A Data-intensive Approach for Evaluating Water-Energy-Land-Food Nexus at Multiple Scales

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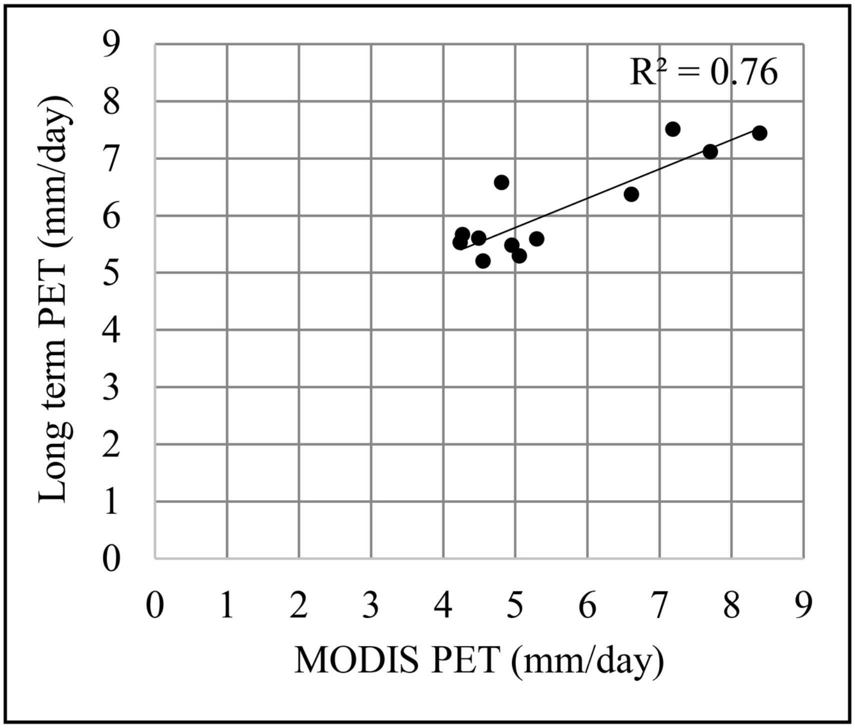
Abstract

Satisfying global food demand places a significant burden on finite resources like water, energy, and land across the world. Ensuring sustainable food production requires an understanding of water, energy, and land at local scales, which is often hampered by the lack of detailed data. Taking advantage of several large datasets, this study focused on the interactions between groundwater, energy, land, and food (WELF) at multiple spatial scales in the Indian state of Andhra Pradesh. Using FAO's CROPWAT model, MODIS evapotranspiration data, and a detailed multiscale agricultural database, we estimated the irrigation water requirements at multiple spatial scales. A detailed estimate of groundwater and energy consumption was obtained, which was used to infer the interactions between WELF. The results from our study allow us to identify local and regional hotspots of groundwater and energy consumption. Our results indicate that regional estimates of groundwater or energy consumption, while indicative of local conditions, are unable to capture the variations at finer scales. The interactions between WELF at multiple scales also indicate that the efficiency of groundwater and energy consumption for various crops varies widely across and within regions. Our study highlights the need to more effectively manage the cultivation of water-intensive crops such as paddy and sugarcane to optimize groundwater consumption. Policy-makers must focus on transitioning towards sustainable agriculture that prioritizes food and water security. Future research must take advantage of extensive datasets to better evaluate the adverse effects on water and energy resources to ensure sustainable food production.


R² = 0.76
Long term PET (mm/day)
MODIS PET (mm/day)
0
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A Data-intensive Approach for Evaluating Water-Energy-Land-Food Nexus at Multiple Scales

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Key Points:

- Developed quantitative metrics for evaluating Water-Energy-Land-Food nexus across multiple scales
- Local estimates of groundwater consumption are considerably higher than regional estimates (~21%)
- Local nexus among WELF may help tailor the policies for global sustainable food production.

Abstract

Satisfying global food demand places a significant burden on finite resources like water, energy, and land across the world. Ensuring sustainable food production requires an understanding of water, energy, and land at local scales, which is often hampered by the lack of detailed data. Taking advantage of several large datasets, this study focused on the interactions between groundwater, energy, land, and food (WELF) at multiple spatial scales in the Indian state of Andhra Pradesh. Using FAO's CROPWAT model, MODIS evapotranspiration data, and a detailed multiscale agricultural database, we estimated the irrigation water requirements at multiple spatial scales. A detailed estimate of groundwater and energy consumption was obtained, which was used to infer the interactions between WELF. The results from our study allow us to identify local and regional hotspots of groundwater and energy consumption. Our results indicate that regional estimates of groundwater or energy consumption, while indicative of local conditions, are unable to capture the variations at finer scales. The interactions between WELF at multiple scales also indicate that the efficiency of groundwater and energy consumption for various crops varies widely across and within regions. Our study highlights the need to more effectively manage the cultivation of water-intensive crops such as paddy and sugarcane to optimize groundwater consumption. Policy-makers must focus on transitioning towards sustainable agriculture that prioritizes food and water security. Future research must take advantage of extensive datasets to better evaluate the adverse effects on water and energy resources to ensure sustainable food production.

Plain Language Summary

1. Introduction

Agriculture is the world's largest freshwater consumer, accounting for 70% of global withdrawals (FAO, 2011), which is projected to increase further in the coming decades to satisfy rising global food demand (Alexandratos & Bruinsma, 2012). As the world population is expected to hit 9.7 billion by 2050 (UN, 2019), there will be substantial stresses on finite resources like water, energy, and land (Marris, 2008; FAO, 2011; Ringler et al., 2013). Groundwater is one of these finite resources, which has been persistently overexploited for agriculture worldwide, particularly in South Asia (Siebert et al., 2010; Wada et al., 2010; Gleeson et al., 2012; Bierkens & Wada, 2019). Though groundwater irrigation has improved farmers' economic stability, several aquifers in the world have been overstressed (Scott and Shah, 2004; Zaveri et al., 2016). Groundwater overdraft has several adverse effects, such as declines in groundwater levels, soil infertility, land subsidence, and damage to riparian ecosystems (Konikow and Kendy, 2005; Sophocleous, 2005; Giller et al., 2009; Perrone and Jasechko, 2019). Declining groundwater levels intensify the energy consumption for agriculture as the energy use depends principally on the depth to the groundwater level. Additionally, the provision of subsidized electricity has accelerated the decline of groundwater levels to as high as 0.3 m/year in countries like India (Rodell et al., 2009; World Bank, 2015). Consequently, such regions will likely increase greenhouse gas emissions and associated energy costs, thereby enlarging the carbon footprint from agriculture (Mishra et al., 2018). For example, the Indian state of Punjab has witnessed a drop of 5.47 m in groundwater levels over 14 years (1998 – 2012), resulting in increased energy requirements and carbon emissions by 67% and 110%, respectively (Kaur et al., 2016).

The introduction of bore wells to cultivate staple crops like paddy and wheat acted as an engine of growth for irrigated agriculture (Pingali, 2012; Zaveri & B. Lobell, 2019; Dangar et al., 2021). The chronic over-exploitation has pushed groundwater out of reach for millions of farmers in countries like India and Pakistan (Shah et al., 2003). Tube wells, particularly in the arid and semi-arid regions, are no longer able to sustain water for the cultivation or for drinking water supply (Hora et al., 2019). Dwindling groundwater quality, due to the upwelling of salt from deep groundwater, is another indicator of unsustainable pumping (Bhatt et al., 2016). Many studies have demonstrated the difficulty in recovering lost groundwater storage (Udmale et al., 2014; Barik et al., 2017). Furthermore, in agrarian countries like India, the energy consumption for agriculture has increased considerably at a compound annual growth rate of 5.6% (Kaur et al., 2016). Green House Gases (GHG) emissions due to the energy utilized from agriculture account for roughly 6% of India's emissions (Shah, 2009). In India, the depleting groundwater levels are widespread in these states: Punjab, Rajasthan, Maharashtra, Gujarat, Andhra Pradesh, and Telangana (Shah, 2009; Rosa et al., 2019). Official data (Ministry of Jal Shakti, 2020) on the numbers of deep tube wells across India show an alarming increase since the 1990s (Figure 1). The importance of limiting the extraction of deep groundwater can hardly be overemphasized.

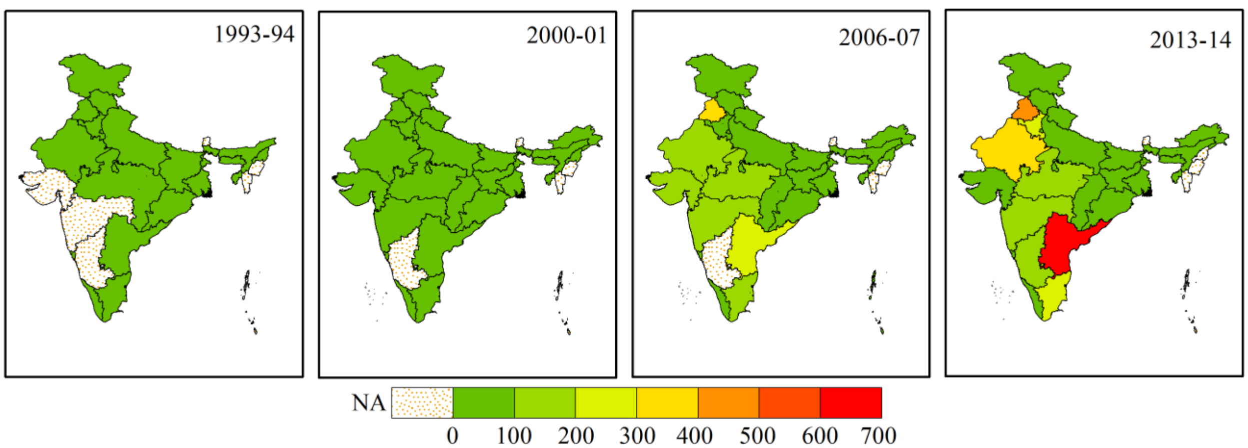

Figure 1: Spatiotemporal trend of increase in numbers of deep tube wells (in 1000s) across India.

Climate change further exacerbates the current situation in the form of higher water demands and reduced crop efficiencies (FAO, 2011; Mancosu et al., 2015; Jain et al., 2021). In tropical countries, the predominant smallholder farming is likely to be highly vulnerable to climate change (Morton, 2007). Additionally, with growing urbanization, and declining soil fertility, there is enormous pressure on the preservation of existing agricultural land (Konikow & Kendy, 2005; Giller et al., 2009; Di Baldassarre et al., 2019). Recent approaches such as conservation agriculture, sustainable intensification, and nutrition-sensitive agriculture are helping to address these multisectoral challenges by improving water management, enhancing soil fertility, and increasing food production (Hobbs et al., 2008; Garnett et al., 2013; FAO, 2014; Cassman & Grassini, 2020; Sampath et al., 2020). However, rates of adoption of these agricultural techniques are rather slow in Asian and African countries (Kassam et al., 2019). Consequently, high levels of undernourishment and hunger are prevalent in these countries (FAO, 2019). Therefore, there is a need to address these multiple challenges cutting across water, energy, land, and food in a holistic manner to make agriculture more sustainable.

1.1. WELF nexus

United Nations has formulated sustainable development goals (SDGs) to address humanity's global challenges (UN, 2015). An integrated approach based on how water resources are connected to other sectors is essential to achieve these goals (Di Baldassarre et al., 2019). However, the inability to quantify connections between different sectors and scales remains a challenge in ensuring resource security and often threatens the equitable distribution of resources among various stakeholders (Hoff, 2011; Bazilian et al., 2011; Endo et al., 2020). Hence, understanding the inter-linkages through the nexus lens has become necessary for enhancing overall sustainability (Ringler et al., 2013; Biggs et al., 2015; Kurian, 2017; Shannak et al., 2018; Nhamo et al., 2018). The synergies and trade-offs between these sectors have been studied in many parts of the world. For example, a study carried out in the Mediterranean region identified hotspots using water and energy productivity, and it was illustrated that irrigation modernization in this region could reduce 8 km^3, but at an increase of 135% in CO_2 emissions (Daccache et al., 2014). Likewise, a case study in Qatar demonstrated that the explicit quantification of connections among WELF guides the decision-making process, and shown that food self-sufficiency strategies are highly sensitive to WELF interactions (Daher & Mohtar, 2015). Despite such studies, the synergies among WELF resource sectors in South Asia have not yet been fully harnessed (Rasul et al., 2019). For instance, India, despite being the world's leading groundwater consumer and the country with the largest area equipped for irrigation (Siebert et al., 2010; Margat & Van der gen, 2013), is also home to almost 200 million malnourished people and 820 million people that live in water-scarce regions (FAO, 2019; CWMI (NITI Aayog), 2019). A recent report warned that India is facing its worst water crisis in history, with groundwater resources diminishing at unsustainable rates (CWMI (NITI Aayog), 2019).

Studies have shown that the net global groundwater consumption is driven by a few heavily exploited hotspots like the Upper Ganges, High Plains, and North China Plain (Gleeson et al., 2012). Intensive cultivation of staple cereals, such as rice and wheat, drives the groundwater consumption at these hotspots (Davis et al., 2019). A few potential improvements in these hotspots can help reduce global groundwater consumption, thereby achieving local, regional, and global sustainability. Though many efforts have been made to understand the inter-linkages between global resources, it is often challenging to capture nexus at smaller scales (Endo et al., 2015). A lack of coordination between multiple levels due to “silo” approaches results in unsustainable resource management (IRENA 2015; Nhamo et al., 2018). Many studies have stressed the need to understand and quantify connections between multiple scales (Ringler et al., 2013; Garcia and You, 2016; Endo et al., 2017; Gaddam & Sampath, 2020). However, data are usually aggregated at national levels (Perrone et al., 2011), making it challenging to tailor policies to local realities (Biggs et al., 2015; Conway et al., 2015). Local-scale data, when available, usually lacks spatiotemporal resolution, and thus limits fine-scale analysis, resulting in a ‘black-box’ perspective (Mcgrane et al., 2018). Recent advances in geospatial data collection are making multiscale analyses possible, which allows for a better understanding of WELF interactions across spatial scales.

This study's main objective is to adopt a multiscale approach to assess the interactions between WELF using detailed agricultural data. The Indian State of Andhra Pradesh is selected for this study due to the availability of vast datasets in this region. The specific objectives of the current study are:

1. To estimate the groundwater and energy consumption at multiple spatial scales from 2014-2019.

2. To quantify the interactions between groundwater consumed (W), energy utilized (E), land cultivated (L) and food produced (F), and identify the vulnerable hotspots pertaining to various interactions at multiple scales.

3. To compare the multiscale estimates of groundwater and energy consumption and interactions among WELF for multiple years.

This study's findings will be of significance to researchers and policy-makers in understanding and managing scarce natural resources across multiple spatial scales. It is envisaged that this study will help in quantifying the vital role of detailed local scale information in estimates of groundwater and energy consumption in food production.

2. Materials and Methods

2.1. Groundwater and energy consumption

We selected the South Indian state of Andhra Pradesh as our study area for this analysis (Figure 2). The state covers more than 160,000 km^2 (DES-AP, 2017) and has thirteen districts, which are further subdivided into several blocks. Agriculture is the state's primary occupation, employing 60% of the population and accounting for almost 40% of the total geographical area (DES-AP, 2017). The state receives, on average, 970 mm of rainfall annually, mostly between June and December from the southwest and northeast monsoons (DES-AP, 2017). The agricultural year is primarily divided into two seasons - Summer/*Kharif* (June to September) and Winter/*Rabi* (October to March). For the current analysis, Kharif season was selected to evaluate the WELF interactions for all districts in the state (district-scale), and all blocks in a district (block-scale). While the district scale analysis was carried out for six years (2014-19), the block-scale analysis was studied only for one year (2017-18) due to the unavailability of detailed data.

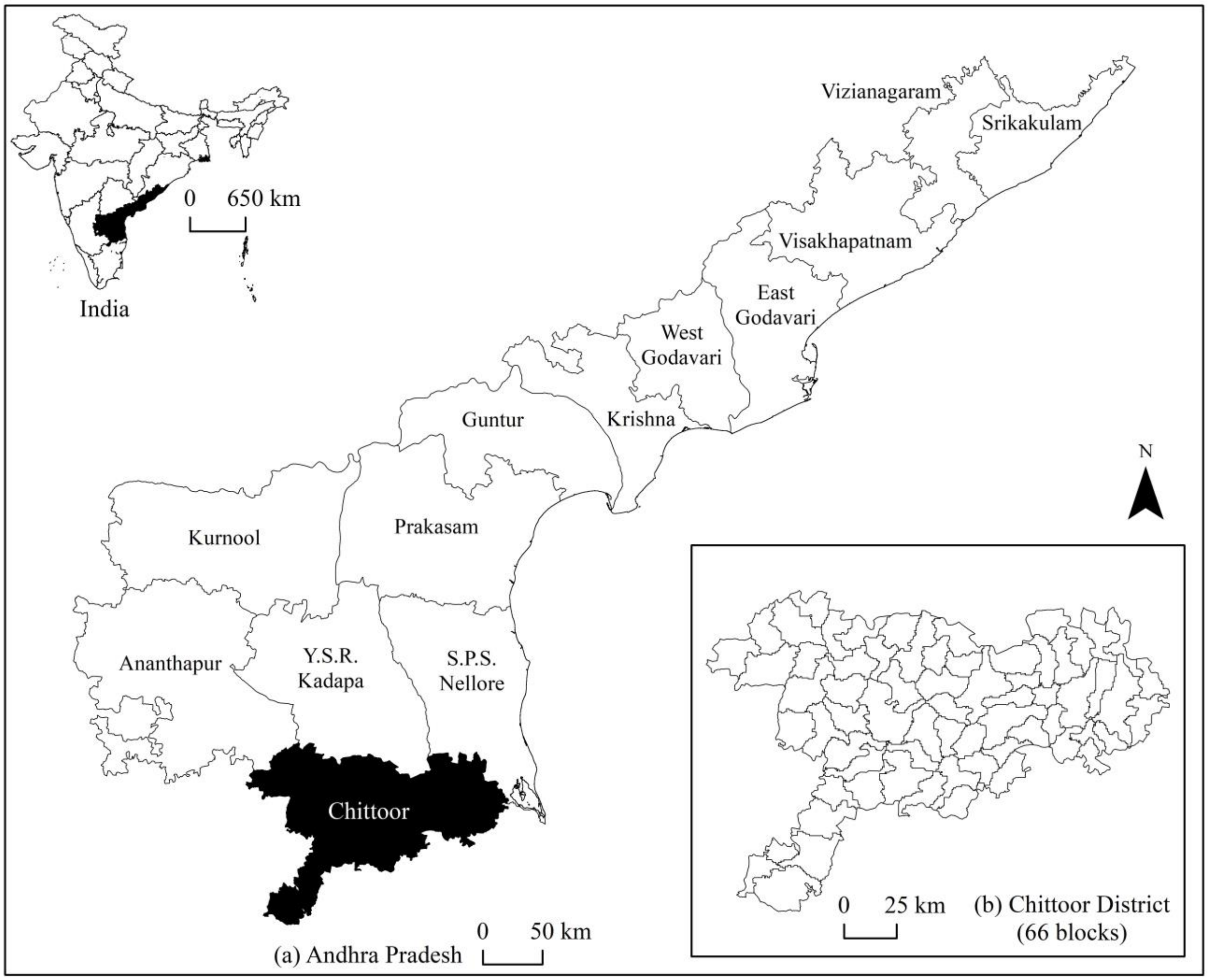

Figure 2: Study area at multiple scales: (a) State of Andhra Pradesh and (b) Chittoor district

This study uses the CROPWAT 8.0 model (Smith, 1992) to estimate irrigation water requirements for various crops at multiple scales. CROPWAT 8.0 implements a soil water balance approach to assess each crop's crop water requirements using the following information: rainfall, reference evapotranspiration (ET_o), soil, and crop characteristics. At both district and block scales, these variables were inferred appropriately from the available data.

Table 1: Data availability at district and block scales

S No	Data	Resolution	Scales	Attributes	Source
1	Agriculture	Farm level (2014-19)	Block-scale District-scale	Crop type, acreage, sowing date, source of irrigation, location of the farm	(CORE, 2018)

2	Production	District-level (2014-19)	District-scale	Crop-wise production and productivity data	(DES-AP, 2020)
3	MODIS Evapotranspiration (ET)	500 m (2014-19)	Block-scale District-scale	Potential Evapotranspiration (PET)	(Running et al., 2017)
4	Long-term PET	District-level (1901-2002)	Block-scale District-scale	Potential and reference ET	(India Water Portal, 2020)
5	Rainfall	Station-wise (2014-19)	Block-scale District-scale	Rainfall data	(WRIS, 2020)
6	Groundwater levels	Station-wise (2014-19)	Block-scale District-scale	Observed Depth to Groundwater Level (DGWL) data	(WRIS, 2020)
7	Borewell depth	Farm-level (2017-18)	Block-scale District-scale	Bore depth, location of well	(GWAD, 2020)

To gather the ET_0 information, we used the long-term ET data that was derived from long-term weather parameters (India Water Portal, 2020) to calculate the minimum, average, and the maximum ratios of ET_o to PET. These ratios were then multiplied with MODIS PET data to estimate minimum, average, and maximum ET_o data for district and block scales. The purpose of generating three ET_o estimates was due to the unavailability of weather data at finer scales, which is typically used to calculate ET_o. The comparisons of the available long-term PET and MODIS PET are available in the supplementary information (Figure S1). These two datasets compare reasonably well with an R^2 of 0.76.

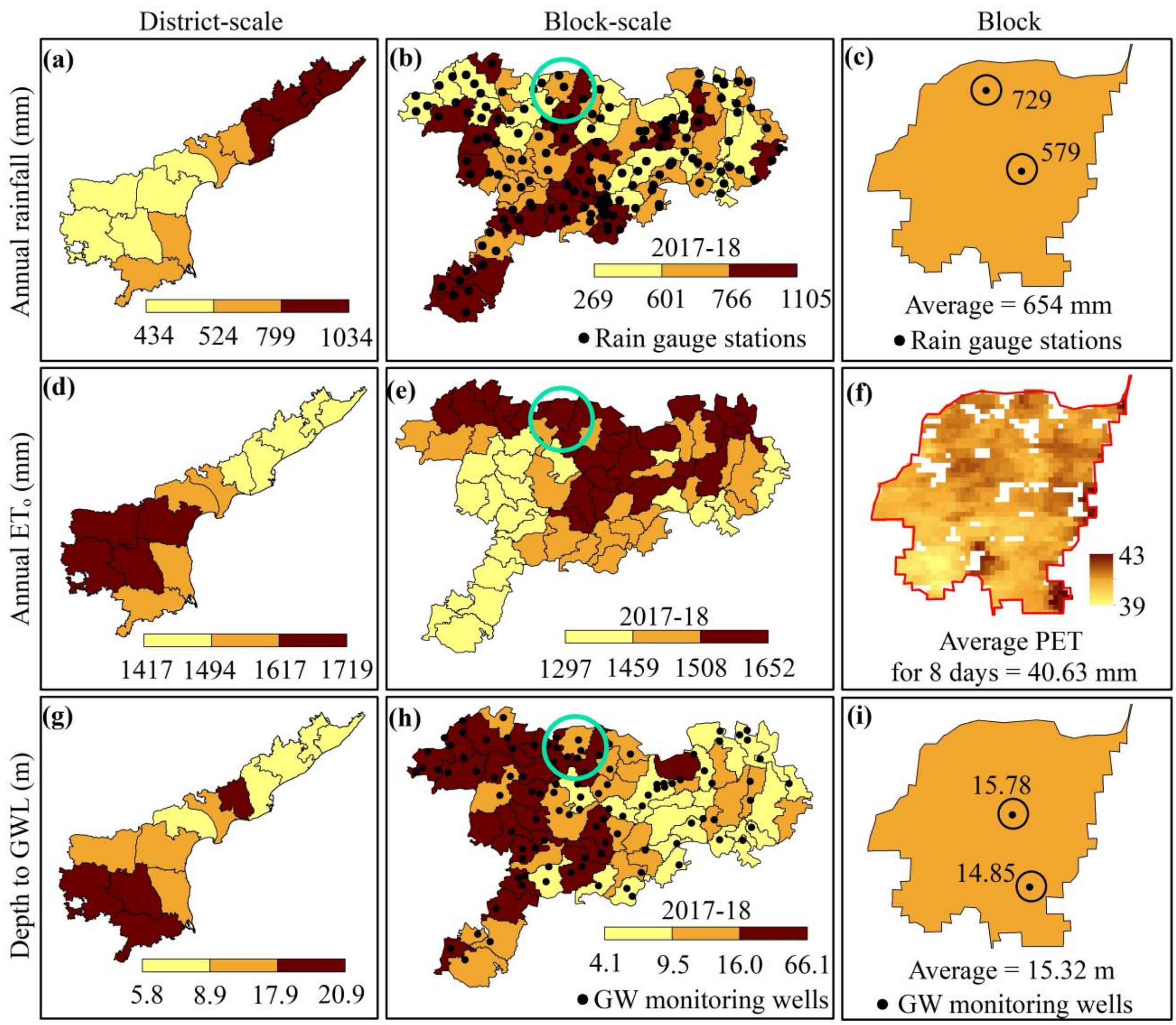

Figure 3: Annual rainfall, annual ET_o, and average depth to GWL data at district and block scales.

The rainfall, ET_0, and depth to GWL plots are shown in Figure 3, which denotes their variation across and within districts. At every spatial scale, the arithmetic average of recorded rainfall/ET_o/GWL was considered to be representative of that scale. For instance, if a district contains N rainfall gauges, its rainfall was simply the arithmetic average of the rainfall recorded in all those gauges. Further, district-level agricultural data was collected, along with the block-level crop data that involves crop type, cultivated area, sowing date, and source of irrigation, was aggregated using an intensive farm-scale database (> 6.6 million farms) (CORE, 2018). This exhaustive local-scale information facilitated the assessment of groundwater and energy consumption at finer scales. These data were incorporated into the CROPWAT model, and the resulting water requirements (mm) for each crop were calculated. Further, the water requirements were multiplied with the acreage under groundwater irrigation for the corresponding crop, to estimate the volume (m^3) of groundwater consumption. Table 2 lists the area under cultivation for 14 major crops grown in the study area. Note that not all crops are grown in a given block within the district.

Table 2: Major crops grown in the study area in the Kharif season. Note that the value for the entire state of Andhra Pradesh refers to the average of crop acreage across 6 years (2014-19), and the values for Chittoor district are for the year 2017-18. Both columns correspond to areas under groundwater irrigation.

Crop	**Groundwater-fed acreage (ha)**	
	State of Andhra Pradesh	**Chittoor District**
Bajra (Pearl millet)	4906	2049
Bengal gram	21166	-
Black gram	18176	139
Chilies	50946	-
Cotton	40868	-
Green gram	1978	23
Groundnut	31657	8216
Horse gram	124	58
Jowar (Sorghum)	641	-
Maize	15946	598
Paddy	248494	12532
Raagi (Finger millet)	600	243
Red gram	5750	108
Sugarcane	47003	17075

Crop water requirements were estimated using the minimum, average, and maximum ET_o data for the *Kharif* season of the year 2017-18. The final crop water requirements were estimated from the average of these three simulations. Consequently, the energy utilized to extract this quantum of water from the groundwater level was computed using the following equation:

$$E = \frac{\rho g V H}{\eta} - - - [1]$$

where, E = Energy consumed [ML^2T^{-2}]; ρ = density of water [ML^{-3}]; g = acceleration due to gravity [LT^{-2}]; V = volume of groundwater consumption [L^3]; H = Depth to groundwater level [L]; η = Pumping efficiency, assumed at 30% (Shah et al., 2007; Mishra et al., 2018).

2.2. WELF Interactions

Using the estimated groundwater (W) and energy (E) consumption estimates along with the land under cultivation (L) and the production (F) of each crop, the following three metrics were developed to quantify the interactions between WELF (Figure 4). They include 1. Food-Water, 2. Land-Water, and 3. Water-Energy. Each metric quantifies the interactions and analyzes the nexus between the various parameters as follows:

$$\text{Food} - \text{water (F} - \text{W) interaction} \left(\frac{\text{kg}}{m^3}\right) = \frac{\text{Crop produced (kg)}}{\text{GW consumed } (m^3)} - - - [2]$$

$$\text{Land} - \text{Water (L} - \text{W) interaction} \left(\frac{\text{ha}}{m^3}\right) = \frac{\text{Crop acreage (ha)}}{\text{GW consumed } (m^3)} - - - [3]$$

$$\text{Water} - \text{Energy (W} - \text{E) interaction} \left(\frac{m^3}{\text{kWh}}\right) = \frac{\text{GW consumed } (m^3)}{\text{Energy used (kWh)}} - - - [4]$$

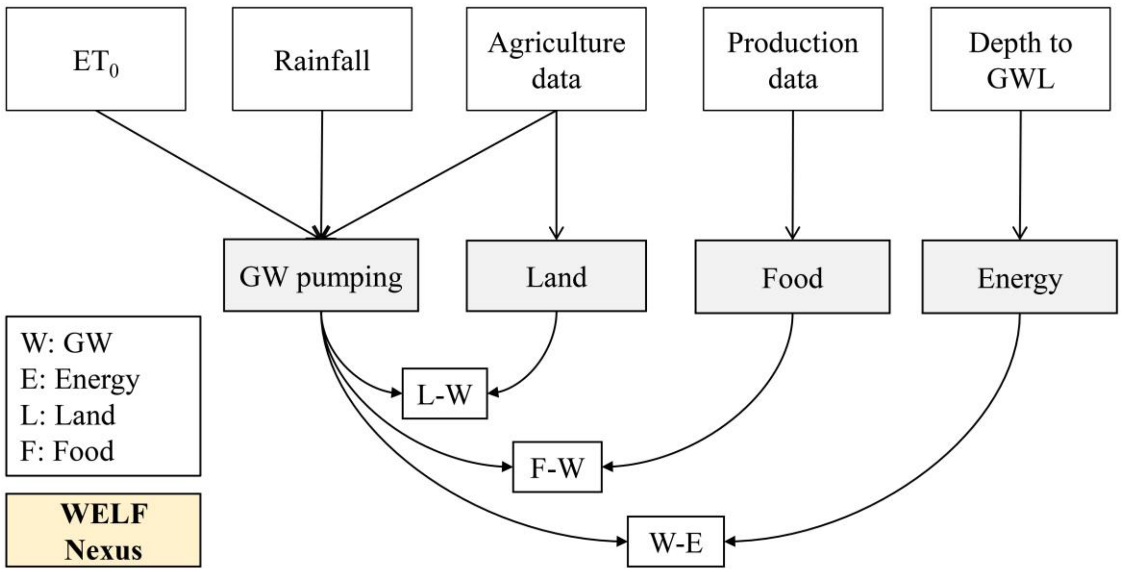

Figure 4: Conceptual workflow for formulating WELF nexus; W: Groundwater consumed, E: Energy used, L: Land utilized, and F: Food produced.

These metrics employ the commonly-used 'two at one-time' analysis (Taniguchi et al., 2017) to evaluate two-way interactions among WELF. The developed metrics assess the productivity of a resource with respect to another resource. For example, the Food – Water interaction metric measures the efficiency of crop production corresponding to the total volume of groundwater consumed in its crop period. Larger values indicate better performance of that interaction in a particular region. These metrics can be applied across multiple scales, thereby also allowing comparison across scales. Further, the estimated metrics at multiple scales can help identify vulnerable hotspots, where policies can be customized to the local challenges. Due to the unavailability of food production data at block scales, the interactions involving food were calculated at the district level only.

To develop further insights into the WELF interactions, the three WELF metrics were compared to three indices: 1. Aridity index (UNDP, 1992),2. Groundwater Irrigation Index (GII), and 3. Groundwater Sustainability Index (GSI). Aridity index is defined as the ratio of annual precipitation to annual PET, which is used to identify the extent of dryness of climate. We define GII as the ratio of area irrigated by groundwater to the total area under cultivation in a given region, which can identify the extent of dependence on groundwater for cultivation. We also define GSI, which was the ratio of number of shallow wells (defined as those wells of depth less than 100 feet) to the total number of wells in a region. This index is hypothesized to indirectly infer the sustainability of groundwater irrigation, i.e., a region with a larger fraction of shallow wells uses groundwater more sustainably than a region with a smaller fraction. Comparing these indices to the WELF metrics may help derive insights at both district and block-scales and provide a theoretical framework for understanding and managing the vulnerable hotspots.

3. Results

3.1. Groundwater and energy consumption

Irrigation water requirements (IWR) of each crop in all districts were calculated for six years, from 2014 to 2019 (see Figure S2). The spatial distribution of IWR for three major crops at both block and district scales – groundnut, paddy, and sugarcane are shown in Figure 5. As shown in Figure 3, the southern regions receive less rainfall, and as a result, the IWR in these districts were consistently higher than in the northern districts. Consequently, the number of borewells in the southern districts is much larger.

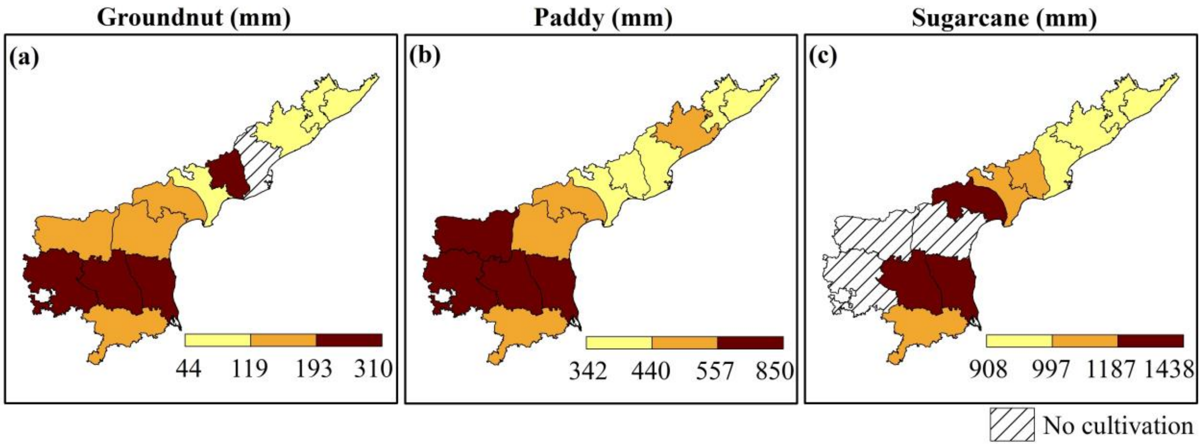

Figure 5: Average of **i**rrigation water requirements (mm**)** for three major crops – groundnut, paddy, and sugarcane from 2014 to 2019

The estimated IWR values were multiplied by groundwater-fed irrigation area to estimate the groundwater volume consumption for each district from 2014 to 2019 (See Figure S3). Figures 6b and 6c shows the spatial distribution of average groundwater and energy consumption across the study area. Note the higher groundwater consumption in the southern districts compared to the northern districts. At this relatively large scale, these southern districts are hotspots of high groundwater consumption. Though the northern coastal districts largely cultivate paddy, their dependence on surface water sources and rainfall, as shown in Figure 6a, results in low groundwater use.

Overall, paddy, maize, and sugarcane account for more than 80% of total groundwater and energy consumption. As shown in Figure 6c, southern districts consume a higher proportion of the total energy as compared to the proportion of groundwater due to deeper groundwater levels in these regions. Further, West Godavari and Chittoor districts are “energy hotspots” as they account for more than 40% of total energy consumption. To escape from the downward spiral of higher groundwater use and corresponding higher energy costs, it is imperative to drastically reduce the cultivation of water-intensive crops like paddy and sugarcane in the southern districts. Such regions have the potential to reduce the carbon footprint of the overall state by optimizing cropping patterns to minimize groundwater consumption.

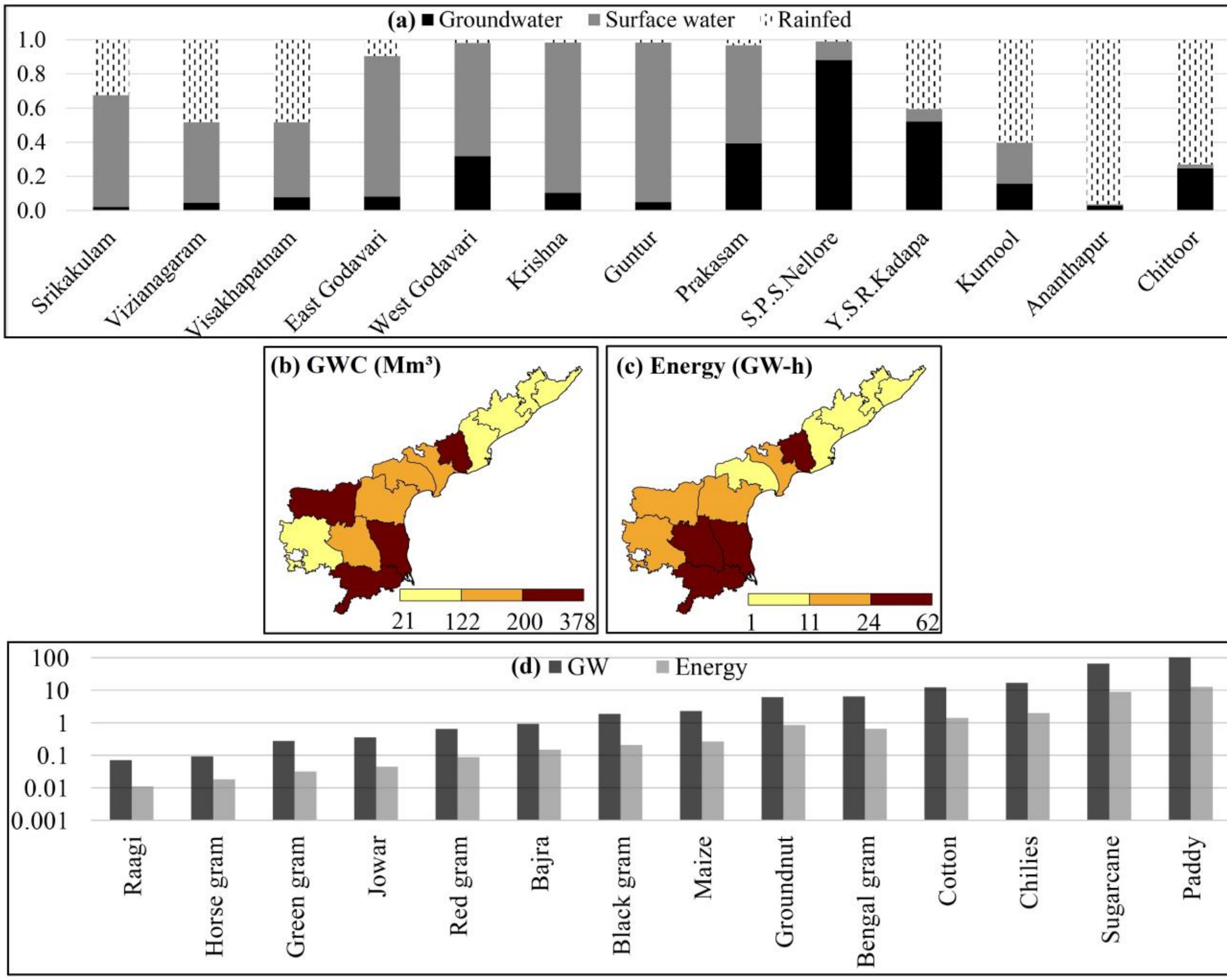

Figure 6: District-wise: (a) Proportion of groundwater-fed, surface water-fed, and rainfed acreage (b) Groundwater consumption estimates (Mm^3), (c) Energy consumption estimates (GW-h), and (d) Crop-wise estimates of groundwater (Mm^3) and energy consumption (GW-h)

Chittoor district, a regional hotspot of high groundwater and energy consumption, was considered for further detailed analysis, and the corresponding results are presented in Figure 7. The district has 66 blocks, out of which 12 blocks consumed more than half of the total groundwater in the district. Interestingly, these blocks accounted for more than half of the sugarcane acreage in the district. This result exemplifies the prominence of sugarcane in understanding the groundwater consumption patterns within the district. Indeed, Chittoor district ranks first in groundwater-fed sugarcane production in the state. On closer examination of the results, paddy and sugarcane accounted for 72% of total groundwater-fed acreage but consumed 91% of all the groundwater in the district. As seen in Figure 7, paddy and sugarcane were predominant in the eastern part of the district, and accordingly, the magnitudes of groundwater and energy draft were higher in these regions. In Figure 7, a clear demarcation of groundwater consumption zones can be observed between the western and eastern parts. In spite of relatively low groundwater use in the western part of the district, groundwater levels are almost 80 – 100 m below ground level in some parts, which can be attributed to a combination of low annual rainfall and high evapotranspiration. Rather than developing policies for the entire district as a whole, it is important to tailor policies to account for such variability at finer scales.

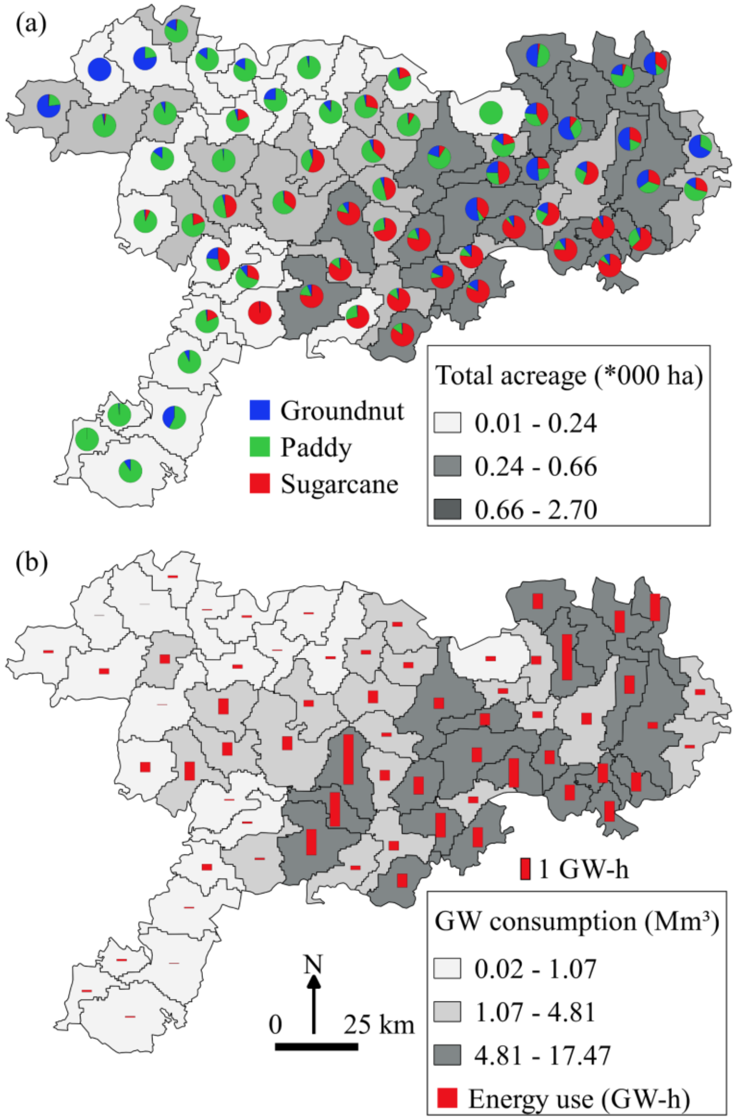

Figure 7: Groundwater-fed acreage, groundwater and energy consumption in Chittoor district. Panel a shows the total groundwater-fed acreage at the block scales, with pie charts indicating proportions of groundnut, paddy, and sugarcane. Panel b shows the groundwater (Mm^3) and energy (GWh) consumption at the block scales.

3.2. WELF interactions

After estimating the groundwater and energy consumption at the block and district-scales, we focused on the interactions among groundwater consumption, energy use, land utilized, and food produced. District scale interactions among WELF were calculated using the three metrics mentioned in Section 2.2. The metrics were computed for each year from 2014 to 2019 (see Figure S4), and then averaged to represent the entire duration. Figure 8 shows the three metrics for the major crops: groundnut, paddy, and sugarcane. Overall, the different metrics highlight various aspects of productivity. As depicted in Figure 8, two districts (Ananthapur & Y.S.R.

Kadapa) showed poor performance in all metrics. All other districts showed varying levels of performance in one or other metrics, indicating that groundwater consumption efficiency with respect to the other three elements – energy, land, and food changes across regions. Quantitatively, the groundwater consumption in Krishna district is 1.3 times higher than in Guntur district. However, the amount of groundnut produced in kg per unit volume of water in Krishna district is 2.2 times higher than Guntur. This shows that Krishna district is utilizing its groundwater more efficiently than Guntur. Nonetheless, the energy consumption in Krishna district is 1.4 times more than that in Guntur. Such insights demonstrate that the conventionally-used 'silo' approaches may not be sufficient to design policies that ensure overall sustainability.

In the case of the most-grown crop - paddy, the performance of interactions in the southern districts was quantitatively poorer than the northern coastal districts, as shown in Figure 8. Srikakulam district was the most productive on all fronts, signifying that abundant rainfall brings about the scope to cultivate more water-intensive crops. East and West Godavari districts, although adjacent to each other, are markedly different in their energy efficiencies for paddy cultivation (the latter performs poorly compared to the former). This variation can be attributed to the deeper groundwater levels in the West Godavari district. Despite performing poorly in terms of energy, West and East Godavari districts' performance in other interactions was alike since both districts received similar rainfall levels. These key messages indicate that West Godavari district is more vulnerable from an energy perspective, which may require attention for policy-makers. While Chittoor district is among the better performing districts with respect to the F-W metric for paddy, it is among the worst performers in the W-E metric for the same crop. Several southern districts also had greater depths to groundwater and consequently are vulnerable from the point of view of energy consumption. Policy-making in these regions must focus on promoting crops that require less water like millets and groundnut (Sampath et al., 2020) to reduce the energy footprint as well as improving groundwater recharge measures.

For sugarcane, the performance of most districts is similar to that of paddy. In general, the northern districts have higher productivities than the southern districts due to higher rainfall amounts and shallower groundwater levels in the north. As explained earlier, sugarcane cultivation in Chittoor district has a drastic impact on groundwater and energy consumption. Similar adverse effects due to excessive sugarcane cultivation have been observed in other Indian states as well (Krishan et al., 2016; Shah et al., 2018). Clearly, a more robust policy on sugarcane cultivation in the context of groundwater and energy costs is required.

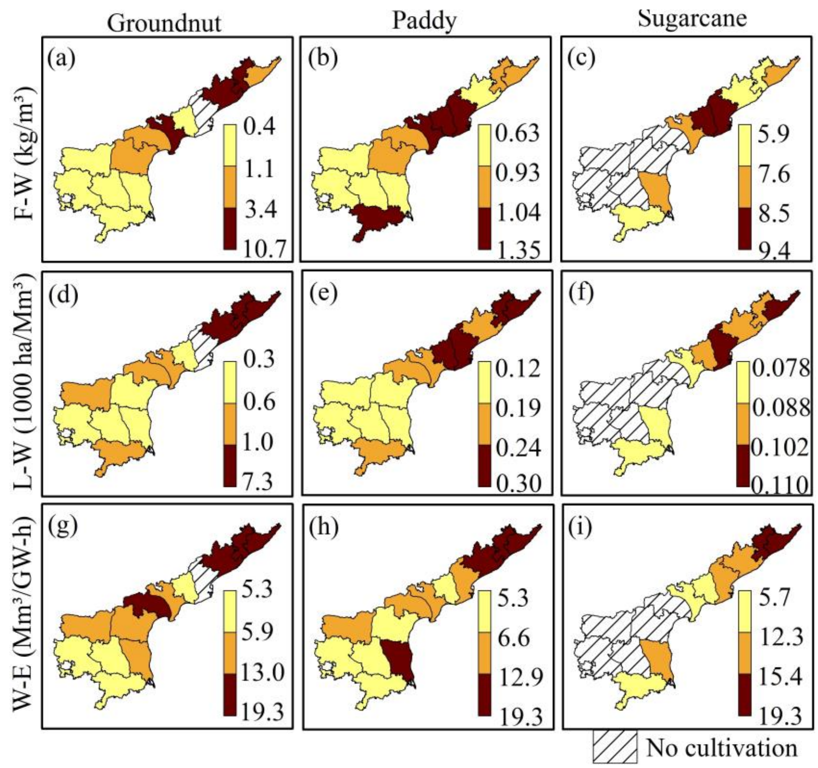

Figure 8: Plots depicting the crop-wise WELF interactions at the district-scale: (a-c) F-W, (d-f) L-W, and (g-i) W-E

To illustrate the significance of each of the metrics for the considered three crops, we chose two climatically distinct districts: 1. Visakhapatnam, and 2. Chittoor. Visakhapatnam is a Northern district with an average rainfall of 1034 mm between 2014 and 2019, while Chittoor, a relatively drier district, received 666 mm. Chittoor was one of the high groundwater consuming districts, accounting for 13% and 19% of total groundwater and energy consumption, while Visakhapatnam accounts for only 3.9% and 2.1%, respectively. Visakhapatnam district, on average, has F-W productivity ten times better than Chittoor district. In other words, Visakhapatnam produces the same quantity of groundnut using ten times lesser groundwater than Chittoor district. Obviously, the heavy rainfall received in Visakhapatnam is the driving factor for this performance. Indeed, a comparison of the GII index with the F-W metric for groundnut shows a weak negative trend (Figure 9a), which indicates that that the F-W productivity of groundnut depends more on rainfall than on supplemental groundwater irrigation. Surprisingly, in the case of paddy (Figure 9b), a similar negative trend between GII and F-W was observed. However, in the case of sugarcane, a weak positive trend was seen, which indicates that sugarcane is the crop that is most dependent on groundwater for supplemental irrigation.

All three crops showed a positive correlation between L-W productivity and aridity index, although it was most prominent in the case of sugarcane (Figure 9d-f). This indicates that in dry sub-humid regions ($0.5<AI<0.65$), it is possible to cultivate more acres of sugarcane with the same volume of groundwater as compared to arid ($0.05<AI<0.2$) or semi-arid regions ($0.2<AI<0.5$). It is projected that climate change will cause significant variations in rainfall, thereby enlarging the area of semi-arid regions (Ramarao et al., 2019). This may force farmers in these regions to rely further on supplemental irrigation, which could negatively affect L-W productivity.

Figure 9g-i showed a strong positive correlation between the Groundwater Sustainability Index (GSI) and the W-E metric for all three crops. Clearly, those districts with more shallow wells were able to extract more groundwater per unit energy consumed. Shallower wells are more sustainable in the sense that shallower aquifers can be recharged relatively easily as compared to the deeper aquifers. Dependence on deep aquifers for irrigation causes increased CO_2 emissions, further exacerbating global warming, thereby causing higher irrigation water requirements. Getting out of this downward spiral will require rejuvenation of shallow aquifers by supply-side (improving recharge) and demand-side (reducing water-intensive crops) measures.

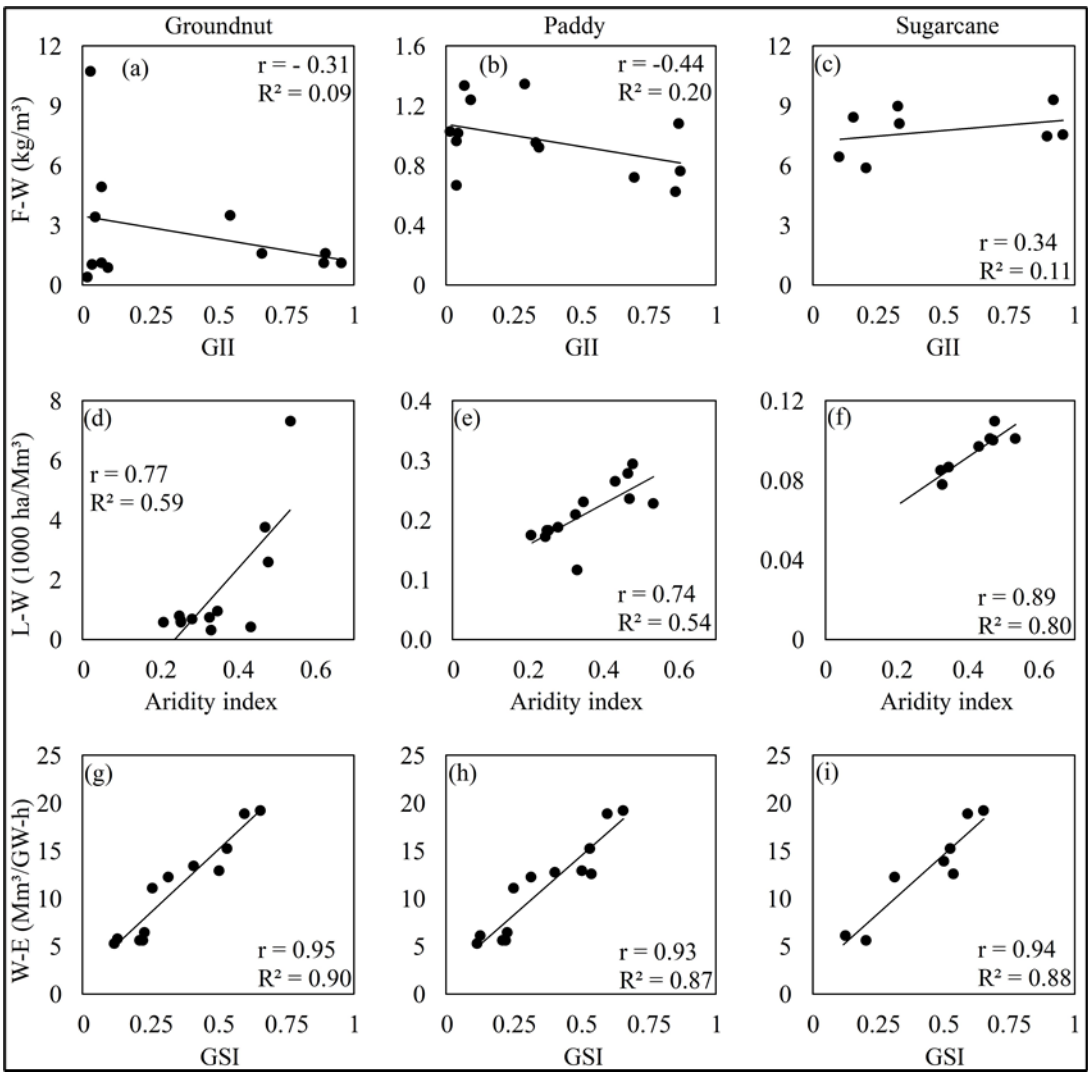

Figure 9: Comparison of WELF metrics with indices for all districts: (a-c) Groundwater Irrigation Index (GII) with F-W metric; (d-f) Aridity index with L-W metric, and (g-i) Groundwater Sustainability Index (GSI) with W-E metric.

At the block scale, interactions were estimated using the aforementioned methodology and are shown in Figure 10. The higher rainfall in western regions in the year 2017-18 reduced the groundwater consumption, which further enhanced the productivity (Figure 10 (a-c)). However, in other years where the rainfall in the western regions was lower, the L-W productivity for Chittoor district was lower than that seen in 2017-18 (see Figure S4). It was interesting that the L-W productivity for sugarcane exhibited much less variability within the district than the other crops. This can be attributed to the higher total water requirement for sugarcane, which cannot be necessarily offset by annual rainfall variations. Additionally, it was noted that blocks in the central and eastern part of the Chittoor district had higher energy productivity (W-E) as the water tables in these regions were relatively shallower. This higher W-E productivity was observed irrespective of the crop cultivated.

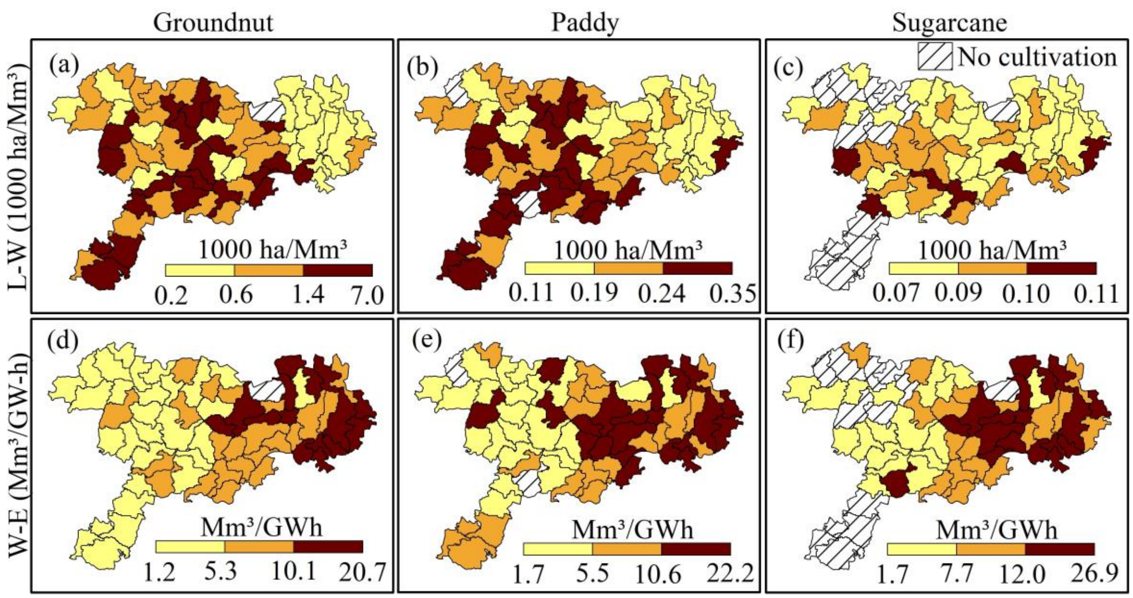

Figure 10: Interactions among WELF for groundnut, paddy, and sugarcane: (a-c) L-W interaction and (d-f) W-E interaction

The comparison between the aridity index and the L-W metric at the block scale (Figure 11 a-c) was similar to that observed at the district scale. Particularly in the case of paddy and sugarcane, the positive correlation between L-W productivity and aridity index was more marked than for gorundnut, as both water-intensive crops are better suited for cultivation in sub-humid and humid regions. The correlation between the W-E metric and the GSI (Figures 11 d–f), was weaker than that observed at the district scale. Nevertheless, regions with higher GSI, i.e., greater number of shallow wells, were seen to have better W-E productivity,

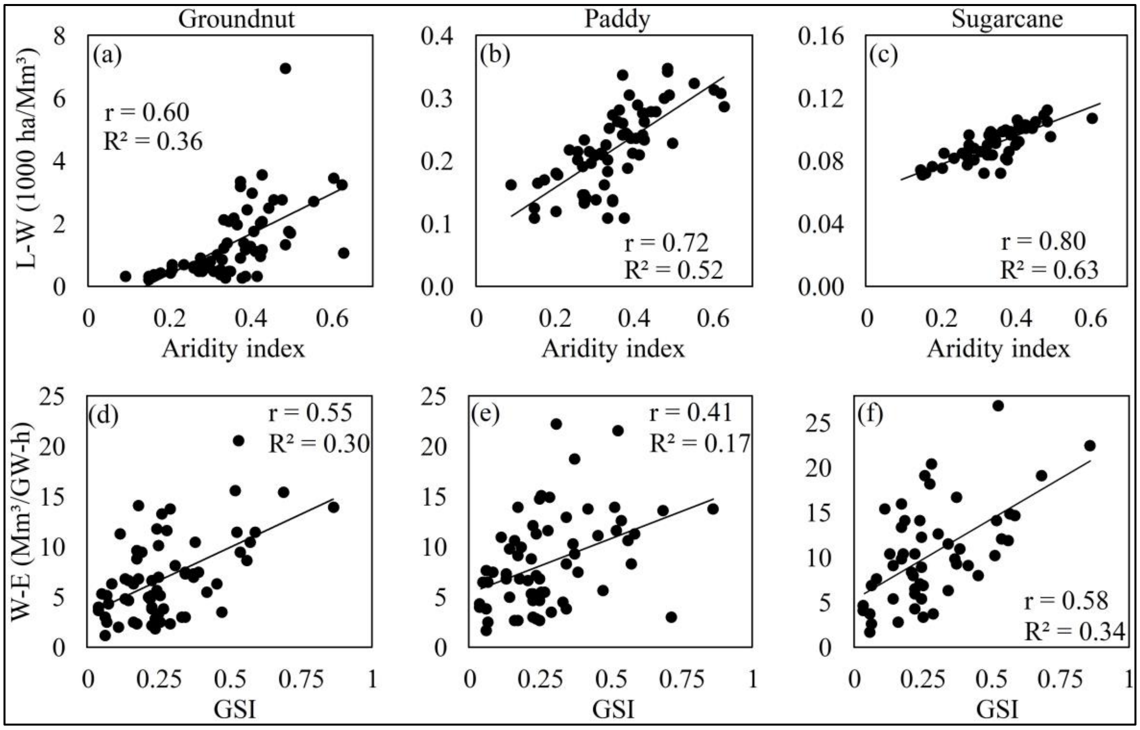

Figure 11: Indices at block-scale: Aridity index and GSI representing the relationships between three interactions – (a-c) L-W, and (d-f) W-E, respectively

3.3. Multiscale comparison

While the metrics at the district level capture, in some aggregated sense, the variations across the district, for policy-making to be truly effective, there needs to be a hierarchy of strategies across scales for sustainable agriculture. The comparison across multiple scales yielded interesting results regarding IWR (mm), groundwater and energy consumption, and the WELF interactions. Table 3 shows the average crop water requirements for the *Kharif* season at block and district scales. For the year 2017-18, where both district and block scale information was available, it was found that the IWR for most crops was underpredicted at the district scale compared to the block scale. The underprediction varies from around 10% to as high as 130%. Clearly, this indicates the importance of detailed local scale data (rainfall and ET) for estimating groundwater pumping. Besides, the variability of IWR across multiple years at the district scale is lesser than the variability across blocks in a single year. For example, in 2017-18, a block in Chittoor district can consume anywhere between 886 and 1480 mm of water for sugarcane, while at the district scale, the variability across six years ranges from 998 to 1213 mm. Therefore, the multiscale analysis highlights the drawbacks of using aggregated information at larger scales, as is typically done for decision-making.

Table 3: Irrigation water requirements for various crops in Chittoor district from 2014 to 2019, and for 2017-18 at block scale. Note that the district values correspond to the district's water requirements for each year. Block values indicate the minimum and maximum of all blocks' water requirements for the year 2017-18

Crop	**Irrigation water requirement (mm)**						
	District						**Block (17-18)**
	2014-15	15-16	16-17	17-18	18-19	19-20	Min - Max
Bajra (Pearl millet)	107	80	113	45	117	46	0.2 - 250
Black gram	147	126	181	106	178	87	10 - 339
Green gram	141	113	156	78	161	74	3 - 284
Groundnut	185	151	204	102	226	88	14 - 444
Horse gram	174	101	244	130	248	117	3 - 368
Maize	159	130	194	88	201	69	9 - 354
Paddy	541	481	583	446	593	415	286 - 915
Raagi (Finger millet)	82	66	119	41	113	30	2 - 248
Red gram	133	109	162	68	170	53	10 - 284
Sugarcane	1170	1134	1213	1061	1180	998	886 - 1480

The total groundwater and energy consumption were estimated at the district and block scales for the year 2017-18. By summing up the values obtained from each block, the total consumption for the district was again estimated. Comparing these two estimates provided several insights. For example, the groundwater consumption for paddy estimated at the district scale for the year 2017-18 was 44.24 Mm^3; however, the comparable number from the block scale analysis was 69.29 Mm^3 – a difference of almost 57%. Our results indicate that the aggregated groundwater consumption from the block scale was 22% higher than the district-scale (see Figure 12). Interestingly, while aggregated groundwater consumption at the block scale was 22% higher than the district scale, the block scale's total energy consumption was around 9% lower than the district scale value. The variation between estimates at the district scale and the block scale also extends to WELF interactions. For instance, the value of Water-Energy interaction for sugarcane in the year 2017-18 in Chittoor district was 6.7, while the same metric at the block scale varied between 1.7 and 26.7 (in Mm^3/GWh). Likewise, for the L-W interaction for paddy crop, the value at the district-scale was 0.29; however, at block-scale, it varied between 0.11 to 0.35 (in 1000 ha/Mm^3). These results highlight the need for multi-scale holistic approaches to help understand issues related to resource exhaustion. The wide variability in results from the local scale further drives home the positive role that detailed data-driven analysis can play in evidence-based policy-making.

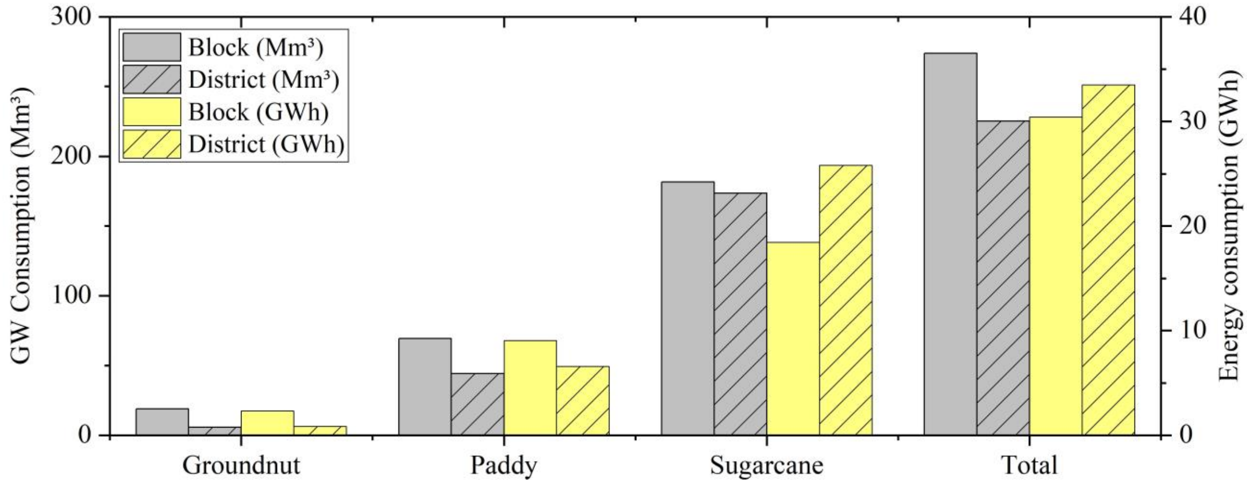

Figure 12: GW and Energy consumption across multiple scales for the year 2017-18

4. Conclusions

The growing global food demand is pressurizing land, water, and energy resources at multiple scales. This study demonstrated a WELF nexus-based approach in the Indian state of Andhra Pradesh to address these concerns. We identified hotspots of high groundwater and energy consumption in the study area at multiple scales. The results from this study helped to understand the interactions between the various resources. For example, in the district of Chittoor, for the same volume of groundwater, almost three times as many hectares of paddy can be cultivated as can be of sugarcane. Such an analysis succinctly conveys the efficiency of the cultivation of each crop in relation to other crops. This metric also indicates that the cultivation of water-intensive crops must be shifted to regions with relatively abundant rainfall. The correlations between aridity index and L-W interaction have shown that the water consumed to irrigate land was better managed in the sub-humid regions. Likewise, the GSI and W-E interaction's relationship depicted that the high energy productivity is strongly correlated with regions where shallower tube wells are predominant.

While the district-scale information is indeed beneficial, it is worth noting that there is considerable variation between the district-scale and block-scale estimates. Although the district-scale information is representative of the entire district, it conceals the variability across the district. While decision-making is primarily driven by aggregated statistics at regional or national scales, such local realities should also be considered in developing policies for sustainable agriculture. These insights may help policymakers devise effective policies, which could sustain food production without adversely affecting available resources. Our results indicate that a few improvements made at local hotspots may reduce groundwater consumption in the entire region. Therefore, bridging the gap between global and local sustainability will require a hierarchy of strategies across all relevant spatial and temporal scales. Future work must focus on using such data-intensive approaches to quantify the interactions between water-energy-land-food so that diminishing global resources can be managed effectively. This study only accounted for water, energy, land, and food; other significant elements like labor, climate, and economy also play a role in agricultural systems, whose inclusion may further improve the understanding gained by this study.

Acknowledgments

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Figure 1.

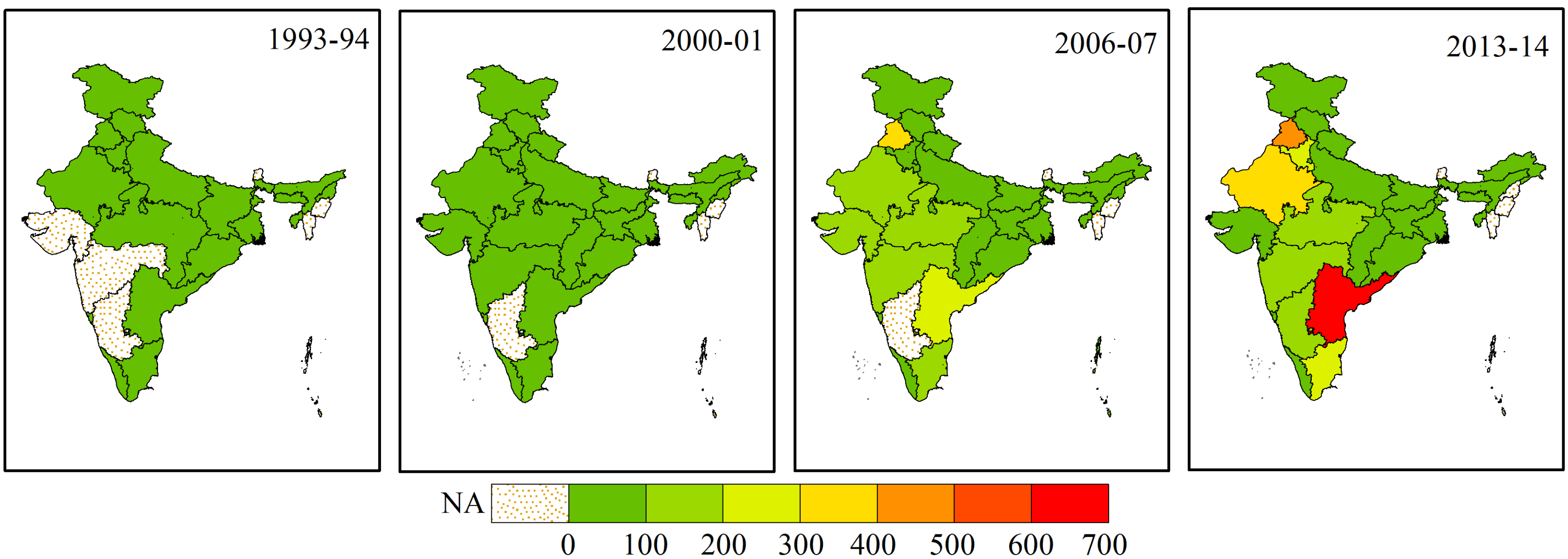

1993-94
2000-01
2006-07
2013-14
NA
0
100
200
300
400
500
600
700

Figure 2.

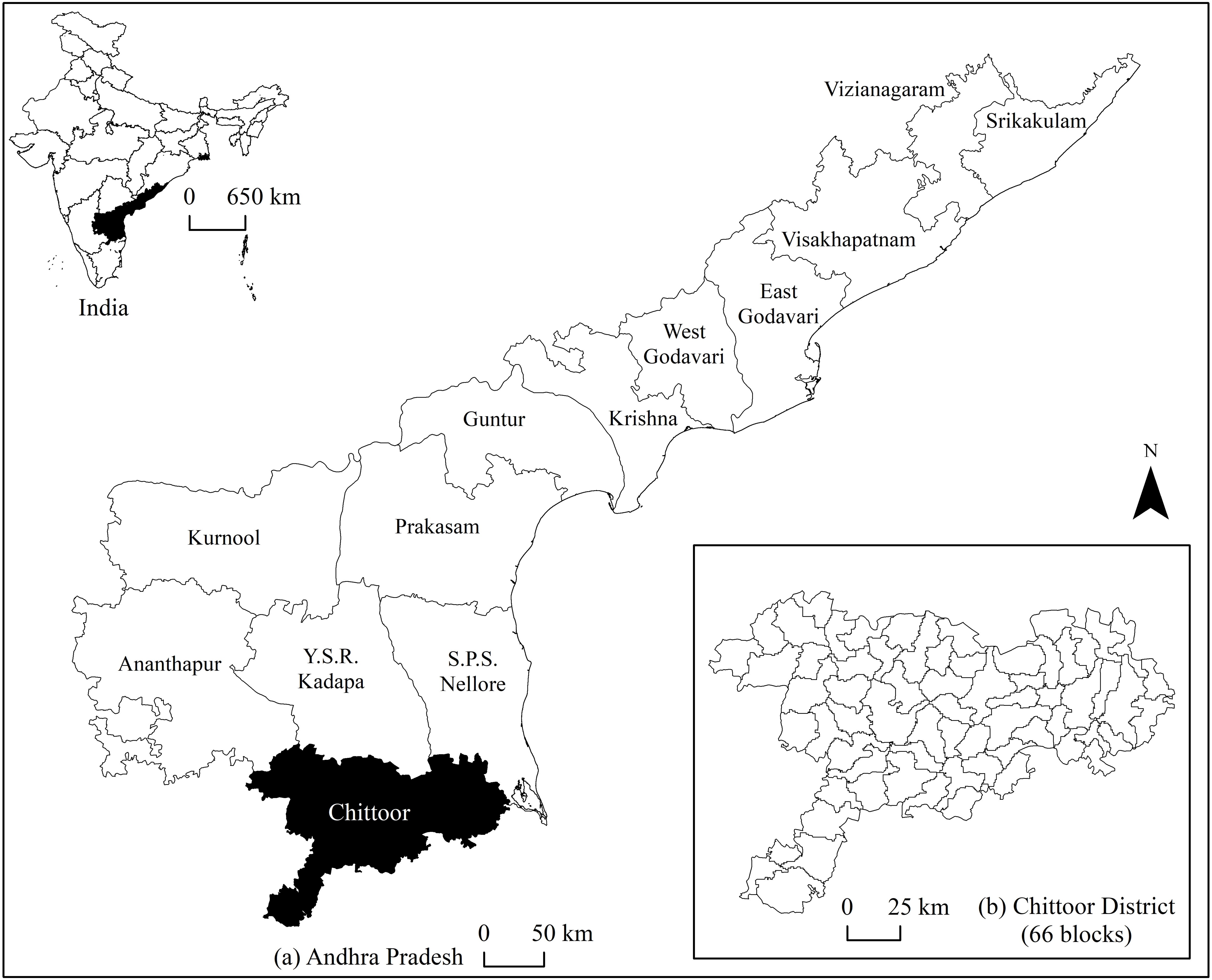
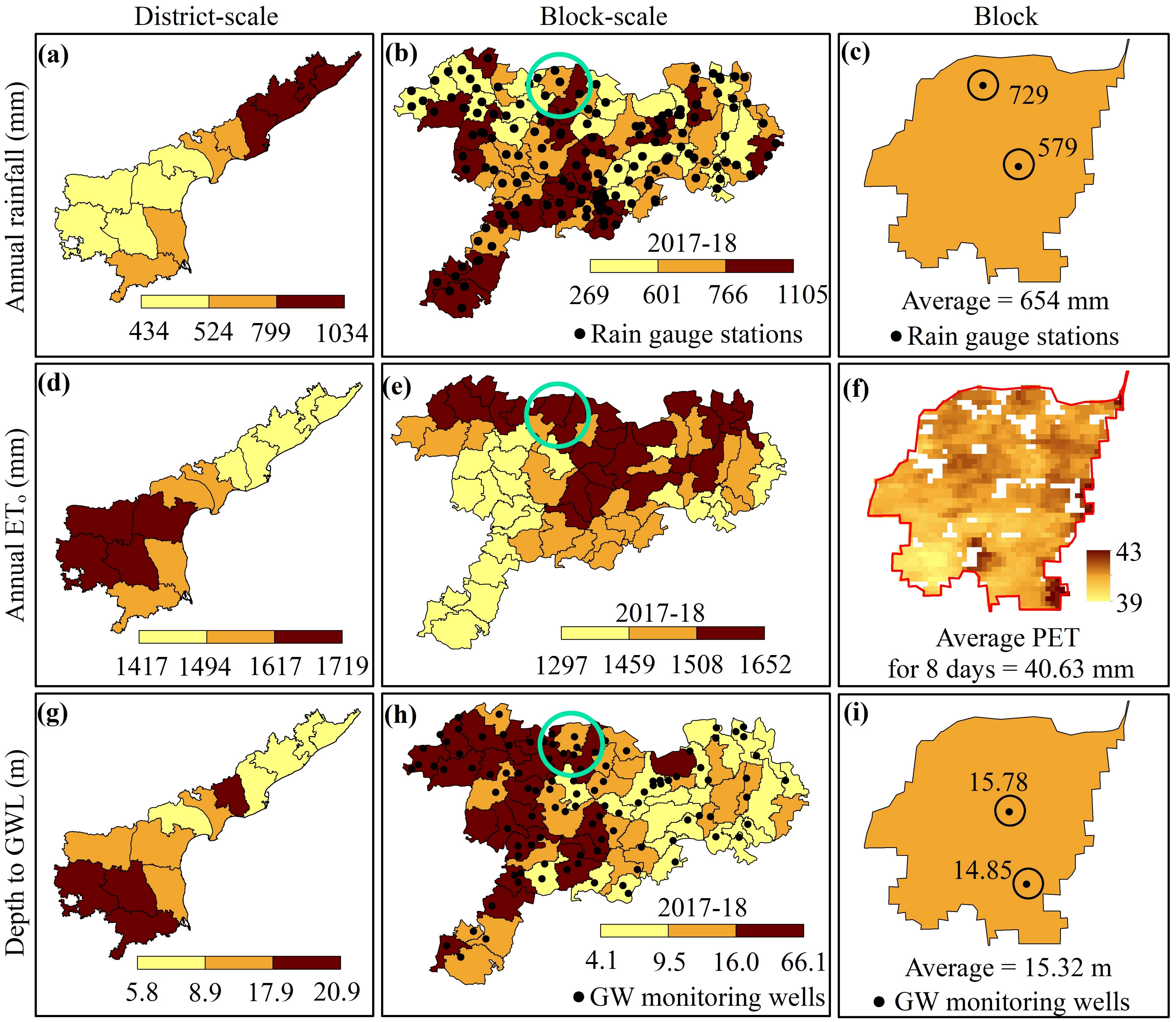

India
0
650 km
Vizianagaram
Srikakulam
Visakhapatnam
East
Godavari
West
Godavari
Guntur
Krishna
Prakasam
Kurnool
Ananthapur
Y.S.R.
Kadapa
S.P.S.
Nellore
Chittoor
N
0
50 km
(a) Andhra Pradesh
0
25 km
(b) Chittoor District
(66 blocks)

Figure 3.



District-scale
Block-scale
Block
Annual rainfall (mm)
(a)
434
524
799
1034
(b)
2017-18
269
601
766
1105
Rain gauge stations
(c)
729
579
Average = 654 mm
Rain gauge stations
Annual ET₀ (mm)
(d)
1417
1494
1617
1719
(e)
2017-18
1297
1459
1508
1652
(f)
43
39
Average PET
for 8 days = 40.63 mm
Depth to GWL (m)
(g)
5.8
8.9
17.9
20.9
(h)
2017-18
4.1
9.5
16.0
66.1
GW monitoring wells
(i)
15.78
14.85
Average = 15.32 m
GW monitoring wells

Figure 4.

ET_0
Rainfall
Agriculture data
Production data
Depth to GWL
GW pumping
Land
Food
Energy
W: GW
E: Energy
L: Land
F: Food
L-W
F-W
W-E
WELF Nexus

Figure 5.

Groundnut (mm)
Paddy (mm)
Sugarcane (mm)
(a)
44
119
193
310
(b)
342
440
557
850
(c)
908
997
1187
1438
No cultivation

Figure 6.


(a) Groundwater Surface water Rainfed
1.0
0.8
0.6
0.4
0.2
0.0
Srikakulam
Vizianagaram
Visakhapatnam
East Godavari
West Godavari
Krishna
Guntur
Prakasam
S.P.S.Nellore
Y.S.R.Kadapa
Kurnool
Ananthapur
Chittoor
(b) GWC (Mm³)
21 122 200 378
(c) Energy (GW-h)
1 11 24 62
100
10
1
0.1
0.01
0.001
(d) GW Energy
Raagi
Horse gram
Green gram
Jowar
Red gram
Bajra
Black gram
Maize
Groundnut
Bengal gram
Cotton
Chilies
Sugarcane
Paddy

Figure 7.

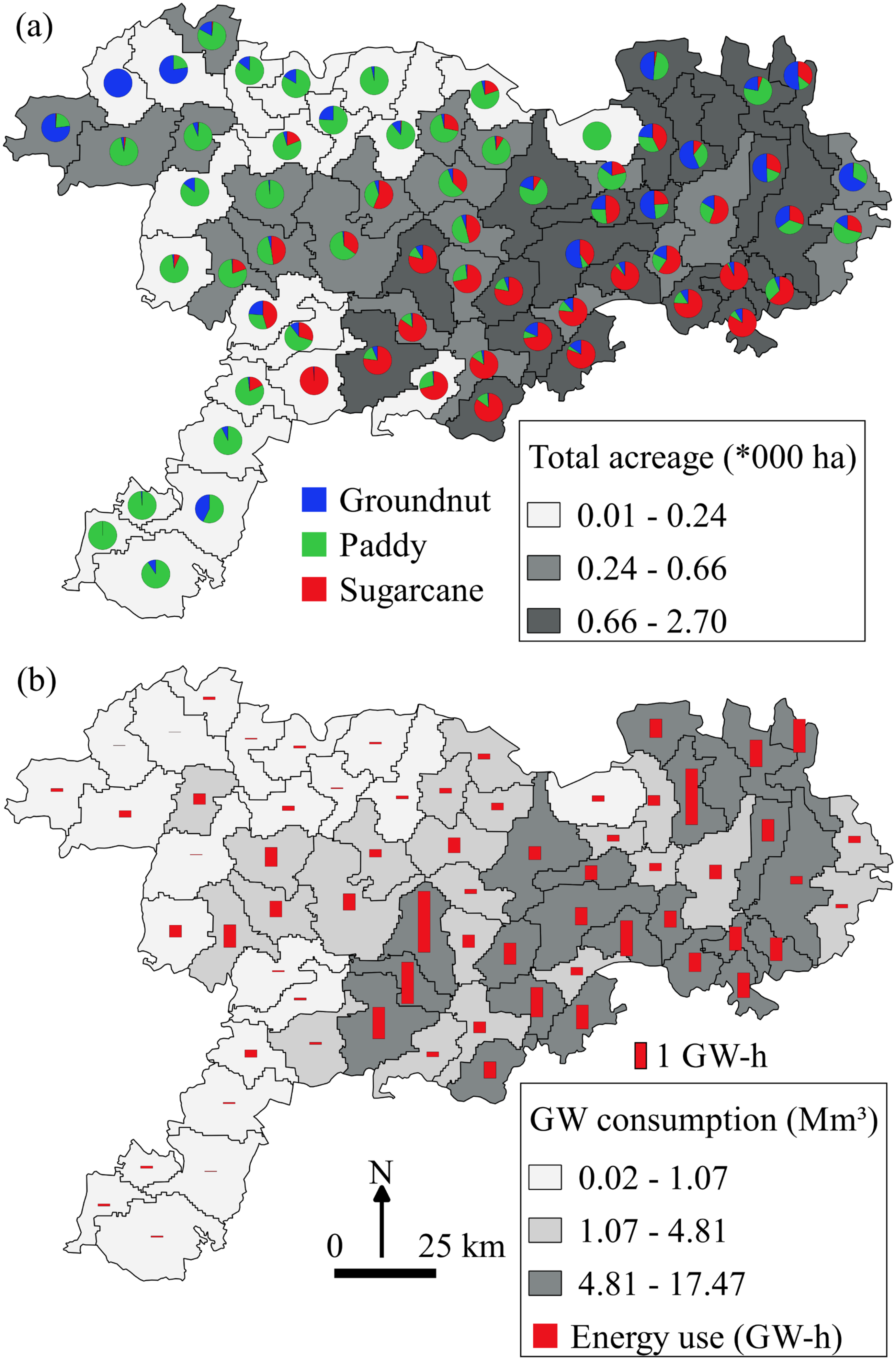

(a)
Total acreage (*000 ha)
0.01 - 0.24
0.24 - 0.66
0.66 - 2.70
Groundnut
Paddy
Sugarcane
(b)
1 GW-h
GW consumption (Mm³)
0.02 - 1.07
1.07 - 4.81
4.81 - 17.47
Energy use (GW-h)
N
0
25 km

Figure 8.

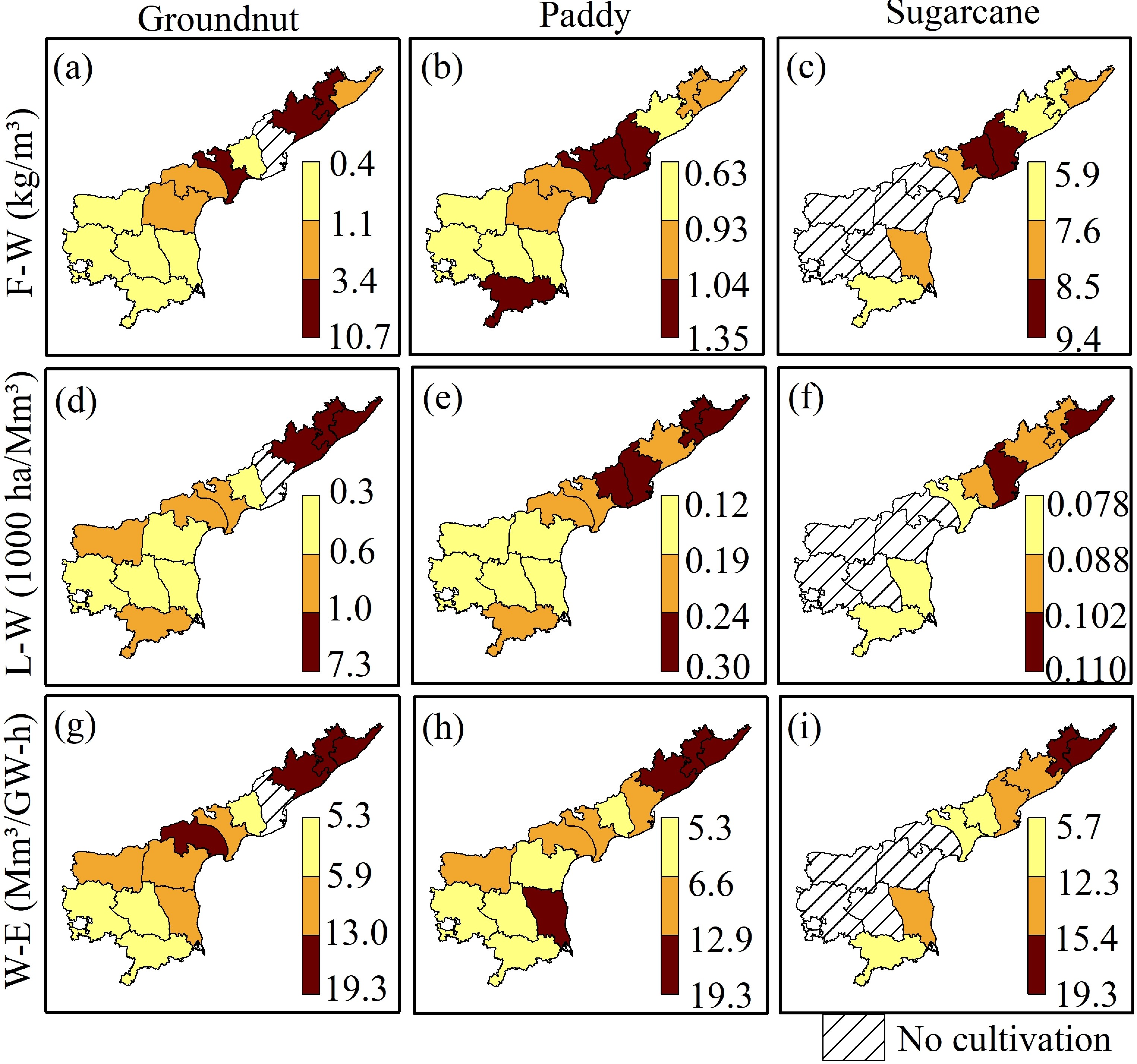

Groundnut
Paddy
Sugarcane
F-W (kg/m³)
L-W (1000 ha/Mm³)
W-E (Mm³/GW-h)
(a)
0.4
1.1
3.4
10.7
(b)
0.63
0.93
1.04
1.35
(c)
5.9
7.6
8.5
9.4
(d)
0.3
0.6
1.0
7.3
(e)
0.12
0.19
0.24
0.30
(f)
0.078
0.088
0.102
0.110
(g)
5.3
5.9
13.0
19.3
(h)
5.3
6.6
12.9
19.3
(i)
5.7
12.3
15.4
19.3
No cultivation

Figure 9.

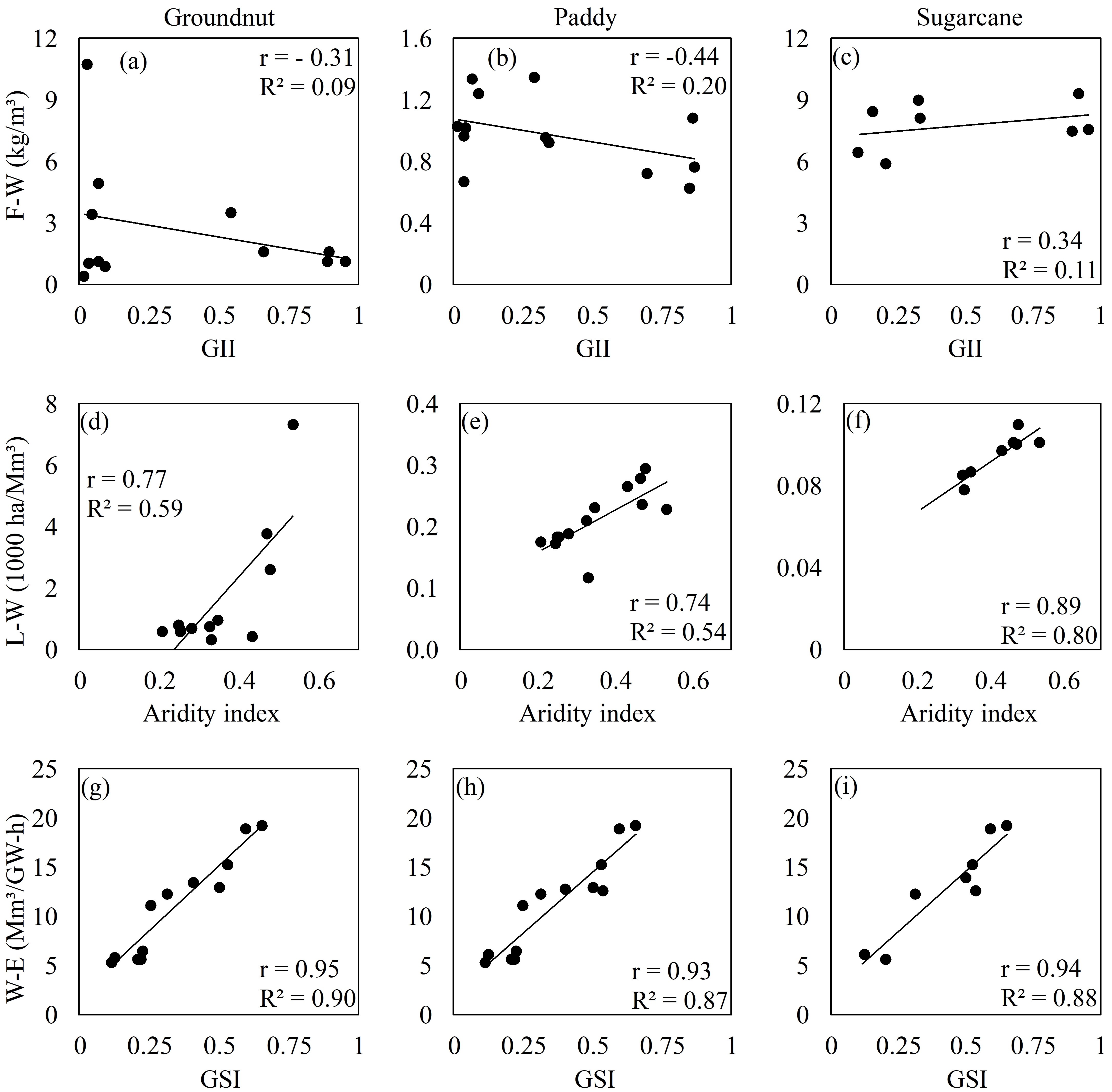

Groundnut
Paddy
Sugarcane
F-W (kg/m³)
(a)
r = - 0.31
R² = 0.09
(b)
r = -0.44
R² = 0.20
(c)
r = 0.34
R² = 0.11
GII
GII
GII
L-W (1000 ha/Mm³)
(d)
r = 0.77
R² = 0.59
(e)
r = 0.74
R² = 0.54
(f)
r = 0.89
R² = 0.80
Aridity index
Aridity index
Aridity index
W-E (Mm³/GW-h)
(g)
r = 0.95
R² = 0.90
(h)
r = 0.93
R² = 0.87
(i)
r = 0.94
R² = 0.88
GSI
GSI
GSI

Figure 10.

Groundnut
Paddy
Sugarcane
L-W (1000 ha/Mm³)
W-E (Mm³/GW-h)
(a)
(b)
(c)
No cultivation
1000 ha/Mm³
0.2 0.6 1.4 7.0
1000 ha/Mm³
0.11 0.19 0.24 0.35
1000 ha/Mm³
0.07 0.09 0.10 0.11
(d)
(e)
(f)
Mm³/GWh
1.2 5.3 10.1 20.7
Mm³/GWh
1.7 5.5 10.6 22.2
Mm³/GWh
1.7 7.7 12.0 26.9

Figure 11.


Groundnut
Paddy
Sugarcane
L-W (1000 ha/Mm³)
(a)
r = 0.60
R² = 0.36
(b)
r = 0.72
R² = 0.52
(c)
r = 0.80
R² = 0.63
Aridity index
Aridity index
Aridity index
W-E (Mm³/GW-h)
(d)
r = 0.55
R² = 0.30
(e)
r = 0.41
R² = 0.17
(f)
r = 0.58
R² = 0.34
GSI
GSI
GSI

Figure 12.

300
200
100
0
40
30
20
10
0
GW Consumption (Mm³)
Energy consumption (GWh)
Block (Mm³)
District (Mm³)
Block (GWh)
District (GWh)
Groundnut
Paddy
Sugarcane
Total