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## Are multiscale water–energy–land–food nexus studies effective in assessing agricultural sustainability?

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## LETTER

## Are multiscale water–energy–land–food nexus studies effective in assessing agricultural sustainability?

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E-mail: [prasvenk@iittp.ac.in](mailto:prasvenk@iittp.ac.in)**Keywords:** multiscale WELF nexus studies, agricultural sustainability, vulnerable hotspots, policymakingSupplementary material for this article is available [online](#)**Abstract**

Several studies have highlighted the need for multiscale water–energy–land–food (WELF) nexus studies to ensure sustainable food production without endangering water and energy security. However, a systematic attempt to evaluate the efficiency of such multiscale studies has not yet been made. In this study, we used a data-intensive crop water requirement model to study the multiscale WELF nexus in southern India. In particular, we estimated the groundwater and energy consumption for cultivating five major crops between 2017 and 2019 at three distinct spatial scales ranging from 160 000 km<sup>2</sup> (state) to 11 000 km<sup>2</sup> (district) to 87 km<sup>2</sup> (block). A two-at-one-time approach was used to develop six WELF interactions for each crop, which was used to evaluate the performance of each region. A gross vulnerability index was developed at multiple scales that integrated the WELF interactions to identify vulnerable hotspots from a nexus perspective. Results from this nexus study identified the regions that accounted for the largest groundwater and energy consumption, which were also adjudged to be vulnerable hotspots. Our results indicate that while a finer analysis may be necessary for drought-resistant crops like groundnut, a coarser scale analysis may be sufficient to evaluate the agricultural efficiency of water-intensive crops like paddy and sugarcane. We identified that vulnerable hotspots at local scales were often dependent on the crop under consideration, i.e. a hotspot for one crop may not necessarily be a hotspot for another. Clearly, policymaking decisions for improving irrigation efficiency through interventions such as crop-shifting would benefit from such insights. It is evident that such approaches will play a critical role in ensuring food-water-energy security in the coming decades.

**1. Introduction**

Water, energy, land, and food (WELF) sectors are central to the sustainable development of agriculture (FAO 2014, Davis *et al* 2019). An integrated approach is essential to achieve sustainability across these sectors (UN 2015, Scanlon *et al* 2017, Di Baldassarre *et al* 2019). This ‘nexus thinking’ has gained broad attention recently, mainly highlighting the drawbacks of ignoring trade-offs between sectors (Lee *et al* 2020). For example, recent nexus studies indicated that increasing food demands led to an unsustainable intensification of irrigation in South Asia (Rasul 2016, Barik *et al* 2017). Therefore, quantifying the

interactions between WELF is imperative for achieving sustainable agriculture.

Agriculture accounts for 70% of global freshwater withdrawals (FAO 2011), which is projected to increase further to satisfy rising food demand (Alexandratos and Bruinsma 2012). As global population is projected to reach around 10 billion by 2050 (UN 2019), the stresses on resources like water, energy, and land will likely intensify further (Marris 2008, FAO 2011, Ringler *et al* 2013). Groundwater, although renewable, has been persistently over-exploited for agriculture (Siebert *et al* 2010, Wada *et al* 2010, Gleeson *et al* 2012, Bierkens and Wada 2019). Groundwater overdraft can result in declining

groundwater levels, soil infertility, and land subsidence (Sophocleous 2005, Giller *et al* 2009, Perrone and Jasechko 2019).

## 2. Groundwater-centric WELF nexus in India

India is the world's leading groundwater consumer and the country with the largest irrigated area (Siebert *et al* 2010). The introduction of tube wells (bore wells constructed by driving a tube into the aquifer) to cultivate staple crops like paddy and wheat has driven irrigated agriculture in India (Pingali 2012, Patle *et al* 2016, Dangar *et al* 2021). Tube wells, particularly in arid and semi-arid regions, can no longer sustain irrigated agriculture or drinking water supply (Hora *et al* 2019). The numbers of deep tube wells across India show an alarming increase since the 1990s (figure S1 available online at [stacks.iop.org/ERL/17/014034/mmedia](https://stacks.iop.org/ERL/17/014034/mmedia)) (Ministry of Jal Shakti 2020). In particular, the state of Andhra Pradesh (AP) has seen a tremendous rise in deep tube wells, indicating significant groundwater over-exploitation.

Energy consumption for agriculture has also increased considerably in India. Except for Gangetic Plains, where diesel pumps prevail, electric pumps are widespread across India; also, the provision of subsidized electricity has accelerated groundwater use (Rodell *et al* 2009). The consequent increase in greenhouse gas emissions and associated energy costs is thereby enlarging the carbon footprint from agriculture (Mishra *et al* 2018). For example, groundwater levels have dropped by 5.47 m in the Indian state of Punjab, resulting in increased energy requirements and carbon emissions by 67% and 110%, respectively (Kaur *et al* 2016).

Growing urbanization and declining soil fertility place enormous pressure to preserve existing agricultural land in India (Giller *et al* 2009, Di Baldassarre *et al* 2019). Recent approaches like conservation agriculture, sustainable intensification, and nutrition-sensitive agriculture are addressing these multisectoral challenges by enhancing soil fertility, improving water management, and increasing food production (Cassman and Grassini 2020, Sampath *et al* 2020). However, adoption rates of these methods are relatively slow in Asia and Africa (Kassam *et al* 2019).

## 3. Need for a multiscale WELF nexus

Global groundwater consumption (GWC) is driven by a few heavily-exploited hotspots like the Upper Indo-Gangetic Plains, the High Plains of central United States, and the North China Plains (Gleeson *et al* 2012). Sustainably managing such regions will hinge on developing and understanding the

groundwater-related WELF nexus. Although the importance of the WELF nexus is well-understood, policymaking along those lines has not been widely implemented, particularly in South Asia (Rasul 2016). A common bottleneck in WELF policymaking is the lack of detailed data to study local-scale WELF interactions (Perrone *et al* 2011, Conway *et al* 2015). However, the integration of local-to-global nexus is necessary for robust policymaking (Endo *et al* 2015, 2017).

The challenges that undermine implementation of local-level WELF policy are often masked by coarse-scale WELF research and policy (Biggs *et al* 2015). Although many researchers highlight the pitfalls of overlooking local scales, WELF nexus findings are primarily available at global or national levels (Endo *et al* 2017, Taniguchi *et al* 2017). Local-level datasets, if available, generally lack spatial-temporal resolution, which leads to a black-box perspective (McGrane *et al* 2018).

The major issue with ignoring local scale realities is that global or national nexus analyses can have unintended outcomes at finer scales. A recent study on the water footprint of wheat production in China revealed that management factors like agricultural machinery and pesticide application were the primary drivers at larger scales, while meteorological factors were more important at smaller scales (Mao *et al* 2021). Likewise, although the depletion of groundwater resources is highly localized, it is often masked by coarser satellite data like GRACE (Aeschbach-Hertig and Gleeson 2012). The same rationale could be applied to the energy and food sectors, which ultimately implies that the WELF interactions also behave differently at different scales (Ramos *et al* 2021, Vinca *et al* 2021). The challenge of detecting local variabilities must be addressed to achieve multiscale WELF policymaking (Bazilian *et al* 2011, Hoff 2011, Endo *et al* 2020). There is limited literature available that systematically assesses the effectiveness of multiscale WELF studies.

The main objective of this study is to systematically evaluate the efficacy of a multiscale WELF analysis. In particular, this study computes the groundwater and energy consumption for groundwater-fed agriculture at multiple scales, ranging from 160 000 to 87 km<sup>2</sup> in a predominantly semi-arid region in southern India. Further, we compute the interactions between the WELF sectors at multiple scales. Finally, we develop a composite index that integrates the WELF interactions to help identify vulnerable hotspots. The findings from this study will help answer the following questions:

- Can coarse-scale analyses provide sufficient insights into the WELF nexus? In other words, is a fine-scale analysis always necessary?
- Are vulnerable hotspots specific to a particular crop?

- How can a multiscale nexus perspective inform policymaking for improving agricultural sustainability?

This study will be relevant for researchers and policymakers as they grapple with the need to sustainably intensify global food production without endangering water and energy security in the coming decades.

## 4. Material and methods

### 4.1. Study areas

This study focuses on the southern Indian state of AP. States in India are divided into districts, which are further subdivided into blocks (figure 1). The choice of study area was driven by the availability of detailed agricultural data at all scales. The agricultural year is primarily divided into two seasons—Summer/Kharif (June to September) and Winter/Rabi (October to March), both of which were selected for the current analysis. The multiscale analysis was performed at the state-scale, district-scale (all 13 districts in the state), and block-scale (146 blocks across three districts). Since lack of precipitation is often the primary basis of groundwater pumping for agriculture, we identified three climatically heterogeneous districts to conduct the block-scale analysis. The coefficient of variation of rainfall (APWRIMS 2021) was calculated to demonstrate the rainfall variability across blocks within each district (see table S2). The three districts selected to perform the block-scale analysis were Vizianagaram (lowest variability—rank 1), S.P.S.Nellore (medium variability—rank 7), and Chittoor (highest variability—rank 13). The entire analysis was conducted for 3 years, from 2017 to 2019, for which all relevant data was available.

### 4.2. Groundwater and energy consumption at multiple scales

We used the CROPWAT model (Allen *et al* 1998) to estimate irrigation water requirements (IWR) at all scales. The model follows a soil water balance equation in which evapotranspiration is the outflux, and rainfall and irrigation water are the influxes. This study uses high-resolution reference evapotranspiration ( $ET_o$ ) data, derived using FAO's Penman–Monteith method, which is available at  $0.1^\circ$  resolution and at daily intervals for 1981–2020 (Singer *et al* 2021). This evapotranspiration information was spatially averaged to obtain the mean  $ET_o$  for the state, districts, and blocks (figure 2).

Rainfall data were collected from the Andhra Pradesh Water Resources Information & Management System for 2017–19 (APWRIMS 2021). The rainfall data was imported into the CROPWAT at monthly intervals, and the effective rainfall, the portion of rainfall stored in the root zone after subtracting losses such as runoff and deep percolation, was calculated

using the Soil Conservation Service method (Allen *et al* 1998). Further, soil and crop-related information of the major crops—paddy, sugarcane, groundnut, red gram, and jowar were collected from literature and imported into the model (Allen *et al* 1998). These crops were chosen for this analysis as they constitute around 75% of the total acreage in the study area (DES-AP 2021). The sowing dates of these crops were collected from the detailed farm-level agricultural data (CORE 2018).

After importing the required data into CROPWAT, the IWR of each crop was estimated at all scales. Subsequently, the GWC was computed by multiplying IWR with the groundwater-fed acreage (CORE 2018, DES-AP 2021). The percentage of groundwater-fed acreage to the total acreage for all crops at three scales (figure S2). After estimating the GWC, the energy consumption for all crops was calculated at multiple scales. Depth to groundwater level (DGWL) data was collected from Water Resources Information System, India, at monthly intervals for the entire study area (WRIS 2021). The energy utilized to extract groundwater was computed using the following equation:

$$E = \frac{\rho g V H}{\eta} \quad (1)$$

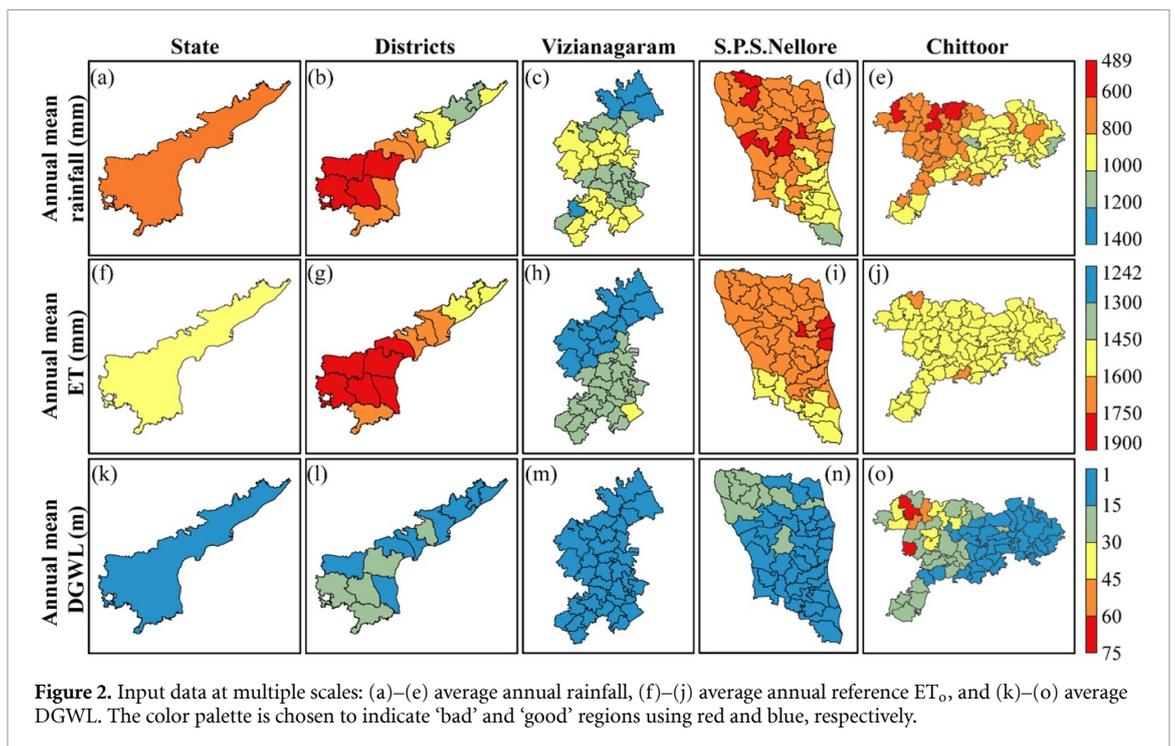
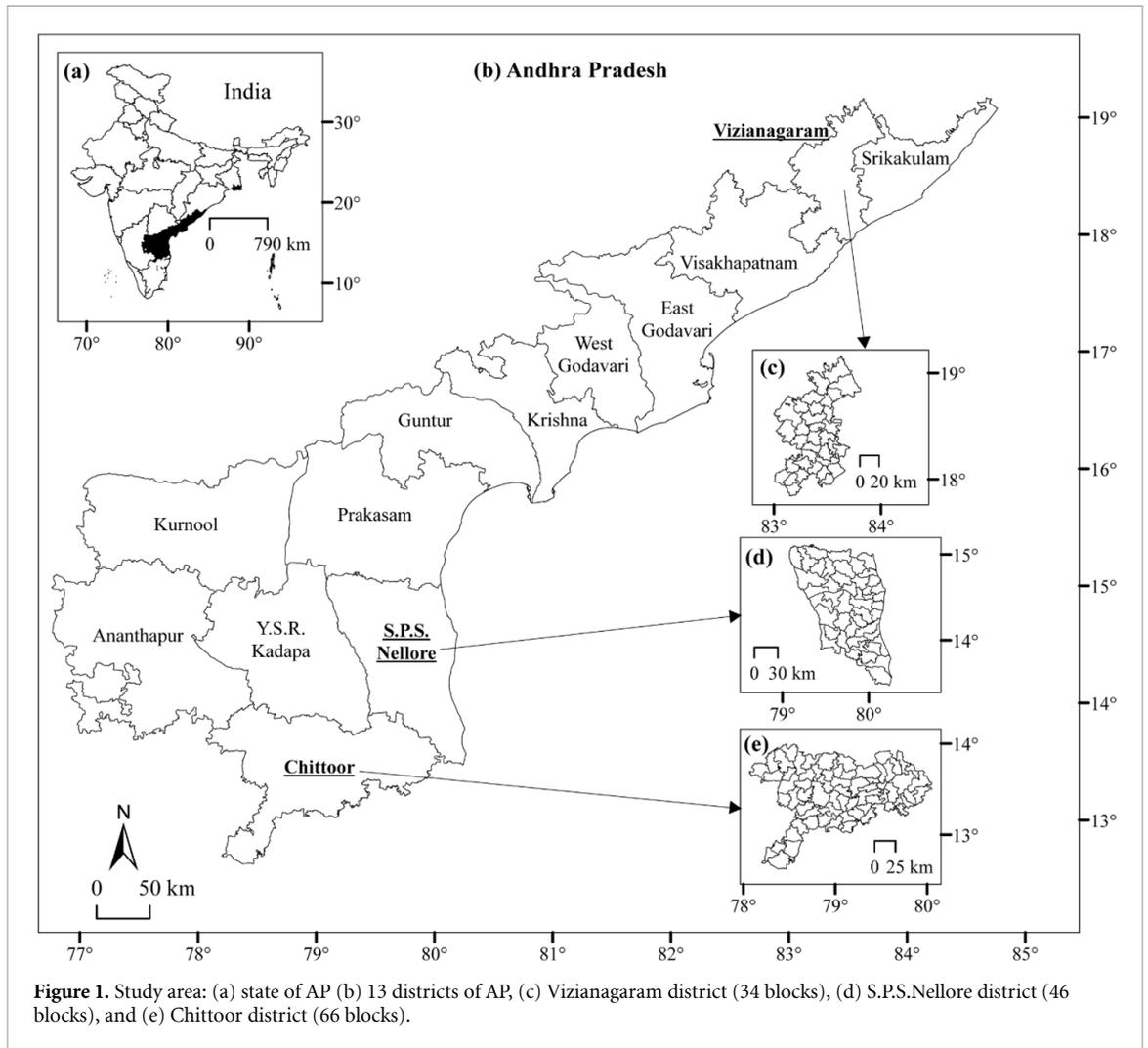
where,  $E$  = energy consumed ( $ML^2T^{-2}$ );  $\rho$  = density of water ( $ML^{-3}$ );  $g$  = acceleration due to gravity ( $LT^{-2}$ );  $V$  = volume of GWC ( $L^3$ );  $H$  = DGWL (L);  $\eta$  = pumping efficiency, assumed at 30% (Nelson *et al* 2009, Mishra *et al* 2018).

### 4.3. WELF interactions

Food production data at the state and district-scale was extracted from the state's official reports (DES-AP 2021). Finally, GWC (W), energy use (E), groundwater-irrigated land (L), and food production (F) were linked using the commonly-used 'two-at-one-time' approach (Taniguchi *et al* 2017), as shown in figure 3.

Using this approach, six equations were established in which the productivity of one resource was assessed in relation to another resource. For example, the food–water interaction (equation 2) metric measures the efficiency of crop production corresponding to the total volume of groundwater consumed for its cultivation. Larger values indicate better performance of that interaction and vice versa. These metrics quantify the WELF interactions at multiple scales, which enables comparison across scales. Due to the unavailability of food production data at block-scales, the food interactions were only calculated at state and district levels, resulting in six interactions at the state and district-scales and three at the block-scale.

$$\begin{aligned} &\text{Food-water (F-W) interaction} \\ &= \frac{\sum_{\text{season}} \text{Crop produced (kg)}}{\sum_{\text{season}} \text{GW consumed (m}^3\text{)}} \quad (2) \end{aligned}$$



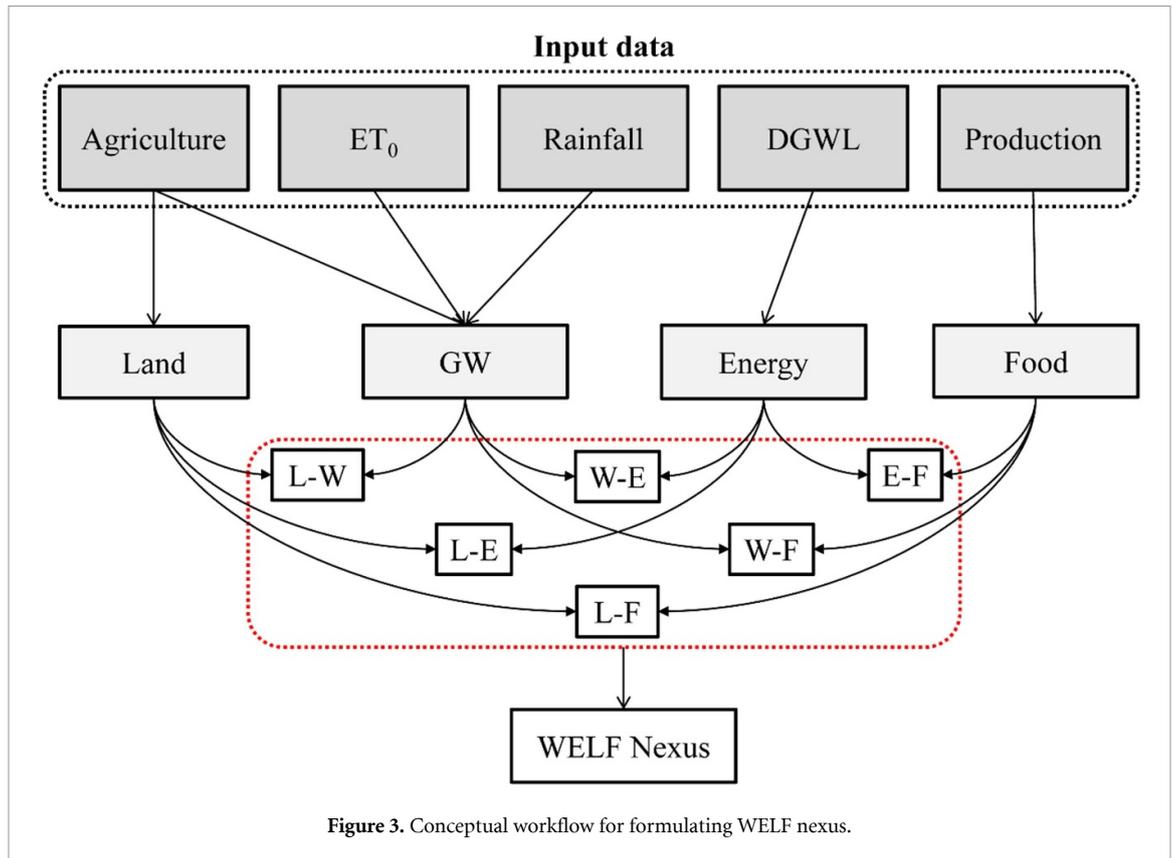


Figure 3. Conceptual workflow for formulating WELF nexus.

$$\begin{aligned} &\text{Food - energy (F-E) interaction} \\ &= \frac{\sum_{\text{season}} \text{Crop produced (kg)}}{\sum_{\text{season}} \text{Energy used (kWh)}} \end{aligned} \quad (3)$$

$$\begin{aligned} &\text{Food-land (F-L) interaction} \\ &= \frac{\sum_{\text{season}} \text{Crop produced (kg)}}{\sum_{\text{season}} \text{Crop acreage (ha)}} \end{aligned} \quad (4)$$

$$\begin{aligned} &\text{Land-water (L-W) interaction} \\ &= \frac{\sum_{\text{season}} \text{Crop acreage (ha)}}{\sum_{\text{season}} \text{GW consumed (m}^3\text{)}} \end{aligned} \quad (5)$$

$$\begin{aligned} &\text{Land-energy (L-E) interaction} \\ &= \frac{\sum_{\text{season}} \text{Crop acreage (ha)}}{\sum_{\text{season}} \text{Energy used (kWh)}} \end{aligned} \quad (6)$$

$$\begin{aligned} &\text{Water-energy (W-E) interaction} \\ &= \frac{\sum_{\text{season}} \text{GW consumed (m}^3\text{)}}{\sum_{\text{season}} \text{Energy used (kWh)}} \end{aligned} \quad (7)$$

Using the interactions computed as explained above, we computed a gross vulnerability index (GVI) for each crop. This index is similar to the standardized groundwater index that uses a non-parametric normal scores transform (Bloomfield and Marchant 2013). In GVI, the individual WELF interactions are ranked within each sub-region (districts of the state of AP or blocks of Vizianagaram, S.P.S.Nellore,

and Chittor districts), which were then converted to exceedance probabilities. These probabilities were transformed into normal scores using the inverse normal cumulative distribution function. The GVI was then calculated for each crop as the average of the normal scores of the six (or three) WELF interactions at the district (or block) scale. Each WELF interaction gets equal weightage in the computation of GVI. The typical values for this index range from  $-3$  to  $+3$ . A negative GVI score indicates a vulnerable hotspot, as this region's performance is consistently poor in most interactions. It is worth noting that the GVI scores are only relevant for individual crops and cannot be compared across crops. This index helps to identify hotspots at multiple scales from a WELF nexus perspective.

## 5. Results and discussion

### 5.1. Multiscale groundwater and energy consumption

As illustrated in the methodology, the crop-wise IWR was calculated and was used to estimate GWC at three scales for 2017–19 (figure S3). At the state-scale, the mean annual groundwater and energy consumption was found to be 3054 MCM (Million Cubic Meters) and 343 GWh, respectively. The state's mean annual GWC and energy consumption were also estimated at the district-scale and found to be 3195 MCM and 422 GWh, respectively. Notably, the district-scale estimates were higher than the

**Table 1.** Average annual GW and energy consumption at district and block scales.

		District scale	Block scale
Total GWC (MCM)	Vizianagaram	34	35
	S.P.S.Nellore	437	544
	Chittoor	461	505
Total energy (GWh)	Vizianagaram	1.7	1.6
	S.P.S.Nellore	43.8	43.5
	Chittoor	77.6	54.7

state-scale estimates by 5% (GWC) and 23% (energy). Two districts, Chittoor and West Godavari accounted for more than 30% of the state's total groundwater use. Due to the high GWC and deeper groundwater levels, the West Godavari district emerged as the largest energy user with 85 GWh. The southern districts of Ananthapur, S.P.S.Nellore, Kurnool, and Y.S.R.Kadapa also contributed significantly to the total groundwater and energy consumption, which could be attributed to low rainfall, high  $ET_o$ , deep water tables, and most importantly, cultivation of water-intensive crops in these regions. For instance, paddy and sugarcane together accounted for nearly 90% of the entire state's total groundwater and energy consumption. Clearly, reducing the water and energy footprint of these regions will require moving away from water-intensive crops such as paddy and sugarcane.

In the block-scale analysis conducted over 3 years (2017–19), S.P.S.Nellore district had the highest average GWC (544 MCM), followed by Chittoor (505 MCM) and Vizianagaram (35 MCM). Although water-intensive crops like paddy and sugarcane were cultivated intensively in all three districts, the GWC in S.P.S.Nellore and Chittoor were much higher due to low rainfall and high  $ET_o$ . The GWC hotspots were clustered in the eastern parts of both districts, where paddy and sugarcane acreage was high (figure S3). In both districts, 20% of blocks accounted for more than 50% of each district's total GWC and energy use. Similarly, four out of thirteen districts constituted almost 55% of the state's total GWC and energy use. These results corroborate the findings from earlier research that indicated the disproportionate role of a few heavily over-exploited regions in driving the overall GWC (Gleeson *et al* 2012).

Table 1 compares the total groundwater and energy consumption for three districts using the results from both district and block-scales. The block-scale GWC values were consistently higher than the district-scale values for all three districts (paired  $t$ -test:  $p < 0.05$ ). Surprisingly, this pattern was reversed while comparing the energy values at both scales ( $p > 0.05$ , See table S3). While GWC depends mostly on rainfall and  $ET_o$ , energy use is principally dependent on DGWL. Unlike Vizianagaram and S.P.S.Nellore districts, the depths to groundwater level

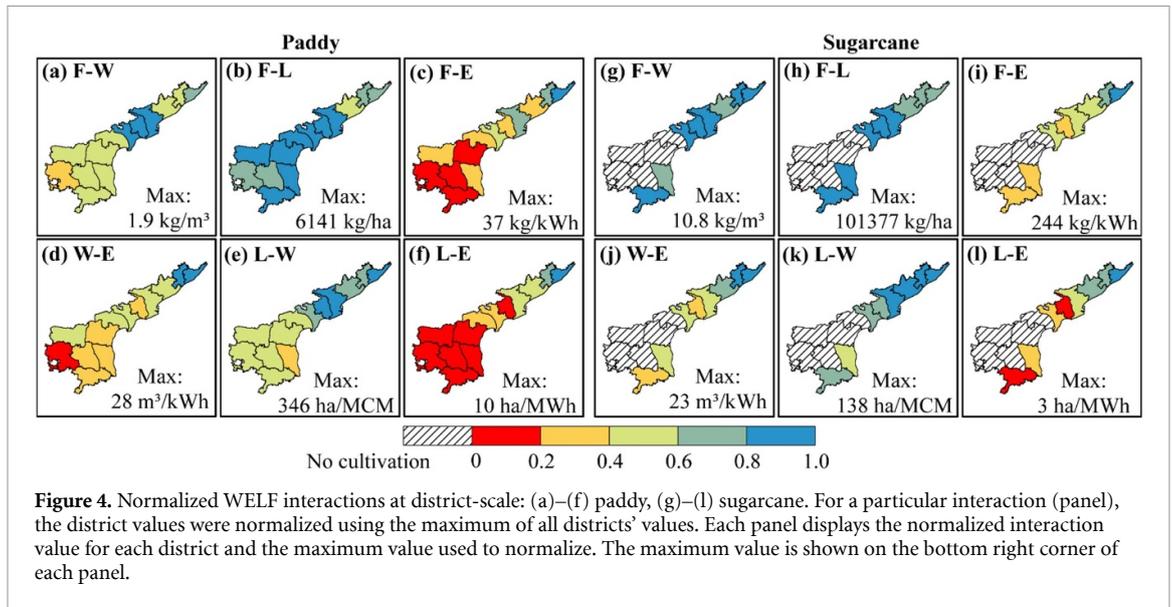
showed considerable variation in Chittoor district (figure 2). This explains the significant departure of block-scale energy values for the Chittoor district from the district-scale.

## 5.2. District-scale WELF nexus interactions

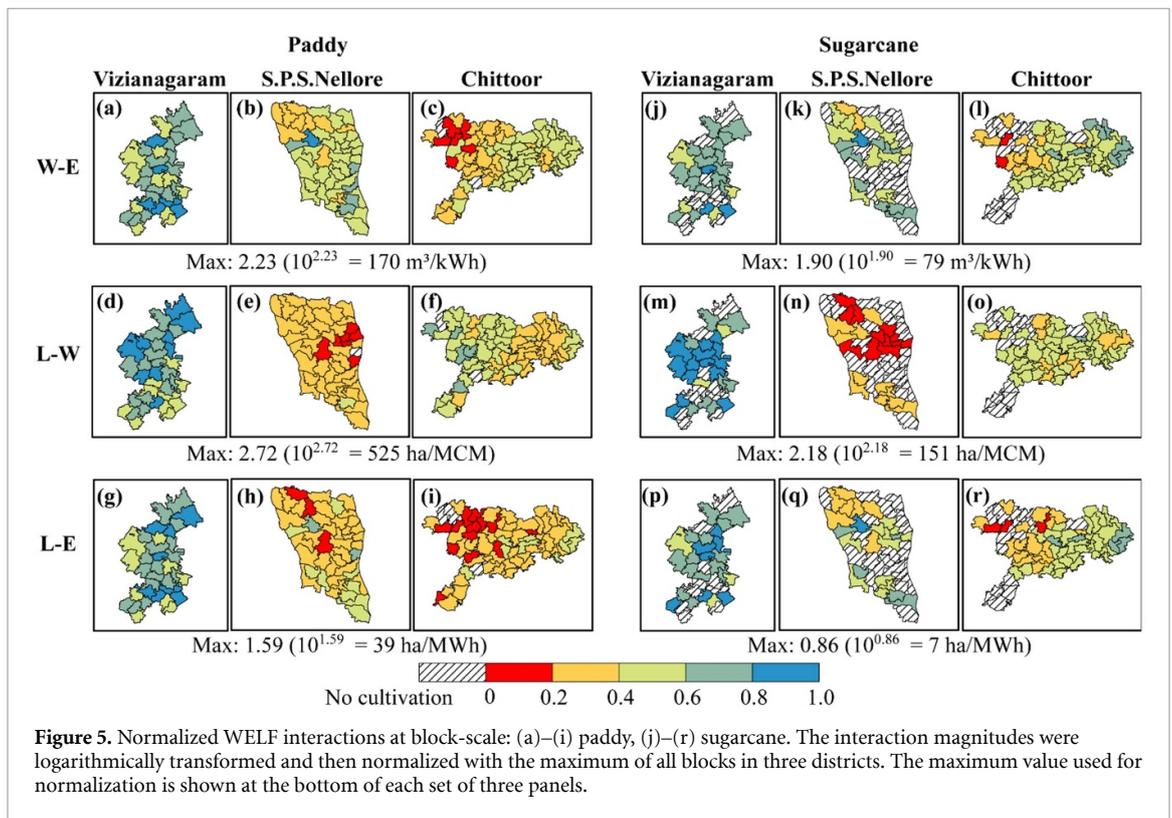
WELF interactions for paddy and sugarcane at the district-scale were computed as explained in the methodology (figure 4; results for other crops are in figures S4–S6). A district was evaluated as a better performer if the magnitude of a particular interaction was higher and vice versa. The F–L interactions for both paddy and sugarcane were fairly uniform across districts (figure 4—panels (b) and (h)). Interestingly, there were relatively fewer differences between the southern and northern regions in F–W and L–W interactions, although the southern districts were relatively worse. The poor performers in F–E, W–E, and L–E were concentrated in the southern districts—Ananthapur, Chittoor, and Y.S.R.Kadapa, indicating deeper groundwater levels. Notably, only those interactions involving energy show marked variability across districts, signaling the need to raise groundwater levels to reduce the energy footprint. Evidently, water-saving methods like drip irrigation could be adapted as a supply-side strategy to relieve the stress on groundwater and thereby enhance the groundwater table, ultimately reducing energy costs (Jain *et al* 2021).

As explained earlier, the GVI was computed for each crop (sample calculations for paddy crop are provided in tables S4–S7), and the district-scale normal scores and GVI are shown in tables S7–S11. A particular region may be classified as vulnerable if its GVI falls below 0 and 'sustainable' if it is above 0. Generally speaking, a region with a positive GVI performs well across all sectors of the WELF nexus and vice versa. In other words, such a region may be more suitable for cultivation of a given crop without adversely impacting other resources. Conversely, a region with negative GVI for a given crop would signify the likelihood of negative consequences on water, energy, or land due to its cultivation.

Of all districts cultivating paddy, the most vulnerable was adjudged to be Ananthapur, while Srikakulam was the most 'sustainable.' Notably, the southern districts of Chittoor, Y.S.R.Kadapa, Ananthapur, Prakasam, and Kurnool had no positive GVI values for all crops. Moreover, we observed that the vulnerable hotspots in water-intensive crops—paddy and sugarcane were collocated, meaning that a vulnerable hotspot in paddy was also a hotspot in sugarcane. The only two exceptions to this observation were West Godavari and Krishna, where cultivating sugarcane was found to be vulnerable. A similar trend was noticed when low water-intensive crops were compared with each other. Therefore, we conclude that the district-level vulnerable hotspots were often independent of crop type.



**Figure 4.** Normalized WELF interactions at district-scale: (a)–(f) paddy, (g)–(l) sugarcane. For a particular interaction (panel), the district values were normalized using the maximum of all districts’ values. Each panel displays the normalized interaction value for each district and the maximum value used to normalize. The maximum value is shown on the bottom right corner of each panel.



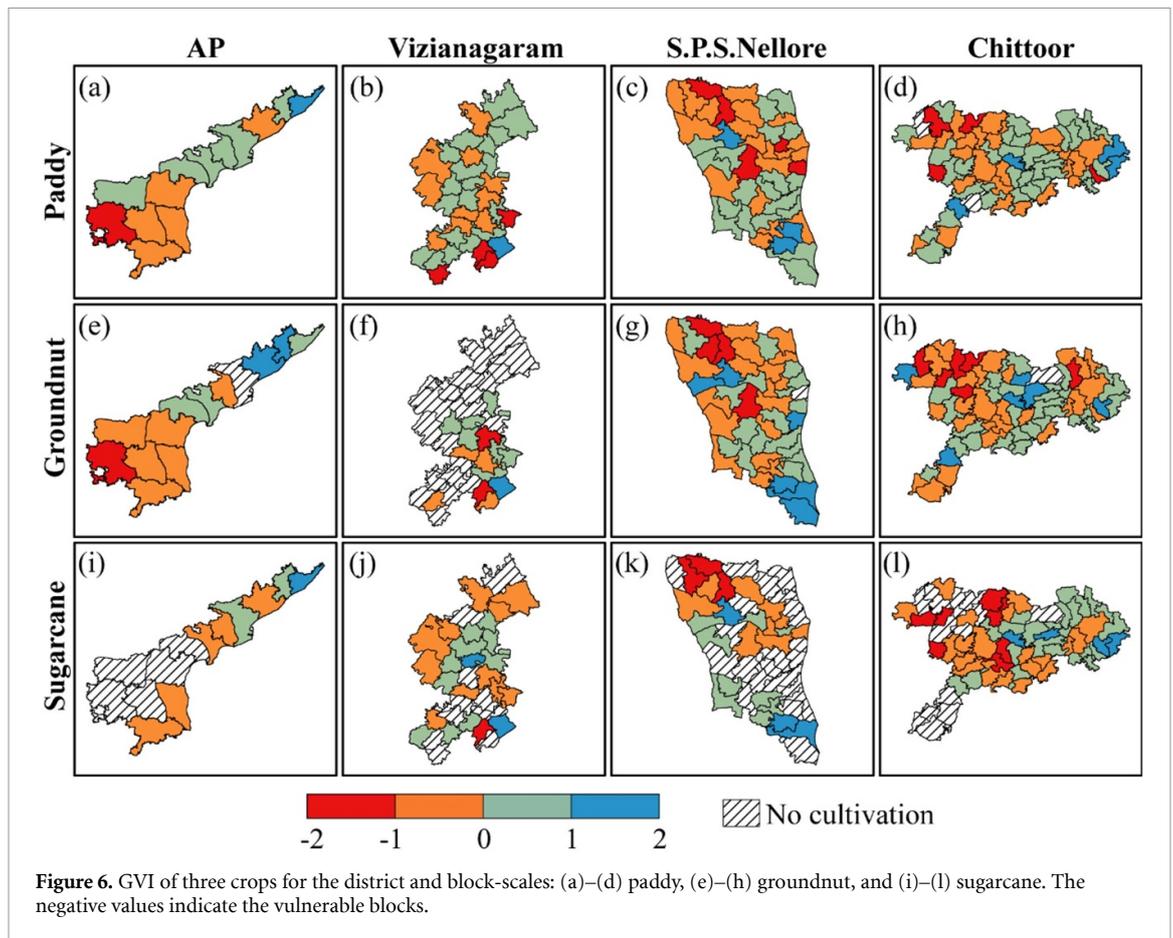
**Figure 5.** Normalized WELF interactions at block-scale: (a)–(i) paddy, (j)–(r) sugarcane. The interaction magnitudes were logarithmically transformed and then normalized with the maximum of all blocks in three districts. The maximum value used for normalization is shown at the bottom of each set of three panels.

### 5.3. Block-scale WELF nexus interactions

This section focuses on the block-scale analysis for the three selected districts for paddy and sugarcane (results for other crops are available in figures S7–S9). The blocks in the Vizianagaram district performed best of the three districts for paddy and sugarcane crops (figure 5). Compared to Vizianagaram District, S.P.S.Nellore and Chittoor had deeper groundwater levels, which worsened the W–E and L–E interactions in the northwestern regions of both districts. On the other hand, poor L–W interactions were observed in the central regions of S.P.S.Nellore (figure 5), which could be attributed to the high  $ET_o$  values

in this region, rendering it vulnerable from an L–W perspective. Apparently, the regions with poor performance in all interactions were not collocated. In such cases, GVI could be used to identify vulnerable regions from a holistic perspective as it encompasses all three interactions.

The block-scale GVI compares the blocks within a district rather than across districts (figure 6). For instance, while Vizianagaram district had positive GVI values for all crops at the district-scale, the block-scale GVI identified those blocks within this district that may be relatively vulnerable. Accordingly, the block-scale GVI values showed that the northern half



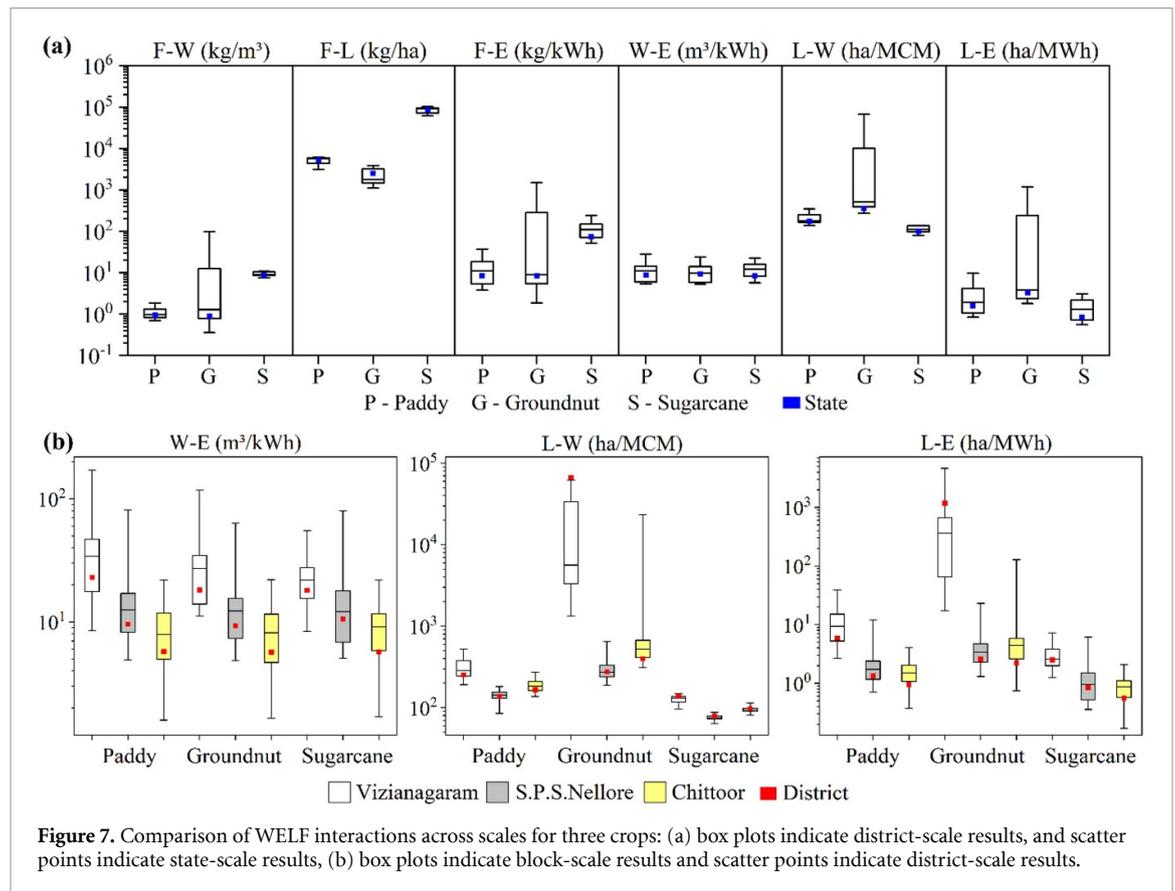
of S.P.S.Nellore and the northwestern blocks in Chittoor were vulnerable for all crops. Several contiguous blocks in the central and eastern Chittoor district were generally 'sustainable' for all crops. Interestingly, vulnerable hotspots at the block-scales were often dependent on the crop type, i.e. a vulnerable hotspot for one crop was not necessarily a hotspot for other crops, which was exactly the opposite of the district-level observation. In summary, this indicates that a coarse-scale analysis may not be sufficient to identify vulnerable hotspots for all crops. Therefore, future nexus studies can not overlook local scale variations in determining vulnerabilities.

#### 5.4. Comparison of interactions across scales

The initial observation from comparing WELF interactions across scales was that the coarse-scale interactions generally underpredicted the finer scale values (figure 7). For instance, while the value of Water-Energy interaction for paddy at the state-scale was 9.0, it varied between 5.4 and 27.8 at the district-scale and 1.6 and 171.1 at the block-scale (all in  $\text{m}^3 \text{kWh}^{-1}$ ). The only exceptions to this observation were the L–W and L–E interactions for the groundnut crop in Vizianagaram district, where the district-scale values ( $66\,786 \text{ ha MCM}^{-1}$  and  $1183 \text{ ha MWh}^{-1}$ ) were an order of magnitude larger than the median of the block-scale values ( $5644 \text{ ha MCM}^{-1}$  and

$360 \text{ ha MWh}^{-1}$ ), respectively. The wide variation in these metrics can be attributed to the finer scale analysis that captured the variabilities in rainfall,  $\text{ET}_0$ , and DGWL, unlike at the coarser scales. The aggregation of variabilities from the finer scale to the coarser scale results in loss of information, which is the main attributing factor for the variation seen in the metrics across scales.

Although coarse-scale estimates can rarely capture the full spectrum of variability at finer scales, this finding may not be relevant for all crops. For sugarcane, the L–W interaction (in  $\text{ha MCM}^{-1}$ ) was 100 at the state-scale and ranged from 79 to 138 at the district-scale. The comparable numbers for paddy were 178 at the state-scale and ranging from 138 to 346 at the district-scale. Interestingly, for groundnut, the L–W interactions were 356 (state), and varied widely over two orders of magnitude from 276 to 66 786 at the district-scale. A similar trend was observed with the district–block comparison (figure 7). This clearly indicates that the finer scale analysis could provide valuable in-depth information for groundnut, but not necessarily for more water-intensive crops like paddy, and especially not for sugarcane. To summarize, this analysis implies that the consequences of overlooking fine-scale variabilities may not be critical for water-intensive crops like sugarcane or paddy. However, for drought-resistant



**Figure 7.** Comparison of WELF interactions across scales for three crops: (a) box plots indicate district-scale results, and scatter points indicate state-scale results, (b) box plots indicate block-scale results and scatter points indicate district-scale results.

crops like groundnut, it is essential to account for local conditions for improving agricultural efficiency.

### 5.5. Limitations

While this study used 0.1° evapotranspiration data to estimate IWR at multiple scales, ET<sub>0</sub> data with even finer resolution could improve the IWR estimates. Further, the WELF nexus analysis was performed using only the groundwater-fed farm acreage. Other farms may also rely on groundwater during extended droughts, which was not included in this study. The energy consumption was calculated using a uniform pumping efficiency of 30% across the entire study area, although pumping efficiencies may change based on the type and age of the pump. Incorporation of detailed pumping efficiency data across the study region would further improve the insights from this analysis. Additionally, food production data was not available at block-scales, which hampered the calculations of block level food-related interactions. This analysis focused only on the role played by WELF in agricultural systems; other significant elements like labor, climate, and economy were not included, whose addition may further improve the understanding gained by this study.

## 6. Conclusions

This study represented a systematic attempt to evaluate the efficacy of multiscale WELF nexus studies.

In particular, this study computed the groundwater and energy consumption for five major crops in the southern Indian state of AP at multiple scales. We used FAO's CROPWAT model to estimate the groundwater use, and thereby the energy consumption for the cultivation of five major crops at three distinct spatial scales between 2017 and 2019. We computed six WELF interactions for all crops and evaluated the performance of each region. The individual WELF interactions were integrated by developing a GVI that was used to identify vulnerable hotspots from a nexus perspective. Our multiscale analysis identified the regions that accounted for the largest groundwater and energy consumption, which were also adjudged to be vulnerable hotspots. Interestingly, we found that for crops like groundnut, a finer scale analysis may be vital for evaluating its agricultural efficiency. Conversely, relatively coarser analyses may be sufficient for water-intensive crops like paddy and sugarcane. Another interesting insight from this study was that vulnerable hotspots at fine-scales depended on the crop type. In other words, a hotspot for sugarcane need not necessarily be a hotspot for paddy and vice versa. Policymakers can benefit from such insights to devise strategies for crop-shifting that could help achieve overall agricultural sustainability. Bridging the disconnect between global and local sustainability will require a hierarchy of strategies cutting across all relevant spatial and temporal scales. While this study focused

on groundwater-fed agriculture, this approach can be extended to surface water-fed/rainfed agriculture also, as well as related sectors such as livestock breeding and biofuel production. Future work must also include additional factors such as climate change, economy, and ecosystems to holistically assess agricultural sustainability.

### Data availability statement

No new data were created or analysed in this study.

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