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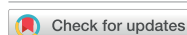
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Irrigated agriculture supports rainfed crops in India through
atmospheric moisture recyclingAkash Koppa^{1,2,*} , Francesca Bassani¹ , Jessica Keune³ , Victoria Deman⁴ , Damian Insua-Costa⁴ ,
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E-mail: akoppa@umd.edu and sara.bonetti@epfl.ch**Keywords:** land–atmosphere interactions, irrigated and rainfed agriculture, atmospheric moisture recyclingSupplementary material for this article is available [online](#)

Abstract

Rainfed crops account for approximately 40% of India's food production and support 60% of its livestock. Although linked to oceanic monsoon rainfall, their productivity also depends on terrestrially-sourced rainfall, particularly in the non-monsoon season. The degree to which rainfed crops rely on moisture sourced from evaporation in upwind irrigated areas remains largely unknown. Using a combination of models and observations, we show that evaporation from upwind irrigated crops contributes 7% (mean) $\pm 5\%$ (spread) of the rainfall over rainfed areas annually, rising to $15 \pm 10\%$ during the pre-monsoon months (averaged over the years 2000–2020). In the absence of this input, water stress experienced by rainfed crops can increase by 5%–10% during the crucial mid to late crop growth phases, potentially affecting yields. Our results reveal an unrecognized atmospheric link between irrigated and rainfed agriculture that is overlooked in current agricultural policies. Planning and managing these systems holistically can help strengthen regional food and water security under future climates.

1. Introduction

More than a billion hectares of land are cultivated with rainfed crops globally [1, 2]. They account for ~60% of the world's food production and more than 90% of the total farmed land in the socio-economically vulnerable parts of sub-Saharan Africa, Latin America, and Asia [3]. In India, with over 140 million hectares of sown area (60% of the total area under cultivation), rainfed agriculture plays a crucial role in ensuring the country's food security [4]. By definition, the productivity of rainfed crops depends on the intensity and timing of precipitation. In India, this implies that rainfed crops are disproportionately tied to the variability of monsoon rainfall (July–September), which contributes 70% of the country's annual rainfall [5, 6]. Furthermore, a significant proportion of rainfed crops in India are also grown in

post-monsoon months (October–December), during which crop growth is supported primarily by residual soil moisture from the monsoonal rainfall. During the monsoon season, it has been observed that even a 10%–15% deficit in rainfall reduces food grain production by up to 10 million tonnes [7]. For example, crop losses during the severe drought of 2002 caused the country's gross domestic product to decline by 1% (equivalent to ~\$5 billion) [8].

The prevailing understanding is that rainfall in India is largely sourced from oceanic evaporation, transported inland from the Arabian Sea and the Bay of Bengal by large-scale coupled ocean-atmosphere oscillations at decadal to subseasonal timescales [9–17]. Although this dependency suggests a strong link between ocean evaporation and rainfed crop productivity in India, atmospheric moisture over the sub-continent is not solely derived from oceanic sources.

Recent evidence suggests that terrestrial evaporation also plays an important role in sustaining rainfall over India through moisture recycling [18]. Such sources of moisture are also crucial for sustaining the growth of rainfed crops during the non-monsoon season. Among terrestrial moisture sources, forests and natural vegetation are widely recognized as the dominant contributors to rainfall [19, 20]. Evaporation from forests, for example, supports up to 18% of crop production worldwide [21]. While forests represent the most effective and sustainable pathway for moisture delivery to downwind crops, the specific role of irrigation as a complementary source of moisture for downwind crops has received far less attention [22]. With irrigated areas expanding rapidly across the globe—an increase of 11% between 2000 and 2015) [23]—understanding how this additional source of moisture affects rainfed crops is important. On the other hand, the relationship between irrigation expansion and its downstream moisture contribution is unlikely to be linear, as atmospheric moisture recycling is governed by non-linear land–atmosphere feedbacks [24].

From the Great Plains in the United States [25] to the Gezira Scheme in East Africa [26] and even the large-scale irrigation projects in India [27–29], several modelling and observation-based studies have shown that irrigation significantly impacts both local and remote rainfall patterns, from subdaily [30] to climatological [31] time scales. Irrigation as a source of moisture, especially over rainfed regions, is particularly relevant in India due to the close geographical proximity between irrigated and rainfed crops. This proximity increases the likelihood of recycled moisture from upwind irrigation precipitating over rainfed crops. This is exemplified by the Indo-Gangetic Plain (IGP), one of the most intensively irrigated regions in the world [32], where large-scale irrigation occurs adjacent to areas with extensive rainfed cropping, and exhibits a high degree of moisture recycling [33, 34]. The potential for irrigation-driven evaporation to contribute to rainfall over rainfed crops is particularly valuable during the non-monsoon season, when oceanic moisture transport is weaker and rainfall is more limited compared to the monsoon season. With a significant proportion of the rainfed crops grown in the non-monsoon season, irrigation contribution to rainfall might be crucial for supporting the growth of rainfed crops. Despite its potential significance, the extent to which rainfed crops rely on moisture sourced from evaporation in upwind irrigated regions remains poorly quantified to date.

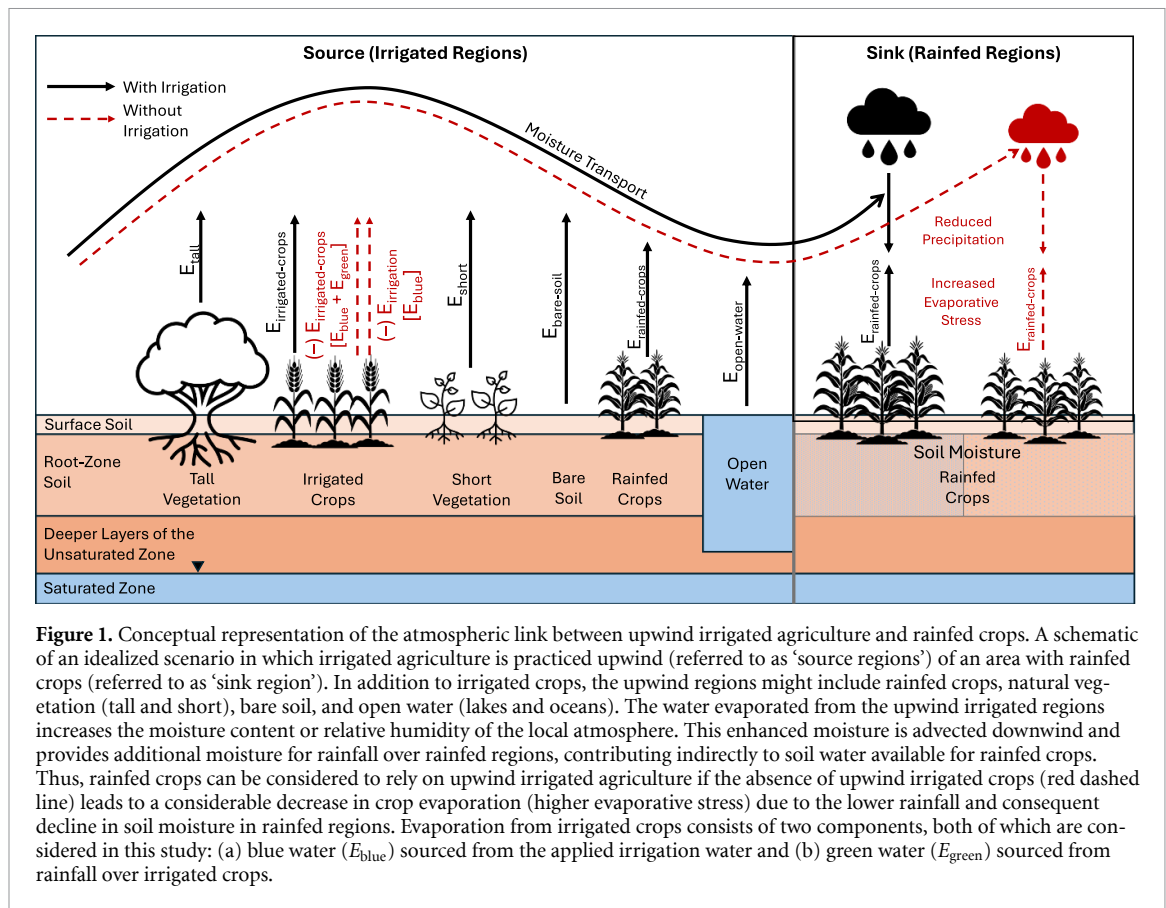
To evaluate the potential reliance of rainfed crops on upwind irrigation agriculture in India, we formulate the following hypothesis (figure 1): evaporation from irrigated crops in upwind regions reduces water stress in rainfed crops by enhancing rainfall via atmospheric moisture recycling. Here, water stress is represented in terms of evaporative stress, which is

defined as the degree to which crop water demand is satisfied by soil moisture (see methods). To test this hypothesis, we use an observation-constrained moisture tracking framework capable of identifying the spatiotemporal source of rainfall (see methods). Specifically, we track the trajectories of simulated air parcels that result in rainfall over rainfed regions (sink region in figure 1) backward in time over 15 d to quantify the contribution of upwind evaporation (source region in figure 1), over the years 2000–2020. The 15 d window encompasses the majority of the long tail of atmospheric water vapour residence time distribution [35], ensuring that most of the evaporative source contributions to rainfall are captured. Previous studies on moisture recycling in India have also restricted the atmospheric residence time of moisture to less than 15 d [36]. This upwind contribution is evaluated both in terms of (a) blue water evaporation (E_{blue}), defined as the part of the total water used by crops that can be directly attributed to applied irrigation, and (b) both blue and green water (E_{green}), which is the part of total crop evaporation which can be attributed to rainfall. With a Food and Agriculture Organization (FAO 56)-based model [37, 38], we explicitly estimate blue and green evaporation from 14 major irrigated and rainfed crops in India (see methods for details and the complete list of crops considered in the study). Finally, we assess the importance of upwind irrigation to rainfed crops by recalculating evaporative stress under a counterfactual scenario where the irrigation contribution to rainfall over rainfed regions is removed.

2. Methods

2.1. Identifying and quantifying the sources of rainfall over rainfed regions

To identify and quantify the land and oceanic sources of rainfall over rainfed regions and to determine the contribution of evaporation from irrigated crops, encompassing both green (E_{green}) and blue (E_{blue}) water components, as well as the contribution from applied irrigation alone (E_{blue}), we proceeded as follows. First, a Lagrangian atmospheric model forced with an atmospheric reanalysis dataset is used to simulate the trajectories of air parcels distributed across the globe. In the next step, the air parcel trajectories that result in rainfall over the target region are tracked backward in both time and space. The target region comprises all $0.5^\circ \times 0.5^\circ$ grid cells in India where both rainfed and irrigated crops each occupy at least 10% of the total land area. This ensures that we accurately represent the cropping pattern in India, wherein irrigated and rainfed crops are grown in close geographical proximity to each other. Furthermore, as moisture contributions decline with distance from the target region, selecting grid cells according to



the above criteria maximizes the likelihood of detecting an irrigation-derived moisture signal in rainfall over rainfed areas. The source region comprises global irrigated land (figure S1). Along the trajectory of the air parcel, the moisture gained (through evaporation) and lost (through precipitation) is considered. Finally, these moisture uptakes and losses are bias-corrected with observation-based estimates and aggregated to determine the contribution of upwind evaporation to rainfall in rainfed regions. We make sure that the contribution of evaporation from upwind irrigated crops to rainfall is estimated for months in which rainfed crops are grown in downwind regions (see methods). In the next section, we first describe the Lagrangian atmospheric model used in the study and then detail the moisture tracking framework used to evaluate the air parcels and attribute moisture contributions from irrigated crops to rainfall over rainfed regions.

2.1.1. Atmospheric transport model simulations

The atmospheric transport of moisture is simulated using the Flexible Particle Dispersion model (FLEXPART) version 10.4 [39, 40], driven by ERA5 atmospheric reanalysis [41]. Approximately 10 million air parcels, uniformly distributed across the globe, are advected forward in space and time. FLEXPART is forced with the following meteorological variables: specific humidity, horizontal and vertical wind components, cloud cover, precipitation,

2 m air temperature, dew-point temperature, sensible and latent heat fluxes, and surface stress in both zonal and meridional directions. For each air parcel, the model records its position (latitude, longitude, and height) and simulates its thermodynamic state, including temperature, density, and specific humidity. Model outputs are generated at 3 h intervals using ERA5 as the driving reanalysis.

2.1.2. Moisture tracking framework

The FLEXPART-simulated trajectories are analysed to identify the moisture sources of rainfall over the study region. Specifically, all air parcels residing over grid cells representing rainfed areas are traced backward in time for 15 d, and their moisture gains and losses along the trajectory are recorded to determine the upwind sources of precipitation. This analysis is carried out using the moisture tracking framework of [42], which evaluates the trajectories through three sequential steps: (a) diagnosis, (b) attribution, and (c) bias-correction. For a detailed description of these steps, please refer to appendix A.

2.2. Observation, reanalysis, and satellite-based datasets

Several reanalysis and satellite-based datasets are used to force and constrain the modelling framework. FLEXPART v10.4 is driven with ERA5 reanalysis data [41], using variables at single and multiple model levels (90 of the 137 available levels, from the surface to

the top of the atmosphere) at 3 h temporal resolution. The ERA5 data, originally available at 0.25° spatial resolution, is bilinearly interpolated to 0.5° for the analysis. The simulations span 21 years (2000–2020).

Precipitation estimates from the FLEXPART-based tracking are bias-corrected using the Multi-Source Weighted Ensemble Precipitation dataset, version 2.8 (MSWEP v2.8) [43], which is available at 0.1° spatial resolution and 3 h temporal resolution. Land evaporation is bias-corrected with the Global Land Evaporation Amsterdam Model (GLEAM) version 4.0a [44], a satellite-based product available at 0.1° and daily resolution, covering the period 1980–Present. Ocean evaporation is constrained using the Objectively Analysed Air-Sea Fluxes (OAFlux) dataset [45], available at 1° spatial resolution and daily temporal resolution. All datasets are bilinearly interpolated to 0.5° , the resolution at which the final analysis is conducted.

2.3. Modelling crop evaporation

To estimate evaporation from irrigated and rainfed crops, a modelling framework [38, 46] based on the FAO-56 [37] model is employed. Using the model, evaporation from the following 14 major crops in India are estimated: Barley, Cotton, Groundnut, Maize, Millet, Potato, Pulses, Rapeseed, Rice, Sorghum, Soy, Sugarcane, Sunflower, and Wheat. For details of the model, please refer to appendix B. Using the model, the evaporative stress in crops satisfied by moisture contribution from upwind irrigated agriculture is calculated using the methodology described in appendix C. Additionally, we also define an irrigation recycling efficiency metric to quantify the value of irrigation applied in a particular region for remote or downwind rainfed crops (refer to appendix D for details).

3. Results and discussions

3.1. Upwind irrigated crops as a source of rainfall for rainfed crops

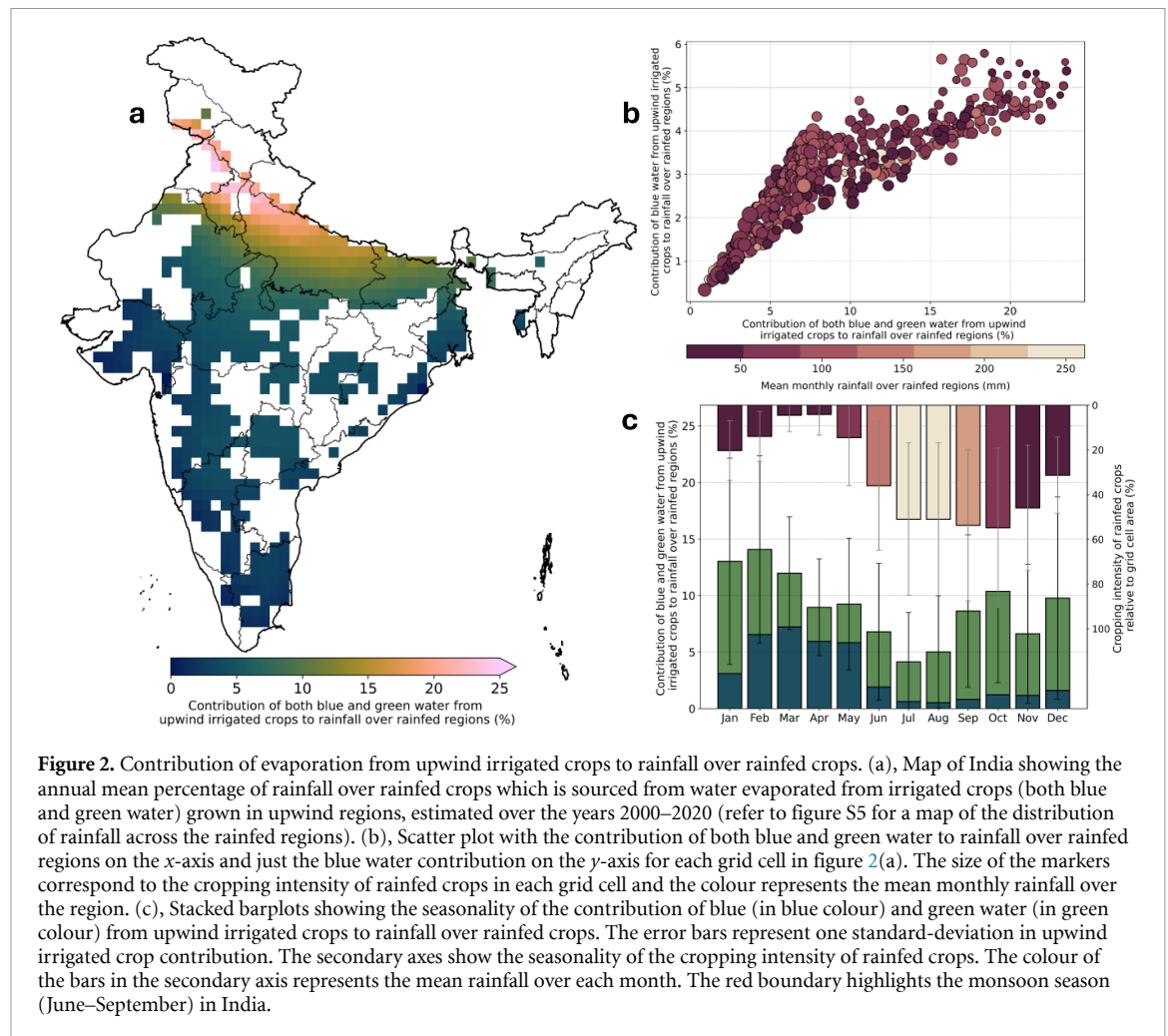
Across all the rainfed crop growing regions in India, evaporation from upwind irrigated crops (both E_{blue} and E_{green}) contributes 7.0% or 53.8 mm yr^{-1} (spatial mean across all the grid cells) $\pm 5.2\%$ or 45.0 mm yr^{-1} (spread, namely the spatial variability of contributions represented here by one standard deviation) of the rainfall. However, we observe large spatial variability in the contribution of evaporation from upwind irrigated crops to rainfall across the country. In the IGP, a northern region with significantly higher irrigation intensity compared to the rest of the country, the contribution of evaporation from upwind irrigated crops is greater than 20%. The interannual variability of the contributions is also high, with a mean standard deviation of 9.3% across India (averaged over all grid cells), and a spatial spread of $\pm 4.5\%$

reflecting the variability of this interannual standard deviation across grid cells (figure S6).

To further highlight the importance of these contributions to rainfall, especially during dry periods, we compare the wettest and driest years at each grid cell (figure S9). We find that the contribution of upwind irrigated crop evaporation to rainfall over rainfed regions is consistently higher during the driest years, particularly in the IGP region, where values exceed 20%. Earlier studies have also suggested high precipitation recycling ratio and enhanced impact of vegetation feedbacks on monsoon rainfall in dry years [18, 47]. During dry monsoon years, when large-scale ocean-atmosphere oscillations and land-sea temperature gradients [13, 14] suppress rainfall, upwind irrigation can potentially buffer the moisture deficits over rainfed regions. Spatially, semi-arid regions in northwestern India, where irrigated cropping intensity is high, also show substantial moisture contributions from upwind irrigated crops. The dry background climate of these regions may amplify the relative importance of this moisture source. However, semi-arid regions in southern India with comparable aridity but considerably lower irrigated cropping intensity show much smaller contributions, suggesting that cropping intensity plays a more dominant role [28].

Next, we isolate the part of the rainfall over rainfed crops that can be attributed only to E_{blue} (i.e. applied irrigation water) in upwind irrigated crop. In figure 2(b), we see that the E_{blue} contribution to rainfall is between 30% and 50% of the total contribution ($E_{\text{blue}} + E_{\text{green}}$), with a maximum contribution of approximately 6%. Spatially, we observe that in addition to the IGP, E_{blue} contributions are significant in the dry western parts of India (figure S7). The relationship between irrigation water (E_{blue} only) and irrigated crop (both E_{blue} and E_{green}) evaporation does not show any discernible pattern with monthly rainfall amount or the cropping intensity of rainfed crops (figure 2(b)).

When the evaporation contributions to rainfall from upwind irrigated crops are aggregated monthly, we observe the emergence of a distinct seasonal pattern (figure 2(c)). First, the contribution of evaporation from upwind irrigated crops (both E_{blue} and E_{green}) is the least during the monsoon season (June–September), which is associated not only with the largest proportion of annual rainfall, but also with the highest cropping intensity of rainfed crops (inverted barplots in figure 2(c)). This is expected as rainfall is the primary source of water even for irrigated crops during the monsoon season, which is reflected in the low contribution of E_{blue} (blue-coloured stacked barplot) compared to E_{green} (green-coloured stacked barplot) in that period. Despite low contributions from upwind E_{blue} , evaporation from irrigated crops (both E_{blue} and E_{green}) contribute as high as 20% to rainfall over rainfed crops in some regions of India



(figure S8) during the monsoon season. This highlights the importance of recycled moisture from land for enhancing rainfall even during the wettest months [18, 36, 48].

While the monsoonal rainfall in India supports the biggest cropping season (termed as ‘Kharif’), rainfed crops are also grown in the non-monsoon months of October–March (termed as ‘Rabi’) and March–June (termed as ‘Zaid’). From our analysis it emerges that, during the non-monsoon season, the reliance of rainfall over rainfed regions on moisture sourced from upwind irrigated crops is considerably higher than in the monsoon season (figure 2(c)). Spatially, the enhanced relative contribution during the non-monsoon season is consistent across the country with the highest increase seen in the IGP region (figure S8). However, during the months of October–December, contribution from upwind E_{green} is considerably higher than E_{blue} , similar to the monsoon season despite the significantly lower rainfall. The discrepancy between E_{green} and E_{blue} contributions is in line with the fact that, in India, rainfed crops post-monsoon rely on soil moisture gained during the monsoon season [49, 50], in addition to the winter rainfall. Applied irrigation (E_{blue}) plays an important role in sustaining rainfall

over rainfed crops during the pre-monsoon months of February–May, where rainfall amounts are the lowest (figure 2(c)). During these months, mean E_{blue} contribution reaches a maximum of 8% in March. Notwithstanding the fact that rainfed cropping intensity in these months is relatively low (maximum 20%), evaporation from irrigated crops in the upwind areas still represent a very important source of moisture for sustaining downwind rainfall and ensuring rainfed crop production.

3.2. Dependence of rainfed crop evaporative stress on upwind irrigated crops

The previous section established irrigated crop evaporation as an important source of moisture for rainfall over rainfed crops. Here, we explore the extent to which rainfed crops depend on this moisture source to satisfy their water demand. Such an analysis is necessary as the translation of rainfall to rainfed crop evaporation is not linear, i.e. a unit decrease in rainfall does not necessarily imply an unit decrease in crop evaporation given that crop water availability is mediated by soil conditions. To conduct this analysis, we develop two counterfactual scenarios in which (a) both the E_{blue} and E_{green} contribution and (b) only E_{blue} contribution from upwind irrigated crops are

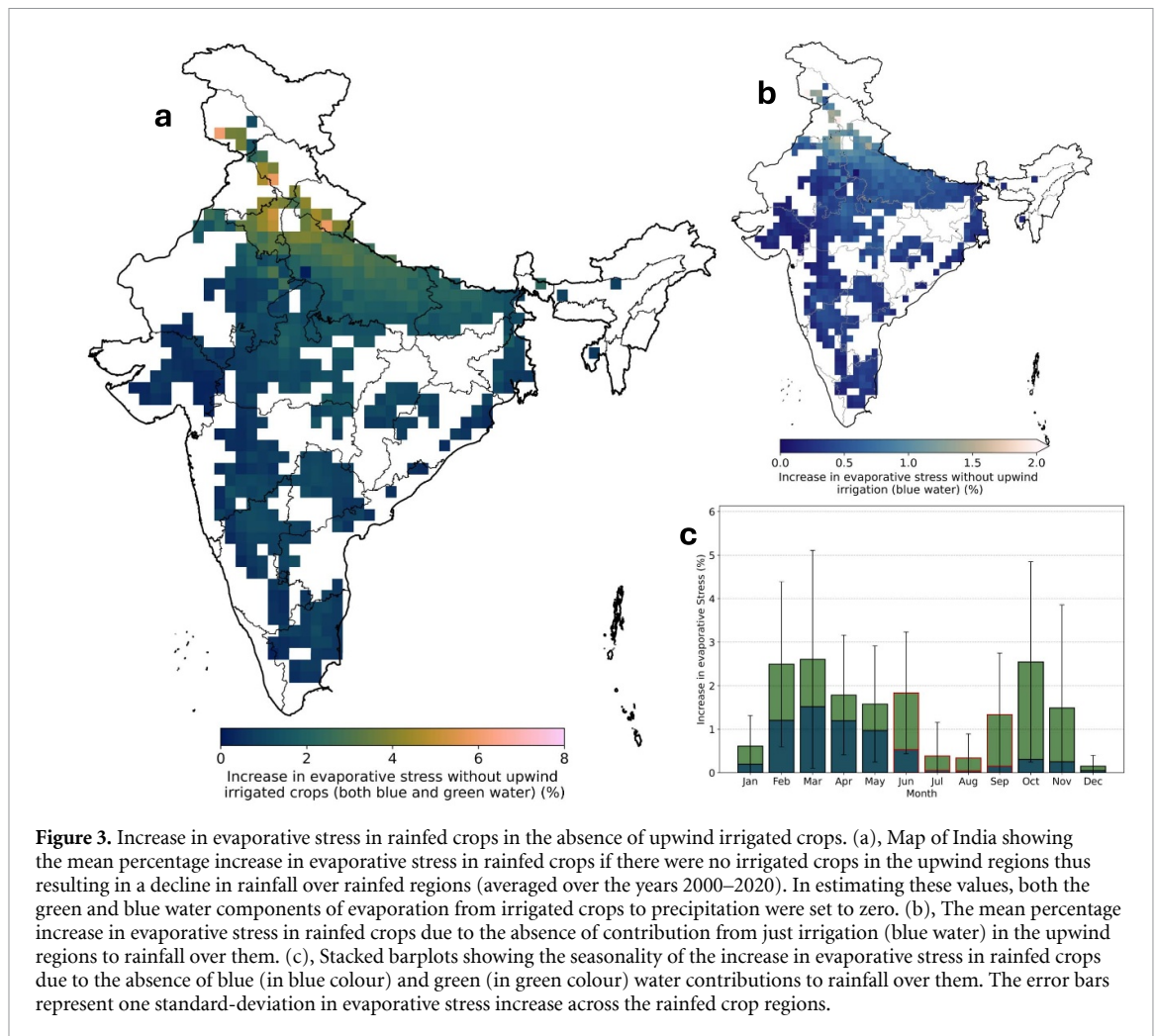


Figure 3. Increase in evaporative stress in rainfed crops in the absence of upwind irrigated crops. (a), Map of India showing the mean percentage increase in evaporative stress in rainfed crops if there were no irrigated crops in the upwind regions thus resulting in a decline in rainfall over rainfed regions (averaged over the years 2000–2020). In estimating these values, both the green and blue water components of evaporation from irrigated crops to precipitation were set to zero. (b), The mean percentage increase in evaporative stress in rainfed crops due to the absence of contribution from just irrigation (blue water) in the upwind regions to rainfall over them. (c), Stacked barplots showing the seasonality of the increase in evaporative stress in rainfed crops due to the absence of blue (in blue colour) and green (in green colour) water contributions to rainfall over them. The error bars represent one standard-deviation in evaporative stress increase across the rainfed crop regions.

removed from rainfall over rainfed crops. Then, the reduced rainfall is used to simulate the evaporation from rainfed crops (see methods for more details). Each counterfactual scenario is compared with the control one (see methods) to determine the increase in evaporative stress in the absence of upwind irrigated agriculture (figure 3).

Averaged across the 21 years (2000–2020), the evaporative stress increase due to the absence of E_{blue} and E_{green} contribution from upwind irrigated crops is $1.5 \pm 1.0\%$. Spatially, the highest increase is seen in the IGP (as high as 8%) (figure 3(a)), consistent with the distribution of rainfall contribution estimates already observed in figure 2(a). Accounting for interannual variability, the average evaporative stress in the IGP region can be as high as 15% (standard deviation of evaporative stress increase is presented in figure S10). The average impact of just the blue water component on rainfed crop evaporative stress is insignificant, with values even in the IGP region reaching maximum 1.5% (figure 3(b)). Furthermore, the evaporative stress increases are highest during the non-monsoon season (figure 3(c)), consistent with the irrigated crop contribution to rainfall in figure 3(c). In the post-monsoon season

(October–December), the availability of moisture from upwind E_{green} is more important than E_{blue} contributions to rainfall in satisfying the water demand of rainfed crops. As expected, the situation reverses during the pre-monsoon (February–May), where the applied irrigation (E_{blue}) forms a key source of moisture for downwind rainfed crops.

However, temporally and seasonally averaged estimates of evaporative stress are not entirely indicative of how important upwind crop evaporation is for rainfed crops and their water use. This is because water stress (represented here by evaporative stress) impacts various phases of crop growth differently. To explore this further, we estimate the 90th percentile increase in daily evaporative stress in the absence of contributions from upwind E_{blue} and E_{green} (figure S11(a)). In the absence of irrigated crops, the 90th percentile evaporative stress is $4.7 \pm 3.4\%$ on average across the whole country. This implies that for 36 days in a year, rainfed crops experience three times more water stress than the annual mean. In the IGP region, the 90th percentile evaporative stress is greater than 15% (also about three times the annual mean), with just the E_{blue} contribution reaching the 10% (figure S11(b)). While the 90th percentile results show that

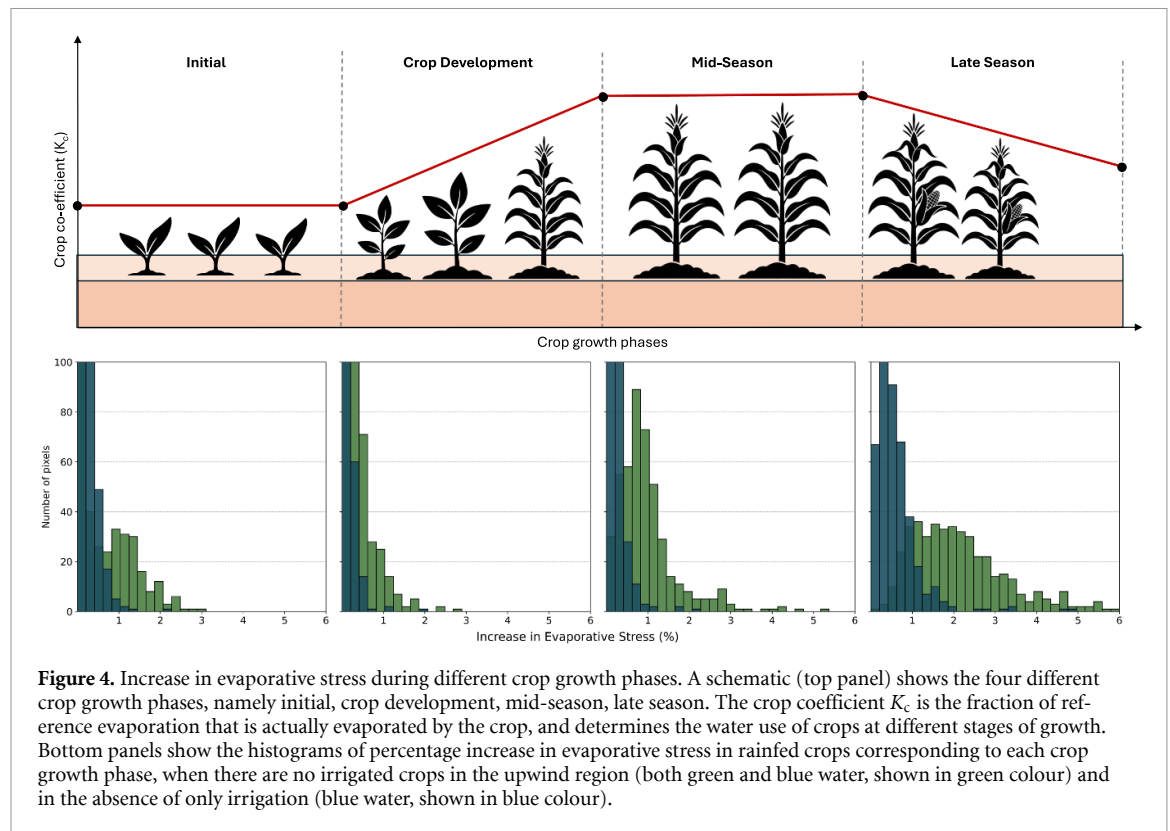


Figure 4. Increase in evaporative stress during different crop growth phases. A schematic (top panel) shows the four different crop growth phases, namely initial, crop development, mid-season, late season. The crop coefficient K_c is the fraction of reference evaporation that is actually evaporated by the crop, and determines the water use of crops at different stages of growth. Bottom panels show the histograms of percentage increase in evaporative stress in rainfed crops corresponding to each crop growth phase, when there are no irrigated crops in the upwind region (both green and blue water, shown in green colour) and in the absence of only irrigation (blue water, shown in blue colour).

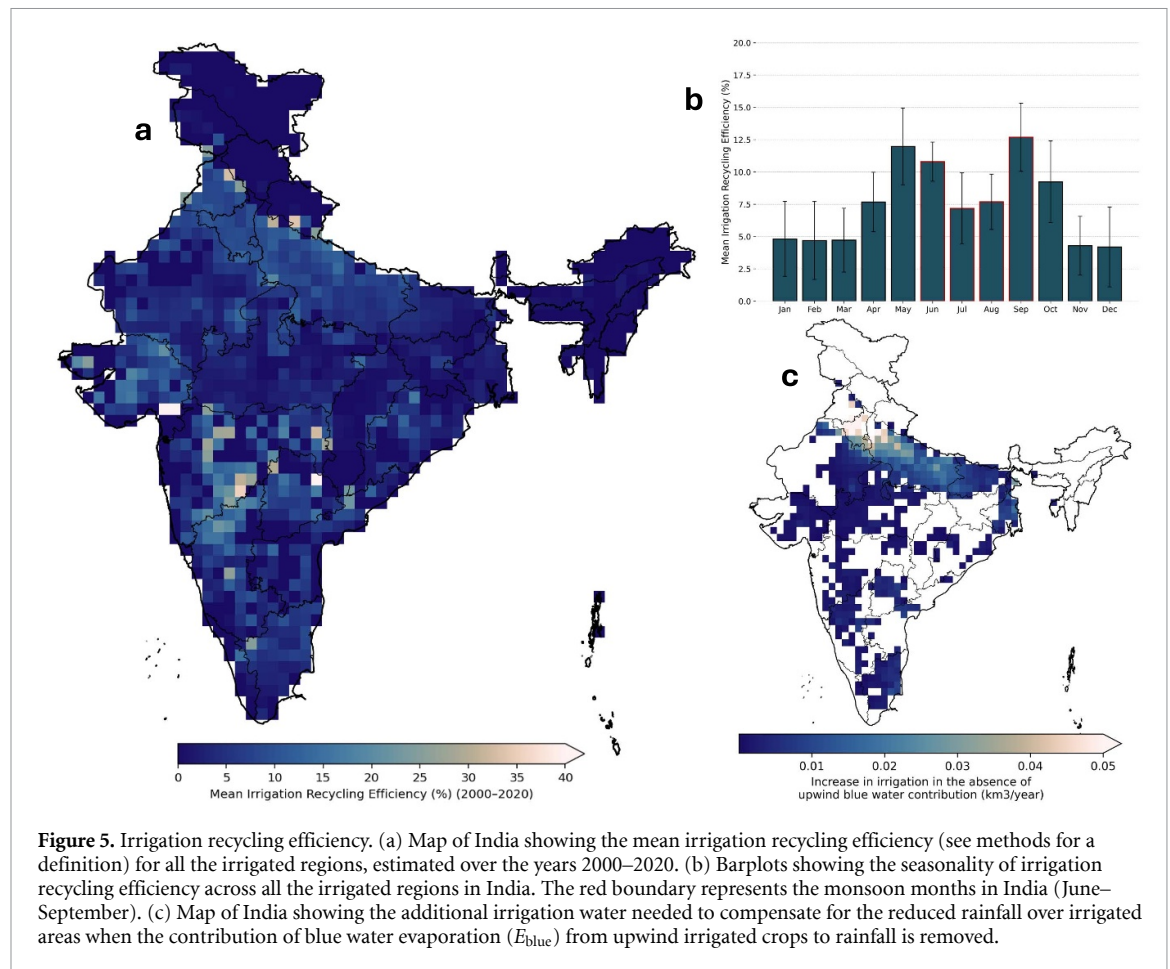
plants exhibit high water stress for a significant period of time in the absence of upwind irrigated crops, it does not provide information on ‘when’ the crops experience it. To better understand the timing of high water stress in the absence of upwind irrigated agriculture, we aggregate the evaporative stress increase estimates of all the grid cells into the four main crop growth phases [37]: (a) initial, (b) crop development, (c) mid-season, (d) late season. From figure 4, it is evident that the highest evaporative stress is experienced by the crops during the mid and late seasons of crop growth. Incidentally, these seasons are widely recognized as being the most crucial for crop productivity. While water stress during the mid season can lead to reduced biomass due to reduced photosynthesis [51, 52], in the late season, it can result in reduced grain size and thus a major reduction in crop yields [53, 54]. We note that the increase in evaporative stress due to upwind irrigated crop evaporation presented here represents the upper limit of water stress that can be expected in the complete absence of any evaporation (blue or green) upstream. However, in reality, this might not be the case as the absence of irrigated crops still implies that there might be evaporation from other land covers such as bare soil, grass, or trees (in place of irrigated crops).

3.3. Irrigation recycling efficiency

Our results so far highlighted the potential for evaporation from irrigated agriculture to supplement the water requirement of downwind rainfed crops. Given that irrigation expansion is already underway across

India and is expected to continue [23], an important question is whether the atmospheric moisture benefits identified in this study can potentially inform where and how such expansion should be planned. To this end, we define an irrigation recycling efficiency metric (see methods and appendix E), which quantifies the fraction of applied irrigation that is recycled into a region with substantial rainfed crop presence (at least 10% of the land area is covered by rainfed crops) (figure 5(a)). Our analysis reveals that, in addition to parts of the IGP, western and southwestern parts of India emerge as prominent hotspots for efficient irrigation recycling. Crucially, many of these hotspot areas are not currently as heavily irrigated as the IGP. We suggest that irrigation recycling efficiency be considered as one of several criteria—alongside conservation of natural vegetation, sustainable blue water use, and socio-economic factors among others—when assessing the feasibility and desirability of irrigation expansion in these regions. Seasonally, we see that the irrigation recycling efficiency varied between 5% and 15%. This is higher than the average during the pre-monsoon months (up to 12.5%), during which any additional rainfall is vital for crop growth (figure 5(b)).

Beyond supporting remote rainfed crops, atmospheric moisture recycling also creates a potential benefit for irrigated crops themselves. Evaporated irrigation water can precipitate back over the same or downwind irrigated regions, inducing a positive feedback loop that reduces the net demand for irrigation from surface or groundwater sources. To



quantify this self-sustaining effect, we estimate the additional irrigation water that would be needed if the contribution of blue water evaporation (E_{blue}) from local and upwind irrigated crops to rainfall were removed. Specifically, the volume of irrigation under actual rainfall conditions is compared with that required after removing only the E_{blue} contribution while all other moisture sources remain unchanged (appendix D). Our results show that this feedback conserves up to 0.05 km^3 of water annually in the intensively irrigated IGP region alone (figure 5(c)). Relative to total irrigation applied annually (0.45 km^3), moisture recycling conserves 1.8% of irrigation water on average across India, rising to 8% in parts of the IGP (figure S12). This volume represents a potential direct saving in both water resources and the energy required for pumping.

4. Conclusion

Typically, large-scale capital investments and policy interventions are primarily aimed at irrigated agriculture, thus creating imbalanced incentive structures that promote irrigation at the cost of supporting rainfed agriculture. In India, these policies include power subsidies for irrigated agriculture [55] and monetary incentives to transition rainfed regions into irrigated

areas [56]. In recent decades, there have been increasing calls for planning irrigated and rainfed crop systems in an integrated manner [57]. While existing studies and policies focus on bridging the socioeconomic link between them, here we show that irrigated and rainfed agriculture are physically connected through atmospheric moisture recycling. This tight link is especially important in countries such as India, where irrigated and rainfed crops are grown in close proximity to each other. Globally, regions where irrigated and rainfed crops coexist in close proximity include parts of Southeast Asia, eastern China, southern Europe, and the US Great Plains (figure S13). Specifically, we show that here this atmospheric link is particularly relevant in the non-monsoon season, and especially crucial for reducing water stress during the mid and late seasons of crop growth, which are critical phases to determine final crop yields.

We note that the value of moisture sourced from upwind irrigated crops for rainfed crop growth quantified in this study is a conservative estimate, given that the analysis was carried out using irrigated crop maps from the year 2000 [32]. However, Asia, and especially northwest India, has witnessed a significant expansion of irrigated area in the last two decades [23] ($\sim 14\%$ by area), pointing to a higher reliance of rainfed crops on upwind irrigation than estimated here. Whether this expansion translates into a proportional

increase in moisture recycling remains an open question, as non-linear land–atmosphere feedbacks can modulate the efficiency with which additional evaporation converts to downwind rainfall [24]. In addition, while MIRCA-2000 remains the most extensively validated global irrigation dataset, crop maps at this scale carry inherent uncertainties, particularly in smallholder-dominated regions where ground-truth data are limited. These uncertainties can both overestimate and underestimate irrigated area in different regions, and can affect the results presented in this study.

It is also worth noting that irrigation amounts were estimated here based on the deviation of soil moisture from field capacity, a widely used methodology in large scale studies [58, 59]. Thus, we do not take into account region-specific irrigation practices which might be important in accurately representing actual irrigation amounts and related moisture recycling during the monsoon season [28]. Particularly, since our methodology computes irrigation as the volume needed to restore soil moisture to field capacity—typically less than what is applied under flood irrigation, the dominant practice in India—the moisture contributions reported here are likely a lower bound. However, this is potentially compensated by the fact that irrigated crops are frequently water stressed because of lack of irrigation, which is also not considered in our methodology. Furthermore, Indian irrigation practices are governed by a complex set of socioeconomic and behavioural factors that are difficult to represent explicitly in models. Incorporating advances in improved representation of local irrigation practices [28] in our moisture recycling estimates remains a priority for future research.

We emphasize that our findings should not be interpreted as advocacy for expanding irrigation at the expense of natural vegetation cover, or reforestation, or afforestation projects. Forests remain the most important terrestrial source of recycled moisture for rainfall [24] in general and agriculture specifically [21]. Rather, our study highlights an overlooked role of irrigation as a moisture source for rainfed crops, especially given the current trend of expanding irrigation worldwide to meet growing food demand. Studies have shown that irrigation can sustainably expand into 35% of the global land area currently under rainfed crops [23, 60]. Thus, the value of atmospheric moisture recycling of evaporation from irrigated crops as an important source of water for sustaining downwind rainfed crops is expected to increase in the future. Finally, by estimating the degree to which irrigation applied in a certain region recycles into a rainfed crop area (irrigation recycling efficiency), our study provides an actionable pathway through which irrigated and rainfed agriculture can be planned and managed jointly.

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Data availability statement

The data required for reproducing the results and figures of the study are available at <https://doi.org/10.5281/zenodo.17238978> [61]. FLEXPART-ERA5 simulations of air parcel trajectories are available upon request from the Hydro-Climate Extremes Lab (H-CEL), Ghent University (please contact Victoria Deman, victoria.deman@ugent.be). All other datasets are publicly available (refer to specific studies cited in the text). The code used for producing the figures and the heat and moisture tracking tool used for evaluating the air parcel trajectories are available at <https://doi.org/10.5281/zenodo.17238978> [61]. Crop-wise results from the study are available via the drop4crop web-mapping platform at <https://drop4crop.epfl.ch>.

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Appendix A. Moisture tracking framework

This section details the three components of the moisture tracking framework used to identify and quantify the upwind sources of moisture: (a) diagnosis, (b) attribution, and (c) bias-correction.

The diagnosis step generates a global dataset of precipitation and evaporation detections by analysing all two-step trajectory segments. For every air parcel and at every time step in the FLEXPART simulations, moisture gains and losses are identified from changes in specific humidity using the following mass balance:

$$e - p = m * \Delta q \quad (1)$$

where e and p (both in kg) denote the net moisture gains and losses for each parcel due to evaporation and precipitation, respectively. m is the parcel mass (kg) and Δq is the change in specific humidity ($\text{kg} \cdot \text{kg}^{-1}$) between two successive time steps along the parcel trajectory. Precipitation is attributed to a parcel if its specific humidity decreases between consecutive time steps ($\Delta q < 0$) and its mean relative humidity (RH) exceeds 80% [62], in accordance with the convection scheme of [63]. The total rainfall over a region of area (A) is then obtained by summing the contributions from all n air parcels:

$$P = \frac{1}{A} \sum_i^n \Delta q_i (\Delta q_i < 0 \text{ kg} \cdot \text{kg}^{-1}, \text{RH}_i > 80\%). \quad (2)$$

Evaporation is detected when a parcel experiences an increase in specific humidity ($\Delta q > 0$) while residing within the atmospheric boundary layer (ABL). The

total evaporation over an area (A) is similarly computed as:

$$E = \frac{1}{A} \sum_i^n \Delta q_i (\Delta q_i > 0 \text{ kg} \cdot \text{kg}^{-1}, z_i < h_{\text{ABL}}^{\text{max}}) \quad (3)$$

where z_i denotes the parcel height (m) and $h_{\text{ABL}}^{\text{max}}$ is the maximum ABL height between the two consecutive time steps. The reliability of the precipitation and evaporation detections is assessed using the criteria described in [42].

During the attribution step, the detection criteria ($\text{RH}_i > 80\%$ and $h_{\text{ABL}}^{\text{max}}$) are applied to identify air parcels that contribute to rainfall over rainfed crop regions. Each parcel satisfying the precipitation criteria within the rainfed region is traced backward for up to 15 d. All moisture uptakes and losses along the parcel trajectory are recorded, and the contribution of upwind evaporation to rainfall over the rainfed sink region is quantified. Since moisture gained by a parcel can be partially lost as precipitation before reaching the sink region, en route losses must be accounted for using an objective approach. Here, we use the linear discounting method of [62], which assumes well-mixed conditions within the parcel at all times. Under this assumption, moisture lost at time step $t = i$ is considered to originate proportionally from uptakes at all preceding time steps ($t < i$). By discounting all en route losses, the fractional contribution of each upwind source region to rainfall in the sink region is obtained, resulting in a mass-conserving source–sink relationship. Thus, evaporation from grid cells closer to the sink region contributes proportionally more to sink precipitation, consistent with the fact that moisture from nearby sources undergoes fewer en route precipitation losses and thus retains a larger fraction of its original moisture by the time it reaches the sink.

In the final step, biases in the detected precipitation and evaporation fields are corrected using observational data. Source region evaporation is adjusted by comparing the unconditional E flux estimated from all air parcels over the source region (derived during the diagnosis step) with satellite-based evaporation estimates. The evaporation in the source region is further decomposed into contributions from: (a) natural vegetation (tall and short), (b) bare soil, (c) rainfed crops, and (d) irrigated crops. By separating the green and blue water components of irrigated crop evaporation, we isolate the specific contribution of upwind irrigated agriculture to rainfall over rainfed regions. Rainfall over the rainfed sink region is also bias-corrected against observational estimates, and the source contributions are rescaled proportionally. All bias-corrections are performed at a daily timescale. The datasets used for precipitation, ocean evaporation, and land surface evaporation from different cover types are described in the following sections.

We note that validating moisture tracking frameworks is inherently challenging due to the absence of observations that directly constrain the quantity and location of moisture uptake along air parcel trajectories. While water isotope observations offer insights into moisture sources, they provide only an integrated signal, distinguishing broad source categories such as oceanic versus terrestrial origin, but not the specific uptake locations [64]. Isotope measurements are also spatially sparse, though future satellite retrievals may help address this limitation [65]. Confidence in our results nonetheless arises from the use of ERA5 reanalysis, which assimilates a wide range of atmospheric observations, as the basis for trajectory simulation, combined with the use of observed P and E fields to constrain moisture sources. Additionally, the moisture tracking algorithm employed here is well-established and has successfully reproduced moisture source regions and recycling ratios reported in the literature [66–68].

Appendix B. Crop evaporation model

Evaporation from each of the 14 crops considered in the study, over a single growing season (LGP), is estimated by summing up the daily actual evaporation over the growing season,

$$E_{cr,LGP} = \sum_{j=1}^{LGP} E_{cr,j}, \quad (4)$$

where the daily crop evaporation is calculated as [37]

$$E_{cr,j} = k_{c,cr,j} \cdot k_{s,cr,j} \cdot E_{0,j}, \quad (5)$$

$E_{0,j}$ being the daily potential evaporation, j the day of the growing period, while k_c and k_s are the crop and water stress coefficients, respectively. The daily potential evaporation is derived from GLEAM4 (v4.0a) daily potential evaporation, corresponding to short vegetation. The crop coefficient k_c varies during the growing season as

$$k_{c,j} = \begin{cases} k_{c,ini} & \text{if } j \in \text{Stage I} \\ j \cdot \frac{k_{c,mid} - k_{c,ini}}{j - l_I} & \text{if } j \in \text{Stage II} \\ k_{c,mid} & \text{if } j \in \text{Stage III} \\ j \cdot \frac{k_{c,end} - k_{c,mid}}{j - l_I - l_{III}} & \text{if } j \in \text{Stage IV} \end{cases} \quad (6)$$

where the length of each stage (l_{st}) is computed as a fraction (p_{st}) of the length of the growing period. Values of the crop coefficients and length of the crop development stages were obtained from the literature [37] (refer to [38] for more details).

The water stress coefficient k_s varies between 0 (maximum water stress) and 1 (no water stress) and is evaluated considering rainfed and irrigated production separately. For the irrigated production the water stress coefficient is set to 1 (no stress) for the entire

duration of the growing period, while for rainfed production it is evaluated as

$$k_{s,j} = \frac{TAW_j - D_{mo,j}}{TAW_j - RAW_j} \quad (7)$$

where TAW (mm) is the total available water content in the root zone, RAW (mm) the readily available water content, and D_{mo} (mm) is the root zone depletion in the morning (i.e. water shortage relative to field capacity). TAW depends on the available water contents AWC (mm m^{-1}) and the root depth $Z_{r,j}$ (m) as

$$TAW_j = AWC \cdot Z_{r,j}. \quad (8)$$

The available water content was taken from the Harmonized World Soil database v1.2, while maximum root depth ($Z_{r,max}$) for each crop were obtained from [37]. The root depth was assumed to linearly increase during the first two growing stages and then maintained constant until harvesting.

RAW is the water that crops use for evaporation before water stress and stomata closure begins and is given by

$$RAW_j = \rho \cdot TAW_j \quad (9)$$

where ρ is the depletion fraction coefficient (here assumed constant over the growing season). Values of ρ for each crop were obtained from [37]. In rainfed crops, the root zone depletion in the morning $D_{mo,j}$ is equal to the depletion recorded at the end of the previous day $D_{ev,j-1}$ minus the daily precipitation value P_j ,

$$D_{mo,j} = D_{ev,j-1} - P_j. \quad (10)$$

Daily precipitation was obtained from MSWEP v2.8 dataset. In the evening the root zone depletion decreases because of evaporation as $D_{ev,j} = D_{mo,j} + ET_{cr,j}$, with $E_{cr,j} = k_c \cdot \frac{TAW_j - D_{mo,j}}{TAW_j - RAW_j} \cdot E_{0,j}$. Note that losses by deep percolation are neglected and capillary rise is assumed equal to zero. Furthermore, water excess leading to negative $D_{mo,j}$ is cut off at zero (exceeding precipitation is assumed to be lost as surface runoff). In rainfed conditions, the water volume transpired by the crop during the growth period is totally green ($E_{g,LGP} = E_{LGP}$). Conversely, in irrigated conditions, the daily volume of irrigation, I_j , is determined assuming that the crop fully transpires with no water stress as $I_j = D_{mo,j} - RAW_j + k_{c,j}E_{0,j}$. In the evening, the root zone depletion is given by $D_{ev,j} = D_{mo,j} + E_{cr,j} - I_j$. Thus, the blue water corresponds to the irrigation water ($E_{b,j} = I_j$) while the green water is the difference between the total E and $E_{b,j}$.

We note that, in the analysis here, no specific assumptions about irrigation methods were made—the right amount (not more, not less) of water needed

to ensure no stress condition is computed and considered as local irrigation requirement. For rice cultivation, we considered an additional volume per unit area of 200 mm, following the approach by [46]. This allows us to account for the water used to prepare the paddy fields by saturating the root zone in the month before sowing or transplanting.

Appendix C. Evaporative stress estimation

To estimate the degree to which evaporation from upwind irrigated crops reduce the evaporative or water stress in rainfed crops, we compare the evaporation estimates from the control simulation where in irrigated crops are grown in the upwind regions and irrigation is applied (termed here as $E_{r,control}$, where r stands for rainfed crops), with evaporation from two counterfactual scenarios: (a) Complete absence of upwind irrigated crop evaporation (both E_{green} and E_{blue} are present) (b) Absence of just irrigation in the upwind regions (only E_{green} is present). For the first scenario, the contribution from both upwind E_{green} and E_{blue} are removed from rainfall over each of the rainfed grid cell, and the evaporation from rainfed crops are recalculated for all the 14 rainfed crops using the modeling framework described above (termed here as $E_{r,noIC}$, where IC stands for irrigated crops). We note that this scenario represents the upper limit of the expected increase in evaporative stress, as removing all irrigated crop evaporation assumes no replacement by evaporation from alternative land covers (e.g. bare soil, grassland) that would occupy the land in the absence of irrigated crops and still contribute some moisture to downwind rainfall. The same procedure is repeated for the second scenario with only the upwind E_{blue} contribution removed from rainfall over rainfed crops (termed here as $E_{r,noIW}$, where IW stands for irrigation water). Then, increase in evaporative stress is given by

$$\Delta E = \frac{(E_{control} - E_{r,x}) * 100}{E_{control}} \quad (11)$$

where x can be noIC or noIW depending on which of two scenarios is being considered.

Appendix D. Increased irrigation requirement in the absence of upwind blue water contribution

A similar approach to evaporative stress estimation (appendix C) is used to determine the increase in irrigation that would be required if blue water evaporation (E_{blue}) from upwind and local irrigated crops did not contribute to rainfall over irrigated regions. Here, the volume of irrigation applied when irrigated

crops are exposed to actual rainfall is the control scenario (termed here as $V_{control}$). In the counterfactual scenario, the contribution of local and upwind E_{blue} to rainfall over irrigated crops is removed, while all other moisture sources (including E_{green} from irrigated crops, evaporation from natural vegetation, bare soil, and oceanic sources) remain unchanged. After removing the E_{blue} contribution to rainfall, the applied volume of irrigation is recalculated (termed here as V_{noIW}). Then, the increase in irrigation volumes is estimated as

$$\Delta V = \frac{(V_{control} - V_{noIW}) * 100}{V_{control}}. \quad (12)$$

Appendix E. Irrigation recycling efficiency

Irrigation recycling efficiency (termed here as η) is defined as the fraction of the applied irrigation water which recycles through atmospheric pathways to contribute to rainfall over a region with rainfed crops. For example, if 100 units of water is applied as irrigation in a certain region and if 50 units of water contributes to rainfall over rainfed regions, η is 50%). η is given by

$$\eta = \frac{(V_{i2r}) * 100}{V_{upwind}} \quad (13)$$

where, V_{i2r} is the volume of E_{blue} from upwind irrigated crops that contributes to rainfall over rainfed crops, V_{upwind} is the sum of volumes of irrigation water applied to irrigated crops in the upwind of the rainfed region of interest.

Appendix F. Validation of datasets used for bias correction of moisture tracking over India

The moisture tracking framework (appendix A) relies on observation-based global precipitation and evaporation datasets for bias-correcting the upwind moisture contributions to rainfall over the sink region. To assess the reliability of these datasets over India, we validate them against independent India-specific reference datasets using the Kling–Gupta efficiency (KGE) [69], a widely used metric that integrates three different aspects of agreement between simulated and observed fields:

$$KGE = 1 - \sqrt{(r - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2} \quad (14)$$

where r is the Pearson correlation coefficient, capturing the temporal co-variability between the two datasets; $\alpha = \sigma_{sim}/\sigma_{obs}$ is the variability ratio, measuring whether the simulations reproduce the observed spread; and $\beta = \mu_{sim}/\mu_{obs}$ is the bias ratio, quantifying systematic over- or underestimation of

the observed mean. A KGE value of 1 indicates perfect agreement, while values below -0.41 indicate that the mean of the observations provides a better predictor than the simulated field [70].

The MSWEP v2.8 [43], used for bias-correcting precipitation is validated against the Indian Precipitation Ensemble Dataset [71], a gridded precipitation product for India based on a dense rain gauge network, and improves upon the widely used data product from the India Meteorological Department. KGE and its three components are computed at each grid cell over the period 2000–2020 (figure S2). Across most of India, KGE values are positive with Pearson correlations above 0.4, indicating that MSWEP captures the temporal variability of rainfall well, though local deviations in the variability and bias ratios are evident in the topographically complex regions of the Western Ghats and northeastern India.

GLEAM v4.0a [44], used for bias-correcting evaporation from natural vegetation and bare soil, is validated against eddy covariance measurements at five flux tower sites in India (table S1) [72–76]. At three sites representing natural land covers—semi-natural grassland (Kanpur), tropical moist forest (KNP), and mangrove wetland (PVM) - GLEAM v4.0a evaporation is evaluated directly, while at the two cropland sites (Berambadi and Dharwad), GLEAM v4.0a evaporation is combined with the modelled crop evaporation (appendix B). KGE values range from -0.05 to 0.40 , with positive correlations at all sites indicating that the evaporation estimates capture the seasonal dynamics reasonably well, though both the variability and bias ratios suggest a tendency to underestimate the magnitude and spread of observed evaporation at most sites.

The spatially distributed crop evaporation estimated by the FAO-56-based modelling framework (appendix B) is validated against the WATNEEDS dataset [77], an independent global crop water use model, for the year 2000. KGE and its components are computed separately for irrigated (figure S3) and rainfed (figure S4) crop evaporation, aggregated across all 14 crops. For irrigated crops, KGE values are positive over much of central and southern India with correlations above 0.4 in most regions, though our estimates are generally lower than WATNEEDS. For rainfed crops, the performance is comparable, with positive KGE values over most of the domain and bias ratios close to 1 over large parts of the country.

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