East Asia. These findings highlight the central role of paddy cultivation in the global water and carbon cycles^{48,49}. ET from soybeans, cassava, and cocoa is almost entirely green, reflecting their predominantly rainfed cultivation.

Between 2000 and 2020, globally aggregated ET shifts from negative to positive standardized anomalies for the majority of crop classes (Figure 2a), and this shift appears for both irrigated and rainfed crops (Figure S3). The heat map integrates the effects of both the expansion of cropped area and rising evaporative demand. The strongest positive changes in ET occur in rice, maize, soybeans, sugar cane, and oil palm (Figure 2a), the classes whose harvested areas have grown the fastest. For example, soybean area has doubled in South America⁹, maize has expanded due to increased feed and biofuel demand⁵⁰, oil palm production has more than tripled since 2000⁵⁰, and cultivation of rice, wheat, and

301 pulses supported by irrigation has intensified in China and India⁵¹. Our results are
302 consistent with previous studies which have shown increased contribution from
303 these crops to global agricultural water consumption since 2000³¹. In contrast,
304 barley, sugar beet, and rye show negative tendencies. These are crops whose
305 cultivated area has contracted. For example, the 2006 reform of the European
306 Union sugar regime cut production quotas by a quarter and ended sugar beet
307 cultivation in several member states⁵², and the area of traditional European ce-
308 reals has declined as production shifted toward oil crops⁵⁰. For these classes,
309 area contraction offsets the potential ET increase due to rising temperatures and
310 atmospheric water demand.

311 Spatially, positive trends are concentrated in India, eastern China, South-
312 east Asia, and southeastern South America, while declines occur in western U.S,
313 southern and eastern parts of South America (Figure 2b). These regions, es-
314 pecially in China and India, coincide with the areas where satellite records show
315 cropland-driven greening through multiple cropping, fertilization, and irrigation conditions⁵¹,
316 and where irrigation has expanded most since 2000²⁴. The decomposition of the
317 trends into its rainfed and irrigated ET components (Figure 2c) shows that in-
318 creases across China are driven jointly by rainfed and irrigated ET (+13 and +10
319 mm yr⁻¹ respectively between 2000 and 2020, rising to +37 mm yr⁻¹ of irrigated

ET over the North China Plain). On the other hand, increases in crop ET across West Africa, maritime Southeast Asia and the Brazilian Cerrado are rainfed-driven (+63–77 mm yr⁻¹, ~ 90% of the total trend), and irrigated-driven increases are concentrated in central and western India (+136 of +160 mm yr⁻¹, 85%) and in mainland Southeast Asia (+31 of +39 mm yr⁻¹, 79% of the total trend). Interestingly, the declines are almost entirely driven by reductions in irrigated ET. A prominent example is the California's Central Valley (-46 of -53 mm yr⁻¹), possibly driven by land fallowing due to the ongoing megadrought⁵³, and the potential impact of California's Sustainable Groundwater Management Act⁵⁴. Other examples in our dataset include Uzbekistan (-47 mm yr⁻¹, 100%), Morocco (-13 of -17 mm yr⁻¹) and the Indo-Gangetic plain, where a -12 mm yr⁻¹ irrigated loss is offset by a +11 mm yr⁻¹ rainfed gain.

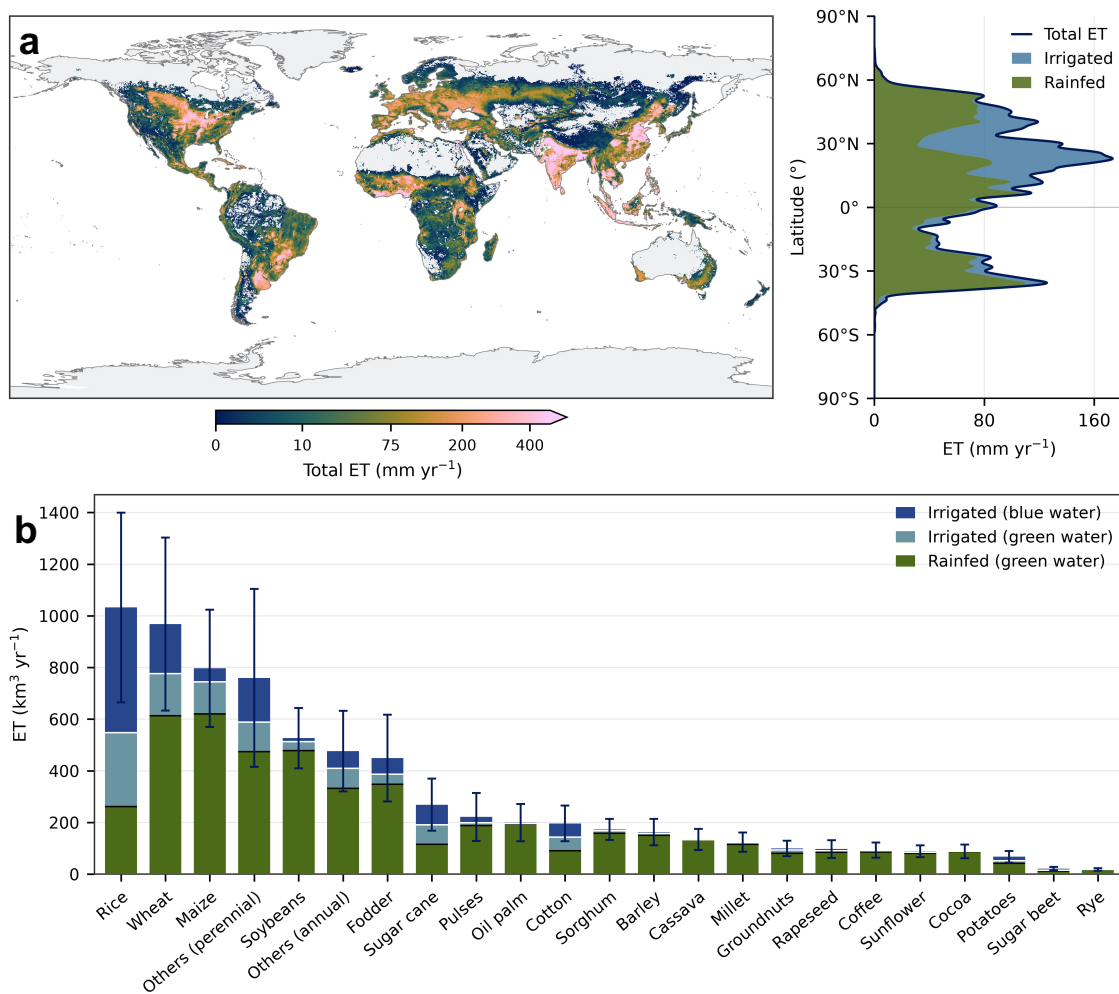


Figure 1: Spatial and crop-specific distribution of total crop evaporation. (a) Map of time-averaged annual total crop evaporation (both irrigated and rainfed crops) computed over the years 2000–2020. Latitudinal averages decomposed into their irrigated and rainfed components are also presented. (b) Globally aggregated total evaporation from 23 crop classes at annual timescales, averaged over the years 2000–2020. The barplots also show decomposition of total crop evaporation into irrigated and rainfed, along with blue and green water components. Note: Total crop evaporation for every pixel is computed as the average of crop-specific evaporation weighted by the fractional area covered by each crop within a 5 arc-minute grid cell.

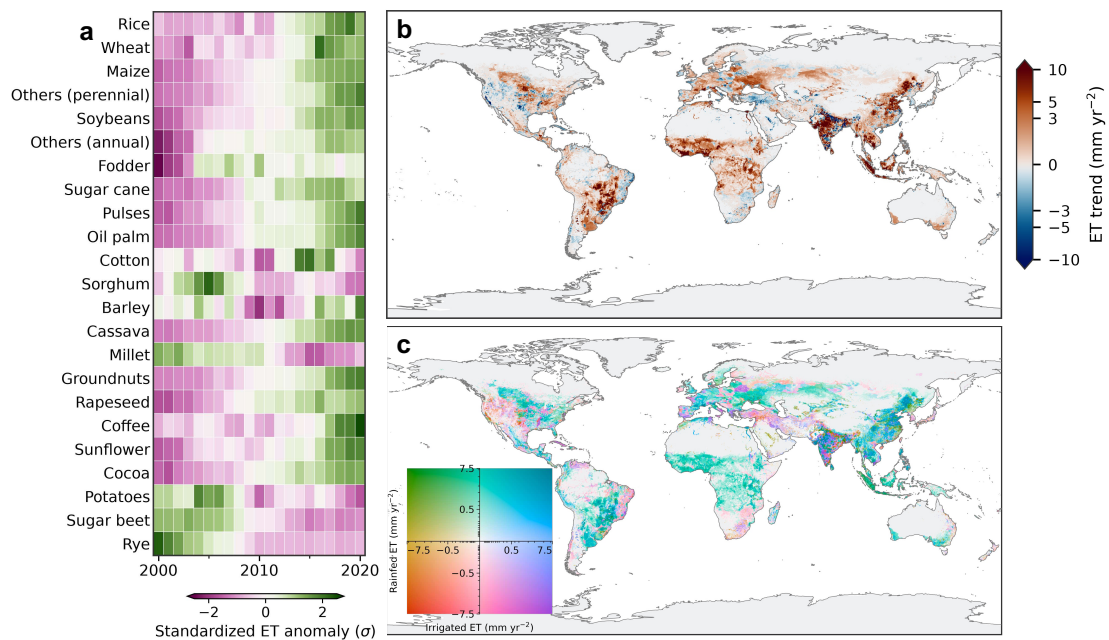


Figure 2: Temporal distribution of crop evaporation. (a) Heat map of globally aggregated standardized total evaporation anomaly for 23 crop classes and over the years between 2000 and 2020. Spatial distribution of (b) trends in total crop evaporation per grid cell over the years 2000–2020, and (c) total evaporation trends decomposed into rainfed and irrigated components. Quadrant 1: Both irrigated and rainfed crop evaporation show positive trend (blue hues), Quadrant 2: Positive trend in rainfed and negative trend in irrigated crop evaporation (green hues), Quadrant 3: Negative trends in both irrigated and rainfed crop evaporation (red hues), Quadrant 4: Positive trend in irrigated and negative trend in rainfed crop evaporation (violet hues)

Comparison with WATNEEDS estimates We validate our crop ET estimates against WATNEEDS³⁰, a widely used global dataset of crop water consumption. While newer datasets such as CropGBWater³¹ are available, they have not yet been used and validated in independent applications. WATNEEDS uses MIRCA2000 to account for cropping areas for the year 2000, precipitation from a combination of satellite-based Climate Hazards Group InfraRed Precipitation with Station version 2.0 (CHIRPS) and raingauge-based Climate Prediction Center Global Unified Gauge-Based Analysis of Daily Precipitation (CPC) data products, and potential evaporation from the Climate Research Unit (CRU) Time Series version 4.01 dataset. For the year 2000, CropET yields a global crop ET of 5,814 km³ against 5,984 km³ from WATNEEDS, a difference of 2.8%. Both totals are consistent in magnitude with the 6,100–6,700 km³ reported for 2010–2020 by a recent assessment covering a larger set of 46 crops³¹. The agreement extends to the decomposition (Figure 3b): CropET estimates 1,858 km³ from irrigated crops (of which 1,067 km³ is blue water) and 3,673 km³ from rainfed crops, against 1,768 km³ and 4,101 km³ from WATNEEDS. Spatially, CropET is lower than WATNEEDS across the high-latitude rainfed croplands of Russia and northern Europe and higher across south and Southeast Asia, West Africa, and southern Brazil (Figure 3a). When decomposed into irrigated and rainfed components (Figure S4),

we see that the high-latitude negative bias originates from rainfed crops, while the positive bias over some parts of India and eastern China originates from irrigated crops. While both MIRCA-OS and MIRCA2000 agree on total irrigated (3% difference) and rainfed (0.1% difference) areas, the bias arises from crop-specific area allocation between the two: MIRCA-OS shows 3.8 Mha more irrigated rice and 2.2 Mha less irrigated wheat over India, and 7.7 Mha less irrigated rice over eastern China. At the crop level (Figure 3c), we see strong agreement between the two datasets. The mean spatial correlation ranges from 0.53 (sugar cane) to 0.90 (oil palm), and the percentage bias in total ET remains within $\pm 20\%$ for most classes, with comparable correlations for rainfed and irrigated components (0.54–0.90 and 0.59–0.92; Figure S5).

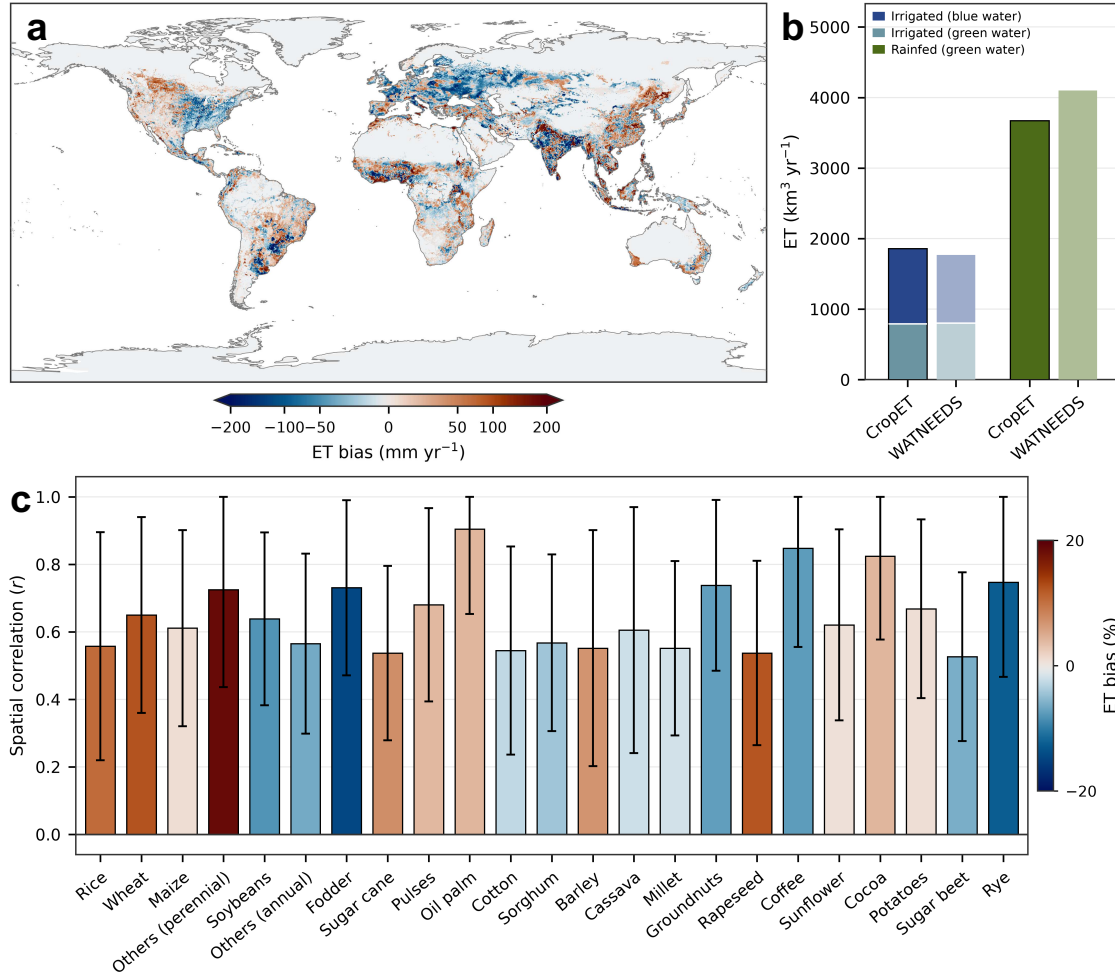


Figure 3: **Comparison with WATNEEDS.** (a) Map of bias in total crop evaporation between CropET and WATNEEDS ($E_{CropET} - E_{WATNEEDS}$) datasets for the year 2000. (b) Comparison between CropET and WATNEEDS for globally aggregated crop evaporation volumes, including their decomposition among irrigated (blue and green water) and rainfed (green water) components, for the year 2000. (c) Mean and standard deviation of spatial correlation in total crop evaporation between CropET and WATNEEDS dataset for the year 2000. The colors of the bars show percentage bias in total ET between CropET and WATNEEDS dataset for the year 2000.

Validation against FLUXNET observations In contrast to other crop evaporation and water use datasets, CropET also provides estimates at daily timescales. To evaluate whether the dataset is robust at such a high temporal resolution, we validate crop evaporation estimates against eddy covariance measurements of latent heat flux at 10 different locations across the globe (Fig. 4a). Across the 31,133 days pooled from the 10 towers, CropET attains a correlation of 0.77, a root mean square error of 1.26 mm d^{-1} , and a KGE of 0.64 (Figure 4b). Site-level KGE ranges from 0.38 to 0.80 (Figure 4a; Table S1), exceeds 0.5 at seven of the ten sites, and lies well above the mean benchmark of -0.41^{55} at all of them. We note that the agreement is obtained without any site-level calibration of model parameters. Through a Taylor diagram 4c, we show that the error structure is systematic. The normalized standard deviation is below unity at every site ($\alpha = 0.64\text{--}0.95$), while the bias ratio β is below unity at eight of the ten sites, indicating that CropET systematically underestimates day-to-day variability. The discrepancy can arise from a number of issues, including the mismatch in the spatial footprint of the CropET dataset (order of kilometers) and the representativeness of the flux tower observations (order of 100 meters). Furthermore, the soil water balance module implemented in the model is simple and does not account for site-specific soil-plant dynamics. Therefore the soil water stress parameter might not fully rep-

381 resent the variability in soil moisture seen at daily timescales. Finally, hydrological
382 processes such as interception loss and capillary rise are not accounted for in
383 CropET. For example, water supply through capillary rise could be important in
384 sites with shallow water tables such as US-Bi2 and US-Twt^{56,57}. Despite these
385 constraints, the performance of CropET at daily timescales highlights both the
386 effectiveness and overall robustness of the framework underpinning it.

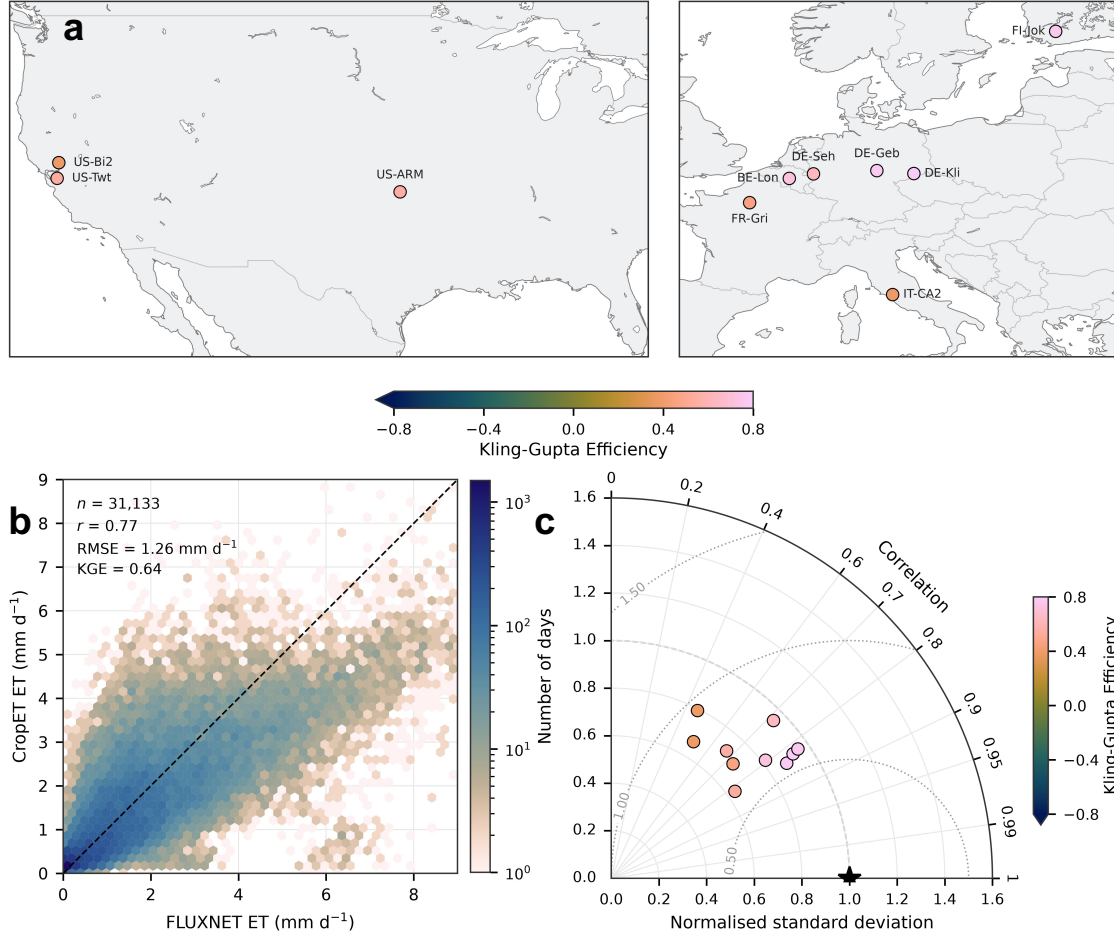


Figure 4: **Validation against FLUXNET data.** (a) Map showing the Kling-Gupta Efficiency computed between daily crop evaporation from CropET dataset and *in situ* observations from 10 eddy covariance towers within the FLUXNET network, spread across the United States and Europe. (b) Scatter plot between daily crop evaporation from CropET and FLUXNET towers. The plot also shows the density of observations available from the FLUXNET sites (c) Taylor diagram showing correlation, standard deviation, and centered root mean square error between daily crop evaporation from CropET and FLUXNET observations. The color of each marker represents the Kling-Gupta Efficiency at each location.

387 **Data availability**

388 CropET data is available at <https://doi.org/10.5281/zenodo.22693342>⁵⁸. We note
389 that due to the size of the dataset, it is hosted on Google Drive. The instructions to
390 download with a detailed README file is available in the above zenodo repository.

391 **Code availability**

392 The source of the CropET model, the scripts used for preprocessing the input
393 datasets and generating the figures are available at <https://doi.org/10.5281/zenodo.22693342>⁵⁸.

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590 **Acknowledgements**

591 The authors acknowledge the Reading Academic Computing Cluster (RACC) at
592 the University of Reading for providing the computational resources used in this
593 work. SB acknowledges funding from the Swiss National Science Foundation
594 (SNSF), Grant number 10000638.

595 **Author Contributions**

596 A.K. and S.B. conceptualized the study and designed the experiments. S.B. wrote
597 the original code in MATLAB for the crop evaporation model. A.K. implemented
598 the model in Python and led the production of the CropET dataset. A.K. and S.B.
599 wrote the paper.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

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