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## Article

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# Exploring the impact of seasonal water variability on agricultural planning: a water-energy-food nexus perspective.

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## Abstract

Increased global warming is projected to alter rainfall patterns, intensifying pressure on water availability. The already acknowledged 2.3 – 2.5°C temperature increase under current policies calls for progress in adaptation planning. We developed a Climate, Land, Energy, and Water systems (CLEWs) model with explicit seasonal crop-growing stages and seasonal hydrological cycles. We applied the method to the case study of Ethiopia and used it to explore the impact of seasonal water variability on agricultural planning in an integrated model and investigate the impact of the adaptation of the agricultural sector on water stress. We compared standardised IPCC scenarios with historical trends and observed that seasonal differences in precipitation increase by 9.5% and 20% on a national scale for medium (RCP4.5) and high (RCP8.5) impact climate trajectories. We found that integrated resource models that do not account for seasonal hydrological variability overestimate available renewable water. Our results show an increase of 223% and 272% of groundwater recharge and surface water in scenarios without seasonal hydrological cycles. This impacts the use of resources in water scarce scenarios (RCP8.5) where the presence of seasonal variability leads to a 63% increase in irrigated area. This study enhances the representation of the water sub-system in an integrated resource model and lays the foundation for progress in adaptation planning.

## keywords

CLEWs, nexus, adaptation, seasonal-variability, agriculture, water-stress

## 1 Introduction

The latest Intergovernmental Panel on Climate Change (IPCC) Synthesis Report highlights that continued warming is projected to increase the variability of precipitation patterns, impacting the overall water cycle (Calvin et al., 2023). Only 7% regions worldwide show regular precipitation, while the 60% face moderate changes and 33% are subject to irregular patterns (Nazeri Tahroudi, 2025). Under current policies, global temperatures are projected to rise by an average of 2.8°C temperature increase over this century, or 2.3-2.5 °C if fully implementing the stated Nationally Determined Contributions (NDCs) (United Nations Environment Programme, 2025). Mitigation strategies are defined as “human intervention to reduce greenhouse gas emissions” (Calvin et al., 2023), are no longer sufficient to deal with these impacts, with calls for progress in more coordinated, systemic adaptation planning to manage resources under climate uncertainty (Calvin et al., 2023; S. Mark Howden et al., 2007). National Adaptation Planning (NAP), introduced in 2012, was designed to achieve two key objectives: reducing vulnerability to climate change impacts, and ensuring policy-coherence in adaptation planning (UNFCCC, 2012).

One key sector that has been placed at the forefront of the climate adaptation agenda at the 30th UNFCCC Conference of the Parties (COP30) was agriculture (COP30 Presidency, 2025). The agriculture sector accounts in low- and middle-income countries for 88-90% of water use (World Bank, 2023). In 2022, 12% of the total global land area was cropland, with Africa, South America and South-East Asia leading the crop land area expansion from 2001 to 2022 by respectively 73, 28, and 22 million hectares (FAO, 2024). Agriculture is also a key driver of economic growth and food security, especially in low- and middle-income countries, where it accounts for 60-80% of employment (Caretta, M.A. et al., 2022). Incorporating adaptation into national planning frameworks allows countries to moderate climate-related harm, exploit beneficial opportunities, optimise allocation of resources and investments (OECD, 2024), support long-term decision making (S. Mark Howden et al., 2007), and informing mitigation targets (S. Mark Howden et al., 2007).

In a global analysis on trade-offs and synergies across climate change adaptation in the water-energy-food (WEF) nexus, food security emerged as the most analysed (Torhan et al., 2022). Food security, and by extension agriculture, has indeed strong interdependencies with climate (being affected by temperature increases and rainfall patterns), land use planning, energy, and water supply. Crop water requirements vary depending on the crop growing stage: initial, development, mid-season, and late-season (FAO, 1977). With the rising concern of climate change impacts, depending on how rainfall patterns evolve, changing cropping patterns or sowing time has been identified as a potential adaptation strategy among others to overcome the potential water demand-supply mismatch (Caretta, M.A. et al., 2022). A qualitative study on nexus approaches to enhance water-energy-food (WEF) security under climate change in the Mediterranean highlighted how a water-centred nexus-based solution can avoid maladaptation, reducing trade-offs and highlighting cross-sectoral synergies (Drobinski et al., 2025). This is crucial, in particular in water-scarce areas, as prolonged droughts induced by climate change have a cascading effect on water, energy, and food security (Drobinski et al., 2025).

However, linking sustainable water management with integrated system analysis might often be challenging. Soleimanian et al. (2022) argues that compiled approaches (meaning that different sector-specific models are linked) are better than integrated models because they are able to represent WEF subsystems more accurately. While the water-energy interlinkage has been widely explored in the literature, using both compiled (Brik et al., 2022; Sridharan et al., 2019) and integrated approaches (Almulla et al., 2023; Groppi et al., 2023), the water-land interlinkage is still best explored with compiled methods combining hydrological simulation models, energy models and GIS tools (Almulla et al., 2020; Falchetta et al., 2022; Nilsson et al., 2021; Ramirez et al., 2022, 2021). However, linking tools can increase complexity while integrated water-energy-food nexus models can unveil cross-sectoral resource use conflicts that can be missed by siloed approaches with less need for iterations and links. Moreover, instead of just coupling inputs and outputs across models, they can allow endogenous optimisation of the resources, considering the system as a whole and avoiding fragmentation across sectors.

Addressing the limitations in representing WEF subsystems in integrated models (Soleimanian et al., 2022), this paper fills that gap by developing an internally-coherent methodology to improve the physical representation of the water system in bottom-up WEF models and its interlinkage with the agricultural sector. Responding to the IPCC's call for more coherent and less sector-fragmented adaptation planning, we want to explore a method that may, with less need for iterations and links, more internal coherence, and reduced computational load, co-optimize the use of resources within one framework. This research has the following objectives:

1. Develop a methodology able to capture seasonal water variability in an integrated bottom-up WEF nexus model.
2. Explore the impact of seasonal water variability on agricultural planning for the case study of Ethiopia.
3. Aligning integrated WEF nexus assessment modelling with adaptation planning.

We applied the methods to the case study of Ethiopia. Ethiopia is particularly vulnerable to climate change, due to the reliance of the agriculture sector – the backbone of its economy (African

Development Bank Group, 2024) – on traditional rainfed farming (GIZ, 2022). Current empirical data collected from the Global Precipitation and Climate Centre (GPCC V7) confirm that rainfall is variable and unpredictable both spatially and temporally (Abebe et al., 2022; Asfaw et al., 2018), contributing to irregular runoff, increased evapotranspiration, and variation in groundwater recharge (Calvin et al., 2023; Federal Democratic Republic of Ethiopia, 2019; World Bank Group, 2024). However, while Ethiopia’s development plans emphasise irrigation expansion to boost agricultural productivity, food security, and poverty reduction (Ministry of Planning and Development, 2022), science-based national planning remains insufficiently aligned with the country’s growing vulnerability to water stress driven by both climate change and human activities (Swedenborg et al., 2025). Moreover, rainfall variability and climate uncertainty are forecasted to increase in Ethiopia (World Bank Group, 2024). Climate uncertainty, rainfall variability, and the need to adapt the agricultural sector to climate change make the method we developed particularly valuable in such a context. We therefore demonstrate its applicability in Ethiopia while keeping the approach general and replicable for other case studies.

## 2 Methods

This study adopts a multidisciplinary approach to capture seasonal water variability in an integrated bottom-up WEF nexus model and explore its impact on agricultural planning. We used a Climate, Land, Energy, and Water system (CLEWs) framework to model Ethiopia’s resource systems with the open source modelling tool OSeMOSYS (Alexander et al., 2025; Ramos et al., 2022). The CLEWs model developed for this case study builds upon an existing model developed in 2020 with the Ministry of Water, Irrigation, and Energy (MoWIE) of the Federal Democratic Republic of Ethiopia and UNDESA (Abhishek Shivakumar, 2020). This study advances current CLEWs modelling approaches by representing crop-growing stages and seasonal variability of the water cycle. With an integrated resource analysis perspective, we compared five scenarios: a baseline, two climate change scenarios representing intermediate (RCP4.5) and high (RCP8.5) impact pathways, and two climate change scenarios with increased irrigation expansion (RCP4.5\_IRR and RCP8.5\_IRR). All of these scenarios were modelled (1) without variable hydrological cycle and crop-growing stages (“NoSeasons”), and (2) with the seasonal variability and crop-growing stages (“Seasons”), to analyse the effects of increasing the granularity in the representation of the water system. Finally, the mismatch between water availability and supply across the CLEW systems, and the implications of the adaptation of the agricultural sector under climate-change scenarios were quantified using a water stress indicator.

### 2.1 Spatial disaggregation of the climate, land and water systems

In this study, we referred to *cluster* as a “portion of land” with specific climate, water and land characteristics. Each cluster is indeed characterised by its specific water cycle, precipitation data, and crop yield. We used agro-ecological data sourced from the Global Agro-Ecological Zoning (GAEZ) dataset developed by the International Institute for Applied Systems Analysis (IIASA) and the Food and Agriculture Organisation of the United Nations (FAO) (Fischer et al., 2021), for quantifying crop evapotranspiration, crop water deficit, and yield in each cluster. The potential yield for each crop has a 5 arc-min resolution (10 km x 10km) and is clustered employing an Agglomerative Hierarchical clustering using Ward’s method (Shivakumar et al., 2021). This method uses the error sum of squares (ESS) for measuring the difference between the value of the average cluster and each data cell within the same cluster. The algorithm returns an elbow graph, which represents the ESS as a function of the number of clusters. The number of clusters ranges from 1 (with maximum error) to the total number of clustered cells (with minimum error). Since the decrease in error from cluster 4 did not exceed two percentage points for each increase in the number of clusters but increased the computational requirements and complexity of the model, we decided to model four clusters.

### 2.2 The land sector

The clustering results returned the land cover area for each cluster based on the land-cover type definition provided in the GAEZv4 model documentation (Fischer et al., 2021). We grouped the 11 land-cover types in cropland, forest, grassland, water bodies, settlements, and other land (which

includes all land areas that do not fall into the previous categories). We then calibrated the model for the year 2020 based on FAO and Ethiopia's national statistics (FAO, 2023; UNFCCC, 2024): the sum of all cover types per cluster must be equal to the total share at the national level for each modelled land-cover type. The characteristics of land use cover for each modelled agro-ecological cluster after calibration can be found in Table S1.

We modelled the six main crops with the largest harvested area documented in FAOSTAT (FAO, 2023): wheat, sorghum, cereals, maize, barley, and coffee. The rest of the crops were modelled under the name “other crops” and assume an average value of yield, water input and output. Each crop is further characterised in four different farming types: mechanised (a more commercial-oriented farming referred to as “high”), traditional (a low mechanised traditional farming referred to as “low”), both available as irrigated or rainfed.

One key decision variable in the model is the allocation of land across competing land covers and uses. The land covers are constrained in the reference year to respect the total land cover for each land-cover type and the total harvested area for each cluster. Water bodies have a constant area that does not change over the modelled time horizon. Forest land follows historical afforestation targets (from 2020-2023) and is free, but not constrained, to reach the government's targets of a total 8.2 million ha of forest by 2050 (Ministry of Planning and Development, 2022). Built-up land grows proportionally with population growth over the modelled time-horizon, assuming that there will not be any population migration across clusters. Other land, on the contrary, has a 2% annual decrease, assuming that part of that land can be used for cropland expansion. Grassland also faces a 1% annual decrease following the same assumption.

Focusing on the agricultural sector, instead, the calibration took into account also the production: the sum of the yield per each crop across clusters had to be equal to the crop production recorded on FAOSTAT for year 2020 (FAO, 2023). If there was a mismatch, we estimated the yield gap (difference between yield assumed in the model and attainable yield obtained from GAEZ) keeping the harvested area per each crop type and cluster constant. From 2021 on, the model was free to optimize the use and allocation of resources for every modelled year. Further assumptions can be found in the CLEWs model dataset on Zenodo. The model allowed also the optimization of the use of resources across clusters, allowing gradual crop shifts to more productive and climate-resilient clusters given the differences of water availability and yield across the modelled agro-ecological clusters.

### 2.3 The temporal resolution: modelling crop-growing cycles

We used climate projections from the GFDL-ESM4 climate model (Karger, D. N., Brun, P., Zilker, F., 2025) to simulate monthly averages since it is, according to the available literature, among the most accurate models in simulating rainfall patterns in Ethiopia (Berhanu et al., 2023). The data were clustered for each agro-ecological cluster and season. The representation of the water balance in a CLEWs model is as follows: for each land-type (both agricultural and not), the amount of water that goes in (precipitation and irrigation if needed) is equal to the output (evapotranspiration, runoff, and groundwater recharge). In published literature all CLEWs models represent this balance with yearly values (Heredia-Fonseca et al., 2025), (Nakkorn et al., 2025), (Ramos et al., 2022), (Sridharan et al., 2020). For the purpose of exploring the impact of seasonal water variability on agricultural planning and its impact on water stress, we enhanced the CLEWs framework and created a methodology to capture seasonal water availability across crop growing stages. We divided the year into two seasons: the dry season from October to April, and the wet season from May to September (Wakjira et al., 2025). The latter is also considered the “foundation of agriculture” (Adane and Asmerom, 2025) because all the main crops grow during this season. We referred to the FAO's crop coefficient curve for distinguishing two main phases for each crop: the growing season (encompassing initial, development, and mid-season stages) and the harvesting season (late stage). Figure S1 represents the behaviour of the single crop coefficient ( $K_c$ ), which is used for quantifying the crop characteristics and the effects of evaporation (FAO, 1998).  $K_c$  is an essential coefficient for determining crop-specific evapotranspiration with respect to the reference crop evapotranspiration  $ET_0$  (FAO, 1977), as described in Equation 1:

$$ET_c = K_c ET_0. \quad (\text{Equation 1})$$

The GAEZ database provides annual (actual) evapotranspiration of reference crops ( $ET_{c,y}$ ) calculated as the total amount of water lost over one year through plant transpiration and soil evaporation (Günther Fischer et al., 2021). With  $ET_0$  being constant, we calculated the evapotranspiration for the growing and harvesting season based on the values of  $K_{c_{mid}}$  and  $K_{c_{final}}$  documented in (FAO, 1977).

We calculated the yearly coefficient ( $K_{c,y}$ ) associated to the average yearly  $ET_{c,y}$  value provided by GAEZ, as a sum between  $K_c$  associated with the modelled middle and late season. Then, assuming  $ET_0$  constant for each crop, the corresponding  $ET_{c,mid}$  and  $ET_{c,final}$  were calculated as shown in Equations 2 and 3:

$$ET_{c,mid} = ET_{c,y} \frac{K_{c,mid}}{K_{c,y}}. \quad (\text{Equation 2})$$

$$ET_{c,final} = ET_{c,y} \frac{K_{c,final}}{K_{c,y}}. \quad (\text{Equation 3})$$

Finally, groundwater recharge was estimated as a fixed share of precipitation across years and scenarios, assuming that percolation and soil properties will not vary across the years. Cross-checking the agro-ecological clusters with their typical environment (Tilahun Amede et al., 2015), we summarised in Table S2 the groundwater recharge factors found in literature and the final modelled value.

## 2.4 The water stress indicator

The scenarios were compared through a water stress indicator. By post-processing CLEWs output data, we were able to assess the stress on water resources, shown by a stress score (see Table 1).

*Table 1 Indicator*

| Indicator | Name                           | Formula                                                              |
|-----------|--------------------------------|----------------------------------------------------------------------|
| r         | Relative seasonal water demand | $\frac{\text{Water Demand}}{\text{Available water}}$                 |
| ws        | Water seasonal stress          | $\min(1, \max(0, r))$                                                |
| S         | Seasonal score                 | $\max(0, \min\left(5, \frac{\ln(ws) - \ln(0.1)}{\ln(2)} + 1\right))$ |

We estimated the water stress as the relative water intra-annual demand variation (r). We associated to the relative demand a water seasonal stress (ws) which was then turned into the water seasonal score (S). We defined as *use* the gross direct withdrawal, and we defined as *supply* the renewable available water coming from runoff water and groundwater recharge. On the demand side, we considered municipal and industrial water demand as exogenous model inputs, increasing over the years with population, but constant across scenarios. The water required for irrigation is, on the contrary, calculated endogenously by the model depending on the optimisation.

The FAO global information system on water resources AQUASTAT (Food and Agriculture Organization of the United Nations (FAO), n.d.), provides data on municipal and industrial water withdrawals per capita. We used 3 arc (100 x 100 m) population raster from 2020 to 2030 (Bondarenko M., Priyatikanto R., Tejedor-Garavito N., Zhang W., McKeen T., Cunningham A., Woods T., Hilton J., Cihan D., Nosatiuk B., Brinkhoff T., Tatem A., Sorichetta A, n.d.) and then projected to 2050 using the UN's projected population prospects (United Nations, Department of Economic and Social Affairs, Population Division, 2024). Population rasters were then clustered based on the clustered agroecological zones. The demand for each year was then estimated by multiplying the water withdrawals per capita by the population for each cluster. Figure 1 represents how GIS data were added in the CLEWs modelling framework and used for modelling the seasonal water variability across crop-growing stages in an integrated model, which is the novelty of this study. Further guidelines on how to model crop growing stages on CLEWs can be found in the supplementary data.

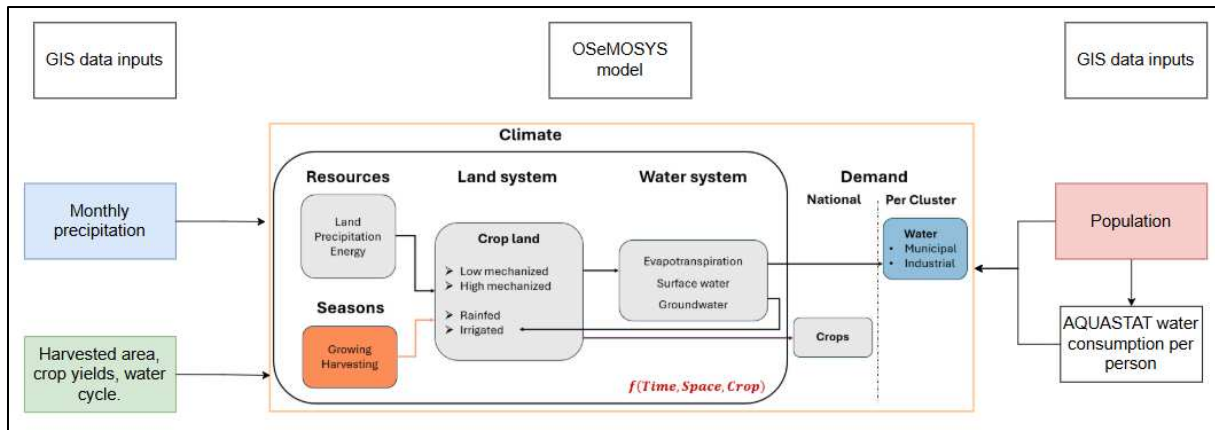


*Fig. 1 Methodological overview of the modelling framework. The yellow box represents a simplified overview of the CLEWs modelling framework. The methodological addition of this research consists in adding crop growing stages (represented as growing and harvesting seasons) which vary depending on time, space and crop. GIS data, were used for pre-processing CLEWs input data and are available in the data availability section. .*

### 3 Results

The clustering method adopted to identify agro-ecological clusters based on potential crop yield returned four clusters, shown in Figure 2. In order to explore the impact of seasonal water variability in a water-energy-food nexus model we divided the results section into three main subsections: water availability, water demand, and final scenario comparison with water stress indicator. The first one explores the impact of climate change on precipitation and renewable surface water availability for each modelled agro-ecological cluster, while the second subsection analyses the impact on crop evapotranspiration and the relative water demand (measured as the ratio between gross water demand and supply) across the clusters.

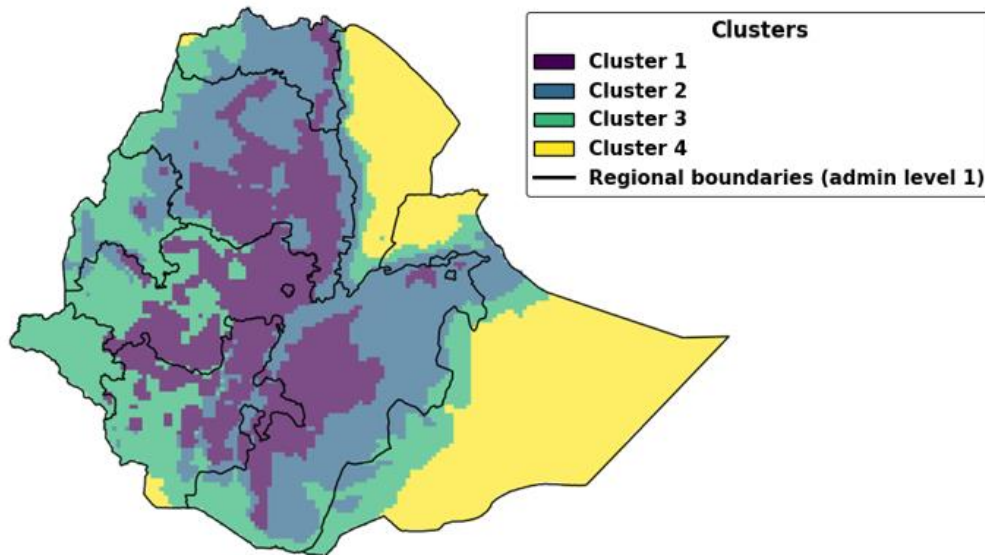


*Figure 2 Modelled agro-ecological clusters. Modelled agro-ecological clusters based on crop potential yields sourced from GAEZ dataset developed by IIASA and FAO(FAO NSL Geospatial Unit, 2022).*

### 3.1 Water availability

Starting with precipitation, intermediate and high impact climate trajectories show an increased variation in seasonal precipitation patterns across clusters. Seasonal differences in precipitation increase, with respect to historical trends, by 9.5 and 20% for medium (RCP4.5) and high (RCP8.5) impact climate trajectories on a national scale, with different variation across the clusters (Figure 3 and Table S3). In line with Wakjira et al. (2025), wet seasons are expected to become wetter while dry seasons drier. Moreover, the seasonal difference across clusters is projected to increase with the increase in climate change impact.

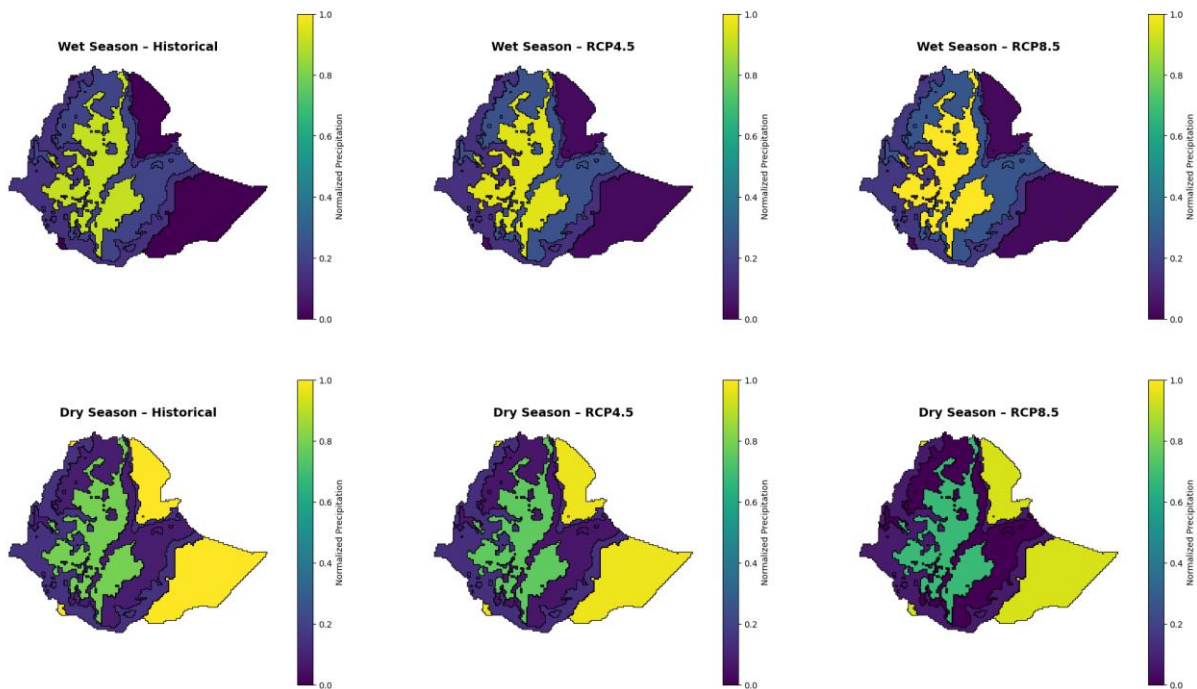


*Figure 3 Normalized precipitation variation for wet and dry seasons. Historical seasonal precipitation for the time interval 1981-2010 as a sum of average recorded precipitation from May to September (wet season) and October to April (dry season).*

The variability of rainfall patterns has an impact on the overall water cycle. Depending on the available water coming from rainfall, there is an impact on the water supplied to and by the plants. We assumed that groundwater percolation (calculated as the share of precipitation that recharges groundwater) is constant across the climate scenarios, assuming that the soil characteristics vary across the clusters but will not change across the scenarios and therefore vary linearly with precipitation. What varies across clusters and scenarios is evapotranspiration and surface water, as outputs, and rainfall and water for irrigation as inputs.

Focusing on the renewable surface water (see Figure 4), it is possible to see a difference in its availability. The driest cluster is number 4 due to its already warm/arid climate, while 1 and 3 show the highest water availability. In clusters 1, 2, and 3, there is an increase in surface water in scenarios with an increase in irrigation with respect to the base case without irrigation (RCP4.5\_IRR and RCP8.5\_IRR, compared to RCP4.5 and RCP8.5). This is because irrigation results in decreased crop evapotranspiration impacting surface water availability (as explained in the following subsection).

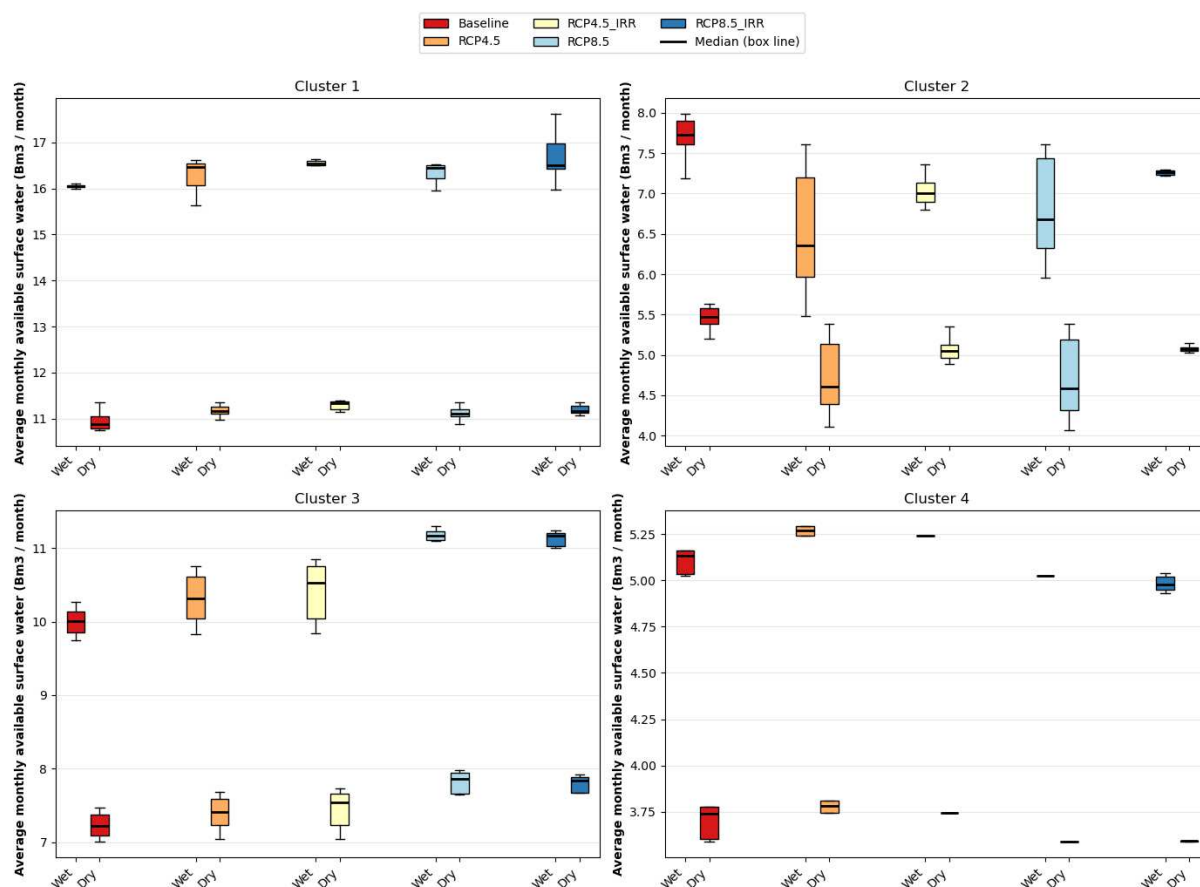


*Figure 4 Surface water availability across clusters and scenarios.*

*The figure represents a box-and-whisker plot showing the distribution of the available surface water (expressed in Bm<sup>3</sup>) across the modelled time interval 2020-2050 for each cluster, season, and scenario. The total water production has been normalised by the length of the seasons: from May to September (wet season) and October to April (dry season).*

We then compared how much seasonal variability impacts CLEWs water results, considering groundwater and surface water production for the year 2050 in the baseline scenario (Figure 5). The variability depends on precipitation, evapotranspiration, and time resolution. In models that do not account for the seasonal variability of the water cycle (NoSeasons results), there is an overestimation of water production. The use, in these models, of a single annual value for rainfall and crop water requirements (evapotranspiration), has a cascading effect on groundwater recharge and surface water production. In the scenario without seasonal hydrological variability, the annual total is distributed across all months, thereby smoothing the differences between wet and dry periods. As a result, the model has a higher average monthly water availability despite land use do not vary across the scenarios. The largest difference can be observed during the dry season, where models that do not simulate seasonal hydrological cycles risk accounting for an overestimation higher than 200% (in this case study, we recorded a 223% increase for groundwater recharge and 272% for runoff water).

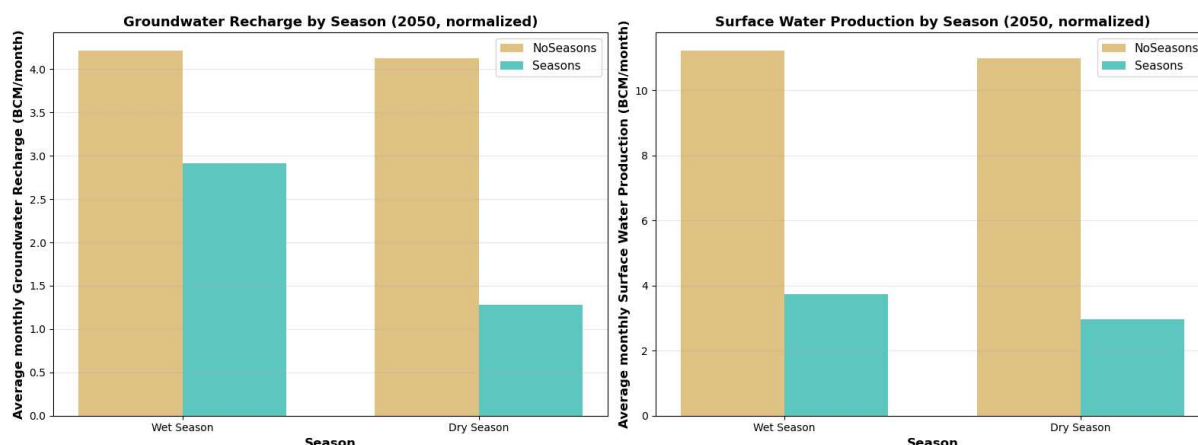


*Figure 5 Impacts of seasonal variability on groundwater recharge and surface water production. The figure shows a comparison of average monthly water output production in the baseline scenario from our CLEWs model across the Seasons case (with seasons) and NoSeasons (the same scenario but without the seasonal hydrological cycle).*

### 3.2 Water demand

Water demand accounts for exogenous demand (municipal and industrial uses) and endogenous demand (water needed for irrigation). Also crops' evapotranspiration can be considered part of the demand, as it impacts the available water that supplies the system, and it is defined as the water needed to meet plants' water loss (FAO, 1977). As discussed previously, cluster 1,2, and 3 show an apparent increase in surface water availability in scenarios with increased irrigation, which might sound counterintuitive. This can be explained by looking at the variation in evapotranspiration across farming types (Table 2)

*Table 2 Variation in evapotranspiration across farming types and crops in Bcm/1000sqKm for cluster 1 in the baseline scenario.*

| FARMING TYPE   | CROP    | VALUE  |
|----------------|---------|--------|
| LOW RAINFED    | Sorghum | 0.4223 |
| HIGH RAINFED   | Sorghum | 0.4192 |
| LOW IRRIGATED  | Sorghum | 0.3256 |
| HIGH IRRIGATED | Sorghum | 0.2383 |
| LOW IRRIGATED  | Coffee  | 0.7302 |
| HIGH IRRIGATED | Coffee  | 0.6449 |
| LOW RAINFED    | Wheat   | 0.4054 |
| HIGH RAINFED   | Wheat   | 0.4084 |
| LOW IRRIGATED  | Wheat   | 0.3111 |
| HIGH IRRIGATED | Wheat   | 0.2671 |
| LOW RAINFED    | Cereals | 0.3451 |
| HIGH RAINFED   | Cereals | 0.3432 |
| LOW IRRIGATED  | Cereals | 0.2558 |
| HIGH IRRIGATED | Cereals | 0.1532 |
| LOW RAINFED    | Barley  | 0.4063 |
| HIGH RAINFED   | Barley  | 0.3977 |
| LOW IRRIGATED  | Barley  | 0.328  |

|                           |        |        |
|---------------------------|--------|--------|
| <b>HIGH<br/>IRRIGATED</b> | Barley | 0.2869 |
| <b>LOW RAINFED</b>        | Maize  | 0.4613 |
| <b>HIGH RAINFED</b>       | Maize  | 0.4403 |
| <b>LOW IRRIGATED</b>      | Maize  | 0.3341 |
| <b>HIGH<br/>IRRIGATED</b> | Maize  | 0.2382 |

Moving from rainfed to irrigated systems results in a substantial decline in evapotranspiration and reductions are observed also when transitioning from high to low input systems. The effects of irrigation on evapotranspiration have been long studied in literature, which argues that its implications depend on variation in humidity and temperature affecting crops' evaporation and transpiration (Gong et al., 2024). Moreover, evapotranspiration is also sensitive to seasonal dynamics and climate change trajectories, changing across seasons and climate change scenarios in line with Scarpore et al. (2022).

Climate change also affects the need for water for irrigation, to which water demand from municipal and industrial uses adds. Figure 6 shows a comparison across scenarios with ("Seasons") and without ("NoSeasons") seasonal hydrological variability to understand the implications of seasonal water availability on harvested area. Almost all scenarios returned similar trends, with only a slight increase in mechanized and irrigated area when moving from "NoSeasons" to "Seasons" scenarios (ranging from 0.4% to 5% increase see Table S5 ). However, this is not true for high impact climate scenarios (RCP8.5), where the presence of seasonal variability leads to a 63% increase in irrigated area and a 17.4% increase in mechanization. All the scenarios reach the same production targets, being the crop demand the same. This means that an increase in irrigation is not driven because of an increase in yields. The only difference across Seasons and NoSeasons scenarios is in the water cycle. We saw that scenarios with seasonal hydrological variability have lower groundwater recharge and surface water production (Figure 5). Moreover, in almost all the clusters, the RCP8.5 scenario exhibits the lowest amount of available surface water (Figure 4 cluster 1,2, and 4) to which a decrease in precipitation, expected during the dry season adds. Apart from increasing crop yields, the adoption of irrigation increases the available surface water (Table 2). In our CLEWs model the surface water is represented as a closed loop across demand and supply since it represents the available renewable water within the system's boundaries. Having higher availability of surface water allows therefore to have the needed supply for supporting the expansion of the associated infrastructure, which is cheaper than investing in groundwater infrastructure. This, in turn, increases the overall water demand, thereby explaining the gradual decrease in irrigated area from the baseline scenario to RCP4.5 and RCP8.5, unless irrigation targets are imposed (RCP4.5\_IRR and RCP8.5\_IRR). It is therefore important to keep in mind that CLEWs follows a cost-minimisation objective function. While the share of irrigated area decreases in scenarios with higher water demand as a cost-optimal trade off between water demand and supply, it increases in comparison to scenarios that do not include seasonal water cycles not capturing the need of adopting irrigation as a cost-effective solution for water scarce seasons.

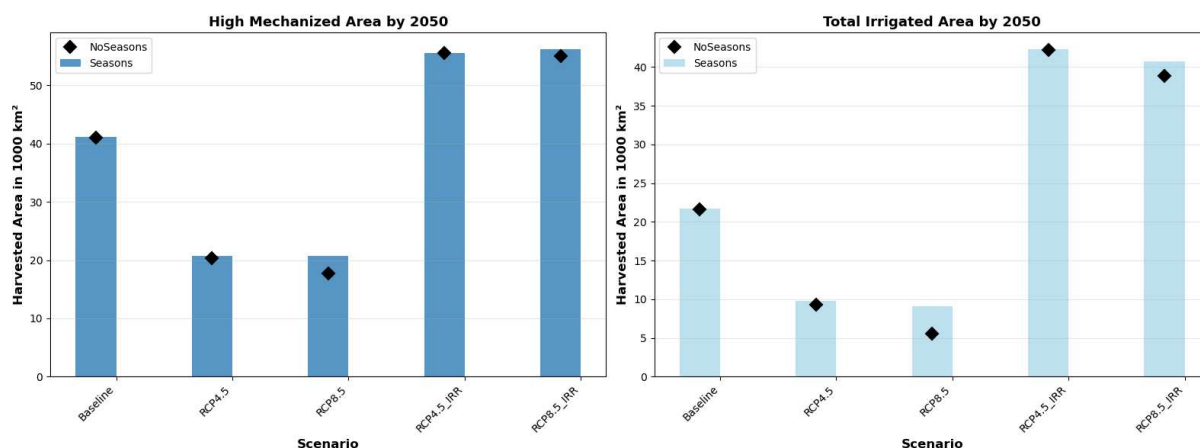


Figure 6 Comparison of mechanised and irrigated harvested area by 2050 across scenarios with seasonal hydrological variability (bars) and without (diamonds).

### 3.3 Water stress across scenarios

The trade-off between water availability and demand was finally captured with the ratio between the gross water demand (irrigation, municipal, and industrial) and the gross renewable available water (surface and groundwater), then translated into the water stress score (Figure 7).

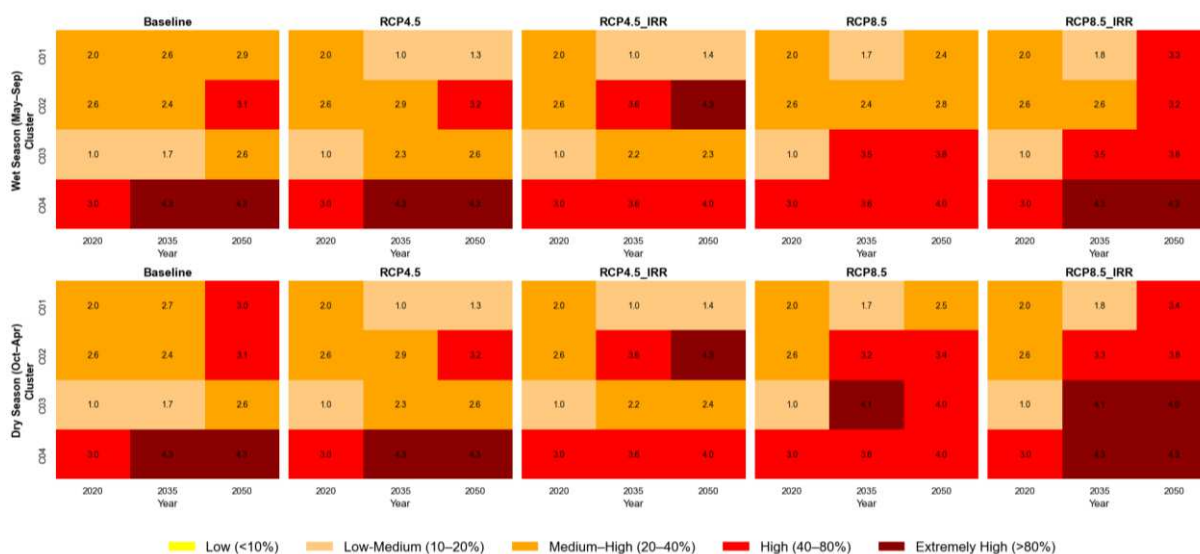


Figure 7 Seasonal water stress score.

The stress spans across five stress levels: low, low-medium, medium-high, high, and extremely high. Higher relative water demand corresponds to higher stress levels. Cluster 4 is projected to be the one experiencing higher stress due to its already warm/arid environment (Tilahun Amede et al., 2015), exacerbated by drier seasons in severe climate conditions (RCP8.5). On the other hand, the stress in the other clusters depends on the adaptation of the agriculture sector to climate change.

With an increase in climate change, the agricultural expansion in Ethiopia can result in most clusters in high or extremely high water stress, in line with the study conducted by (Swedenborg et al., 2025). Moreover, while in the baseline and middle impact scenarios there is not a significant difference in water stress across seasons, in high impact scenarios (RCP8.5) it is possible to see an increase in stress in dry seasons due to the lower water availability and higher seasonal variability. Cluster 4 experiences

stress due to its already warm/arid environment, but clusters 2 and 3 are the ones experiencing the highest stress. This is because of crop-land adaptation to climate change. Climate change will indeed have an impact on crop yields, which vary depending on the RCP and cluster (Table S6). The model was free to optimize crop-land allocation, and therefore, we allowed crop migration across clusters, based on yield and use of resources. While an increase in crop yields in cluster 2 leads to increased harvested area (Figure S2) and therefore water need due to crop migration, in cluster 3, the increased water stress in RCP8.5 occurs due to the increase in water needed for irrigation.

Moreover, while the irrigated harvested area in the RCP4.5 and RCP8.5 scenarios is 55% and 58% lower than the baseline, respectively (Figure S3), the intensified water stress underscores a techno-economic trade-off. Within the CLEWs cost-optimisation framework, the reduction in irrigated area reflects a least-cost solution to avoid the escalating infrastructure costs associated with higher crop water requirements under climate change. However, despite this overall decline, these climate scenarios still maintain a higher share of irrigation than versions lacking seasonal hydrological cycles. The "NoSeasons" scenarios overestimate accessible resources, reducing the cost-optimal need for irrigation infrastructure. By contrast, the inclusion of seasonality highlights dry-seasonal water scarcity trade-offs, forcing the model to retain a higher level of irrigation to mitigate reduced renewable water availability, even at a higher system cost.

## 4 Discussion

Increased variability in rainfall patterns caused by climate change leads to evident differences in water availability across wet and dry seasons. The case study of Ethiopia was useful for identifying when and where increased temporal resolution in a CLEWs model is needed for supporting adaptation agendas. It showed that medium (RCP4.5) and high (RCP8.5) impact climate trajectories will increase water stress by 2050 across all modelled clusters. The water stress emerges from the interaction of crop yield responses, crop water deficits, and changes in evapotranspiration under climate change, assuming the resource use across the country is optimised. For instance, high-yielding regions such as Tigray and Oromia (largely within the agro-ecological zone of cluster 2) experience the highest increase in water stress, due to the adaptation of the country's agricultural sector to climate change. On the other hand, regions such as Gambela, Benishangul-Gumuz, Ormonia, and Southern Nations, Nationalities and Peoples' Region, are projected to see increased water stress due to increased crop water deficit (see results cluster 3). In severe climate conditions (RCP8.5), the overall water stress exacerbates in scenarios with a boost in irrigation, reaching 1.22 hectares of irrigated harvested area by 2050 in the RCP8.5\_IRR scenario. On the other hand, middle-impact climate trajectories, as seen in cluster 2 an increase of one water stress scoring point by 2035 and 2050 in the irrigation scenario (RCP4.5\_IRR), with respect to the RCP4.5. Ethiopia's willingness to boost irrigation up to 3.6 million hectares by 2050 (around seven times the current 0.4 million hectares) (Ministry of Planning and Development, 2022) will therefore need to be planned, considering resource stress assessment and the impact of climate change, in order to avoid maladaptation. In this context, national government programs such as the Climate Resilient Green Economy (CRGE)(Federal Democratic Republic of Ethiopia, 2019) and the Long Term Low Emission and Climate Resilient Development Strategy (LTLEDS)(Ministry of Planning and Development, 2022) should adopt resource-based indicators to evaluate agricultural investments.

Recent nexus studies often ignore the spatial resolution (Gao et al., 2024). In this study, we split the area into agro-ecological clusters modelled based on crop-potential yield. This decision complements the increased temporal resolution in representing hydrological cycles, since hydroclimatic change is characterised by marked differences across space and increasing instability over time (Nazeri Tahroudi, 2025). Globally, only 7% of regions have regular patterns with low seasonal variability (Nazeri Tahroudi, 2025). Within Ethiopian borders, we showed marked differences in water stress across clusters, depending on the spatial variation of precipitation, whose percentage deviation in severe climate conditions (RCP8.5) decreases, during the dry season (October-April), from historical values by 6.9% in cluster 1 and 3, 8.9% in cluster 2, and 10.5% in cluster 4 for severe climate conditions (see Table S3). The variation of precipitation has subsequently an impact on the overall water cycle, and hence resource stress.

This study represented the first attempt to explore the impact of seasonal water availability on agricultural planning, by representing seasonal hydrological cycle and crop-growing stages in the integrated CLEWs framework. Our results proved that in severe climate change conditions (RCP8.5) the increased difference in seasonal precipitation patterns leads to non-negligible differences in water stress across seasons (and therefore water availability and demand). Moreover, when moving from “NoSeasons” to “Seasons” scenarios, there is an overall increase in the share of mechanized and irrigated area, peaking (with 17.4% and 63% increase respectively) under the worse (and driest) climate change trajectory RCP8.5. Neglecting variable hydrological cycles in integrated models can overestimate the available renewable water, hindering the adoption of mechanization and irrigation in least-cost solutions. The scenario comparison also highlights the gap between physical and techno-economic models. While the first ones can simulate resource behaviour based on physical rules, techno-economic models prioritise cost-efficiency in the optimization process, while the physical availability of resources is represented only through model constraints. The increased temporal resolution in the water cycle in a CLEWs framework, and the seasonal variability of the water cycle, are hence relevant, particularly in countries where this gap is already high or has increased due to climate change (Nazeri Tahroudi, 2025). Adding seasonal variability in a CLEWs model leads to increased complexity and computational requirements (especially if modelling more than two seasons), but *we recommend* the use of more granular temporal resolution for representing crop growth stages in countries where there is already a high seasonal variability, and/or there is the willingness to assess the impact of climate change on water stress, and/or the study has to support adaptation strategies. Knowing *when* shifts in seasonal water availability will occur can support agricultural adaptation by changing cropping patterns or sowing time (Caretta, M.A. et al., 2022). For instance, in our study, we saw that the dry season is forecasted to have an increase in water stress, especially under severe climate conditions (RCP8.5). A change in cropping patterns could shift crops’ growing and harvesting stages earlier during the year to avoid incurring increased resource stress. Moreover, in this case study, we modelled two seasons and six main crops. However, the high flexibility and modularity of CLEWs models allow future users to increase temporal granularity and focus on specific seasons and crops if there is a need to understand when and where to allocate the resources, investments, and support adaptation agendas. For policymakers, seasonal water stress findings can be used to optimise irrigation systems, improve water-use efficiency, regulate sustainable limits on water extraction, and identify climate-smart practices that increase productivity while minimising water consumption.

However, despite the methodological advancement in representing the water sub-system in an integrated model, there are still hydrological limitations. The hydrological limitations in a CLEWs model include a limited representation of the water system, which entails only the renewable water cycle (water coming from precipitation and then converted into surface and groundwater by the land system) and does not consider geospatial proximity to the agriculture sector expansion of other water sources (such as streamflows or return flows). Because of this, the increase in water stress depends only on the expansion and adaptation of the agriculture sector and the competing water demand of the industrial and municipal sectors, modelled exogenously. Future studies should further downscale CLEWs results to better capture the spatial disaggregation and incorporate climate-smart agriculture practices, assessing their impact on the use of resources.

Despite these limitations, our results align with and complement previous findings (S. Mark Howden et al., 2007): under severe climate scenarios (here represented by RCP8.5), pressures on resources intensify even when the agricultural sector adopts adaptation measures. While in a middle-impact climate trajectory (RCP4.5), it is still possible to adapt to climate change, migrating crops and supporting agriculture with moderate irrigation increase, under severe climate conditions adaptation is no longer sufficient because of the gradual depletion of resources and unavoidable damage costs (S. Mark Howden et al., 2007). This implies that although adaptation is essential for improving food security and the efficiency and sustainability of resource use under climate change, mitigation remains crucial to prevent conditions from worsening beyond the point where adaptation alone is no longer viable. Integrated adaptation and mitigation analysis and planning are therefore needed to shape future agendas and to respond to uncertain climate change impacts.

## 5 Conclusions

We explored the impact of seasonal water variability on agricultural planning. We integrated water seasonal variability and crop-growing stages into the CLEWs framework. With this method we were able to investigate how agricultural adaptation under climate-change scenarios may affect water stress aligning integrated resource planning with adaptation strategies. Incorporating seasonal variability is essential to accurately capture deviations in water outputs across seasons, especially in countries where seasonal rainfall patterns are highly variable across seasons. Ignoring these dynamics can lead to substantial overestimation of available renewable water, hindering the adoption of mechanisation and irrigation in least-cost solutions. Overall, this study demonstrates that the absence of integrated resource assessments and multidisciplinary approaches in national planning can lead to unintended and potentially counterproductive impacts on natural resources. While disciplinary models remain valuable for addressing localised or sector-specific challenges, strategic planning necessitates the application of interdisciplinary modelling frameworks that capture interactions among climate, water, agriculture, and ecosystems. Addressing the limitations in representing the water subsystem in integrated models, this paper fills that gap by representing seasonal water cycles. The results showed that, especially in high-impact climate trajectories (RCP8.5), the increased seasonal variability of water demand and supply leads to a non-negligible impact of the agricultural sector on seasonal water stress. Representing crop-growing stages unveils conflicts in the use of water when it is scarce during the year, and it is crucial to represent it in integrated resource assessment studies that explore water scarce scenarios or informing adaptation planning in the agricultural sector.

## CRedit authorship contribution statement

**Camilla Lo Giudice:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Francesco Gardumi:** Writing – review & editing, Project administration, Methodology, Supervision, Conceptualization. **Daniel Adshead:** Writing – review & editing, Visualization, Supervision. **Fitsum Salehu Kebebe:** Writing – review & editing. **Solomon Tesfamariam Teferi:** Writing – review & editing.

## Declaration of competing interest

The authors declare no competing interests.

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## Data availability

- The full dataset used for modelling CLEWs with crop growing stages for the case study of Ethiopia, can be found at: <https://zenodo.org/records/18015853>

## Code availability

- The Indicators4CLEWs repository is available on GitHub at <https://github.com/Camilogiu/Indicators4CLEWs>

## Appendix . Supplementary data

- Guidelines for modelling crop-growing stages in OSeMOSYS available at: <https://dx.doi.org/10.17504/protocols.io.14egn1n6mv5d/v3>
- Supplemental information.

## Declaration of generative AI and AI-assisted technologies in the manuscript preparation process.

During the preparation of this work the author used GitHub Copilot to support the design and debugging of the Indicators4CLEWs code used for quantifying water stress. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

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## Supplementary Files

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- [SupplementaryFigures.docx](#)
- [SupplementaryDataset.docx](#)