

1 **Dynamics of crop category choices reveal strategies and tactics used by**
2 **smallholder farmers in India to cope with unreliable water availability**

3
4 Mariem Baccar^a, H  l  ne Raynal^a, Muddu Sekhar^{b,c}, Jacques-Eric Bergez^a, Magali Willaume^a, Pierre
5 Casel^a, P. Giriraj^b, Sanjeeva Murthy^b, Laurent Ruiz^{c,d*}

6
7 *corresponding author Laurent.ruiz@inrae.fr

8 a AGIR, INRAE, Universit   de Toulouse, Castanet-Tolosan, France

9 b Civil Engineering Department, Indian Institute of Science, Bangalore, India

10 c Indo-French Cell for Water Sciences, Interdisciplinary Center for Water Research, Indian Institute of
11 Science, Bangalore, India

12 d UMR SAS, INRAE, Institut Agro, Rennes, France

13 **Highlights:**

- 14 - We monitored crop choices, weather and groundwater level in 205 irrigable farms for each
15 cropping season for 10 years
16 - Crop species were clustered into crop categories based on water requirement
17 - We used Sequence Analysis to build a typology of crop categories sequences per season
18 - Tactical adaptations to variations in water availability varied across farm types
19 - Diversity of possible crop categories was pivotal for farming system.

20
21 **Abstract:**

22 CONTEXT

23 Altering cropping choice is a potentially effective lever to cope with unreliable water resources, but
24 given the multiple factors driving crop choices, assessing if farmer actually use it specifically for this
25 objective remains difficult.

26 OBJECTIVE

27 We aimed at analyzing whether and how irrigated farmers choose crop categories with different water
28 requirements to cope with limited water resources in peninsular India.

29 METHODS

30 We monitored, during 10 years, crop choices, weather, and groundwater for the three cropping
31 seasons in 205 irrigable farms in the Berambadi watershed, in southern India. We categorized crops
32 according to their seasonal water requirement. We performed Sequence Analysis and Agglomerative
33 Hierarchical Clustering of crop categories choices for each cropping season over 10 years to build farm
34 typologies of strategic crop category choice. For each type, we correlated the variations in crop
35 category choices to variations in rainfall and groundwater availability, to identify tactical adaptations.
36 Finally, the succession of farm strategies across seasons allowed us to identify and characterize the
37 main strategical pathways followed by farmers, each of them linked with specific tactical adaptations.

38 RESULTS AND CONCLUSIONS

39 Sequence analysis of crop category choices revealed different types of crop category sequences,
40 reflecting farmer's different strategies, which were not significantly linked with groundwater
41 availability. However, within each type, correlations between variations in water availability and crop
42 categories highlighted specific tactical adjustments. We identified five main pathways across the three
43 cropping seasons, including combining long-cycle irrigated crop and other crop categories, specializing
44 in short-cycle irrigated crops over two or three seasons, specializing in rainfed crops or abandoning
45 agriculture.

46 SIGNIFICANCE

47 The opportunity for farmers to choose their crop among a range of species encompassing a large range
48 of water requirements allow them to base their system resilience on a large diversity of strategies and
49 tactics. This suggests that some farmers empirically estimate the water balance of their cropping
50 systems at seasonal scale to take tactical decision. Providing them with science-based tools to refine
51 this estimation could therefore help them taking better decisions. This also implies that modelling
52 farmer decisions must account for their diversity. Maintaining or increasing the capacity of farmer's to
53 cultivate a broad range of crop with different seasonal water requirement is important for farming
54 system resilience, and should therefore be part of the agenda of policy makers for agricultural or
55 environmental regulations.

56

57 **Keywords:** sequence analysis; groundwater irrigation; cropping pattern; crop choice; crop diversity

58

59 **1. Introduction**

60

61 Altering crop choice and increasing crop diversity are among the possible efficient levers that can
62 contribute to the adaptation of agriculture to declining water resources (Howden et al., 2007; Lin,
63 2011; Babaeian et al., 2021; IPCC, 2022), This is particularly the case in India, which relies heavily on
64 groundwater for irrigation (Shah, 2009) and where the fast decline of groundwater resources (Fishman
65 et al., 2011) is threatening agricultural productivity and food security (Bhattarai et al. 2021). Due to its
66 importance for water balance and groundwater recharge (Anuraga et al., 2006), shift in crop choices
67 is expected to be a major lever for adapting to shrinking and uncertain water resources and changes
68 in rainfall patterns in India (Kumar et al., 2020). However, very few studies in India have been devoted
69 to studying changes in cropping patterns with changes in water resources, and in situations of declining
70 groundwater levels they have found either little or no cropping pattern adaptation (Tripathi and
71 Mishra, 2017; Patil et al., 2019; Blakeslee et al., 2020; Bhattarai et al. 2021), a decline of water-
72 intensive crop (Fishman et al., 2011) or a counterintuitive shift to water-intensive crops (Shiferaw et
73 al., 2008).

74 This lack of conclusive studies might be partly due to the difficulty to gather relevant time-series of
75 crop choice, which must be collected at the farm level (Leenhardt et al., 2012a). Crop rotations can be
76 retrieved from existing public databases (Nowak et al., 2022; Upcott et al., 2023), remote sensing (Mas
77 et al., 2019; Biarnès et al., 2021 ; Zhang et al., 2022), or extensive surveys at household level.
78 Econometric analyses can reveal how actors adapt to long-term changes in mean climate (Mendelsohn
79 and Massetti, 2020) and many studies highlight the complexity of the decision-making process involved
80 in crop choice, which depends on a broad range of factors such as market information, operational
81 cost, labour availability, credit facilities, pest control, weed control, and land tenure status (e.g.
82 Moniruzzaman, 2015). However, disentangling this complex process to assess the importance of
83 climate or water resources variations in the decision remains a challenge (Labeyrie et al., 2021).

84 A difficulty lies in the dual nature of crop choice. The theoretical framework elaborated by farmers'
85 decision-making modelers (Risbey et al., 1999) distinguishes between strategic decisions, which
86 engages the farm on a long term (several years) and tactical decisions, which are taken at yearly or
87 seasonal scale. Crop choice belong to these two categories, as at the strategic level farmers decide on
88 a cropping system in the long term, in accordance with the farm objectives and structure, available
89 resources and general context, while at the tactical level, yearly or seasonally, they can decide to alter
90 they crop choices, based on short term signals (Risbey et al., 1999; Robert et al., 2016a). As a

91 consequence, the cropping pattern analysis needs to be carried out at the same time between farms
92 (to identify different strategies) and in time (to identify tactical adaptations specific to each strategy).
93 Classically, statistical analysis of crop time series involves retrieving probabilities of crop successions,
94 using for example Markov chains, in order to infer a predictive model of land use (e.g. Salmon-
95 Monviola et al., 2012; Dupuis et al., 2022). However, such an approach is not well adapted for
96 comparing farms in space and therefore to distinguish strategic and tactical decisions. Sequence
97 analysis (SA) is a promising method for such an objective, as it allows to quantify the similarities of
98 qualitative sequences both longitudinally (across years) and transversally (across farms). SA was
99 originally introduced in computer science (Levenshtein, 1966) and later in genetics to study DNA and
100 RNA sequences (Levitt, 1969). Today, SA is common in several disciplines analyzing ensembles of time
101 series such as marketing (Silberer, 2012), economics (Le Goix et al., 2019), social sciences, medicine,
102 and history analysis (Salonen et al., 2020), but to our knowledge, it has never been used for studying
103 cropping systems.

104 Another difficulty, which is more specific to the case of smallholders' agriculture in the tropics, is linked
105 with the high diversity of cultivated crop species (including crop associations). To simplify the system,
106 many authors (e.g. Patil et al., 2019; van Zonneveld et al., 2020) cluster these species into crop
107 categories that are assumed to represent "functional" groups. This allows to develop models in which
108 functional groups are an important filter in crop choice decision-making (Dury et al., 2012). Modelers
109 define filter criterion of functional groups according to various factors that can be agronomic (Dogliotti
110 et al., 2003), or related to resource requirements (Robert et al., 2018). Then, other filters allow to
111 select the crop species depending on many other criteria within the possible range of options. Based
112 on this rationale, in order to specifically study the impact of water resource on cropping choice, this
113 clustering could be based explicitly on the estimation of seasonal crop water requirement, which has
114 been identified as one of the main factor driver crop choice decision in Indian farms (Robert et al,
115 2016b). Daily crop water requirement depend on several factors related to phenology (which drives
116 the transpiration demand), rooting depth (which drives access to soil water) and stress tolerance (Allen
117 et al., 1998). Crops with deep roots and good stress tolerance are usually cultivated with no or only
118 occasional irrigation and can be categorized as "rainfed"; while among strictly irrigated crops, the most
119 determining factor controlling seasonal irrigation requirement is the duration of their cultural cycle
120 (Brouwer and Heibloem, 1986) which can therefore be used to classify them.

121 The objective of this paper is to test the hypothesis that in a water-limited context, seasonal crop water
122 requirement is a primary factor driving crop choice, and therefore that analyzing sequences of crop
123 categories based on crop water requirement can help reveal strategic and tactical farmer's decisions.
124 For this, we analyzed farmers' cropping patterns using a 10-years' time series of monthly observations,

125 including crop choice and groundwater table level, on a panel of 205 irrigable farms in the Berambadi
126 watershed in southern India, where weather variability combined with the recent development of
127 borewells and irrigated agriculture led to an high pressure on groundwater resources. We categorized
128 crop species according to their water requirement and used sequence analysis (SA) on crop category
129 sequences to build a typology of farms with different patterns of crop categories, and we explored if
130 these categories could be interpreted in terms of farmer's strategies. Then, for each farm type, we
131 analysed year to year variations of crop categories and explored if these variations could be interpreted
132 in terms of tactical adaptations to variations in water resource availability.

133

134 **2. Material and methods**

135 **2.1. Study area**

136 The Berambadi watershed (Figure 1) is situated in the southwest of India (11°43'00" to 11°48'00" N,
137 76° 31'00" to 76° 40'00" E) and covers an area of 84 km². It belongs to the Kabini Critical Zone
138 Observatory (Sekhar et al., 2016; SNO M-tropics, <https://mtropics.obs-mip.fr/>), part of the OZCAR
139 research infrastructure (Gaillardet et al., 2018). The bedrock is a granitic gneiss and the aquifer, typical
140 of hard rock granitic areas (Wyns et al., 2004), is composed of two layers, one fissured layer of a few
141 meters thickness at the surface of the fresh bedrock, with high hydraulic conductivity but low porosity
142 and one weathered layer (gneissic saprolite) with low hydraulic conductivity but large porosity (Boisson
143 et al., 2015) with a thickness of about 15 m (Braun et al., 2009). Two main soil types are found, 1–2 m
144 deep red soils (Ferralsols and Chromic Luvisols) on the hillslopes and 2 m deep black soils (Vertisols
145 and Vertic intergrades) mostly in the valley bottoms (Barbiero et al., 2010; Gomez et al., 2019).

146 Daily weather data were available from the Maddur meteorological station in the East part of the area
147 (Figure 1). The climate of the area is tropical sub-humid (aridity index P/PET= 0.7), with average rainfall
148 and PET of 800 mm/year and 1100 mm/year respectively (Sekhar, et al., 2016). The monsoon regime
149 determines three distinct cropping seasons of roughly 4 months each: (i) Kharif, which comprises the
150 Southwestern monsoon period; (ii) Rabi, the Northeastern monsoon period and the winter season;
151 and (iii) Summer, the hot and dry season.

152 The cultivation of irrigated crops in the watershed started in the early 1990s and increased since then
153 thanks to intensive groundwater pumping (Sekhar et al. 2011; Sharma et al, 2018). Individual borewells
154 have been largely encouraged by public policies that provided farmers with subsidies and free
155 electricity for groundwater irrigation (Fischer et al., 2022). This dynamic has led to groundwater over-
156 exploitation, with considerable impacts on ecosystems (Buvaneshwari et al., 2017; 2020) and socio-
157 economic development (Fischer et al., 2022), which, in the absence of collective management,

158 threatens the viability of irrigated agriculture in the area (Landy et al., 2021). The decrease in
159 groundwater table level disconnected groundwater table from river beds, turning main permanent
160 rivers into ephemeral streams (Srinivasan et al., 2015; Buvaneshwari et al., 2017). In hard rock aquifers,
161 pump yields are small and often insufficient to fully satisfy the needs of water-intensive crops on large
162 surfaces (Fishman et al. 2011), and they vary in time with water table level as hydraulic conductivity
163 decreases sharply with depth (Boisson et al., 2015; Collins et al., 2020). In Berambadi, farmers reported
164 not only that their borewells might dry up but also that the pump yield varies with years or seasons
165 (Robert et al, 2017a).

166 Farmers in Berambadi own on average 1.2 ha of land, either on one or several independent pieces of
167 land, called “farms” in English and “jeminu” in Kannada (local language). The size of a farm can vary
168 greatly (from 0.1 to several hectares) but typically it is about half a hectare, which for each season can
169 be either dedicated to a single crop or divided into several plots for growing different crops depending
170 on farmer's preference and strategy and on its access or not to groundwater. An extensive household
171 survey carried out in 2014 (Robert et al., 2017a) show that crop choice depends on a large variety of
172 socio economic factors, such as caste, education, farm size, market prices, labour availability, contract
173 opportunities, grain stocks, farm distance to local market or a main road, but also on expected water
174 availability (seasonal rainfall and borewell yield). Interestingly, for a large majority of irrigable farms,
175 cropping systems include a mix of irrigated and non-irrigated crops. Specific farmer’s interviews
176 focused on decision rules suggests that priority is given to crops with large water requirement: first
177 long-cycle crops, then short-cycle irrigated crops and finally other short-cycle crops with little or no
178 irrigation requirement (Robert et al., 2017b). However, these declarative qualitative statements
179 inform little on the importance of water availability on the final crop choice.

180 Thus, we conducted an inductive approach (Goddard & Melville, 2004), to explore whether and how
181 water variability has an effect on the cropping decision by analyzing crop choices over a 10y period. To
182 minimize the effects of factors specific to crop species, we explored farmers' choices of functional crop
183 categories based on their irrigation requirements, estimated with the FAO method (Brouwer and
184 Heibloem, 1986). We classified the crops species into three main crop categories: (i) rainfed crops (R)
185 do not require irrigation and, in Berambadi, their cycle span over only one season (mostly Kharif or
186 Rabi); (ii) short-cycle crops (SC) are strictly irrigated crops, with a cycle spanning over only one season
187 (Kharif or Rabi or Summer); (iii) long cycle crops (LC) are strictly irrigated crops, with a cycle spanning
188 over two or three seasons, making their cumulative water requirement higher than the previous ones.

189

190 ***2.2. Data acquisition, curation and preprocessing***

191

192 We set up an intensive data monitoring at 205 farms comprising at least one borewell in working
193 condition, distributed across the Berambadi watershed (Figure 1), over 10 years (March 2010 to March
194 2020). The sampling was designed to explore the spatial variability of groundwater table level, but not
195 specifically to be representative of the farm diversity over the area. Monitoring consisted of monthly
196 visits to each of these farms to measure the water table at the borewell and record all crop species
197 present.

198 We measured the groundwater level with a manual piezometric level sensor (skinny dipper device,
199 Haron instruments) at least 3h after switching off the pump. Indeed, pumping induces a local decline
200 in water table depth (drawdown), and point measurements during pumping periods are impossible to
201 interpret. After switching off the pump, the local water table level tend to come back to the “static
202 level”, which represent the hydraulic head outside the radius of influence of the borewell. The time
203 taken to reach the static level depends on local aquifer transmissivity, and we checked in a range of
204 wells that 3 hours was enough to recover at least 90% of the local groundwater level drawdown due
205 to daily pumping. Therefore our measurements were reasonable approximation of the groundwater
206 static level. The survey was still manageable as electricity for pumping is freely provided by the
207 government to farmers only for a few hours per day (6h/day, split into 3h in the night and 3h in the
208 day from 2010 to 2015, and 7h/day split into 3h in the night and 4h in the day since 2015). Qualitative
209 information was also gathered about the status of the monitored borewell (dry, abandoned, clogged,
210 pump failure...). We estimated pump yield by measuring with a chronometer the time needed to fill a
211 25-L bucket. The yield value for each well was taken as the average of 3 measurements carried out at
212 a 30-minute interval, with the first measurement at least 30 minutes after starting the pump. We
213 measured pump yield in September 2012 (N=117) and May 2017 (N=80). The second survey was
214 carried out because, compared to 2012, groundwater levels had declined dramatically and it allowed
215 us to explore a wider range of water table depths.

216 We observed the crops present in farm monthly. When there was more than one plot in the farm, all
217 the different crops and/or fallows present were noted. Recording the area and location of each crop
218 species within the farm would have been too time consuming, as the number and size of plots often
219 varies from one season to the other. Therefore, we cannot interpret the data in terms of crop rotations
220 but only in terms of the occurrence of crop species on a farm. For data curation (Figure S1), we first
221 discarded from the database the farms (N=17) having had dried borewells or pump failure during more
222 than 30% of the study period, as we were interested in irrigable farms (N=188). To fill the gaps in the
223 groundwater levels time series, we interpolated the levels of the previous and following months in the

224 same farm. The dataset comprised 36 different crops species. We discarded those present in less than
225 2% of all the observation per season (N=5). For the remaining ones (N=31), we reconstructed their
226 dominant cultural cycle (season(s) of sowing/planting, cycle duration), using our observations and
227 expert knowledge (Table S1). Missing values due to short gaps in observations for individual farms
228 were filled in by taking into account crops present in the previous and following months and cultural
229 cycles.

230 Finally, these qualitative data were prepared for statistical exploration. We allocated each crop to one
231 of the three crop categories (R, SC and LC) mentioned in section 2.1 (Table S1) and we added a category
232 for fallow (no-crop, noted NC). We allocated each crop within the time series to the season when it
233 was sowed or planted (Kharif crops if sowed from March to June, Rabi crops if sowed from July to
234 October, and Summer crops if sowed from November to February). As several crops categories can be
235 sown on the same plot during a given season, we aggregated the different crop categories sown or
236 planted on the same farm in the same season of the same year, into a new variable called “state” (in
237 the analysis method). Each state corresponds either to a single crop category or a combination of
238 several crop categories. Eight distinct values of states were identified in the database (Table 1).

239 We decided to consider the succession of states across years for individual farms for each season
240 independently. Indeed, variations of crop categories from one season to the next can be due to
241 agronomic or climatic constraints (e.g. most long-cycle crops are sown in Kharif, rainfed crops are
242 barely possible in Summer). Such seasonal variations would have introduced “noise” if we had carried
243 out the analysis on sequences including all the seasons. Moreover, farm surveys suggest that farmers
244 are taking their decisions on crop choice at the beginning of each of the three seasons (Robert et al.,
245 2017b) regardless of the crop choice made in the previous season. We therefore created three datasets
246 (one for each season) of interannual state sequences for each farm.

247

248 **2.3. Statistical analysis**

249

250 We carried out the data analysis in three steps, which will be detailed in the next sub-sections.

251 First, we used Sequence Analysis to quantify pairwise sequence dissimilarities, then Agglomerative
252 Hierarchical Clustering (AHC), in order create group of farms based on sequence similarity. Our
253 objective was to build a typology of state sequences across farms, which would reflect different
254 strategies of crop category choice per season. In a second step, we explored whether, for each of the
255 types of state sequences previously identified for each season, indicators of availability of rainfall and

256 groundwater were correlated with variations in year-to-year crop categories choices, which would
257 reflect tactical adaptations to year to year variations of water availability. Finally, we built a farm
258 typology based on the combination of the seasonal types, illustrating the diversity of farmer's
259 strategies and tactical responses to variations in water resources.

260

261 ***2.3.1. Typology of sequences by season***

262

263 In the SA method, a sequence is a set of longitudinal data and each sequence is composed of a
264 succession of states (the states correspond to what is observed) in individual farms. In our study, a
265 state corresponds to the choice of either one crop category or a combination of two or three crop
266 categories (Table 1) - observed on the farm, for a given season and a given year. Note that sometimes
267 there is no choice to make for a given farm in a given season, as the land is already occupied by a long-
268 cycle crop. This explains why the number of farms "making choices" varied across years and across
269 seasons. The SA methods consists in the quantification of the dissimilarities between individual
270 sequences, in other words it is a quantification of how far two sequences are. To calculate the
271 dissimilarities between the sequences, several metrics can be used the most commonly used being the
272 Longest Common Subsequence (LCS), the Longest Common Prefix of two sequences (LCP) and the
273 Optimal Matching distances (OM) (Elzinga, 2008). As our objective is to identify similar cropping
274 patterns, we chose LCS that corresponds in our case to the longest common subsequence of crop
275 categories over the ten years data. We ran SA using the R TraMineR package (Gabadinho et al., 2011),
276 which includes a broad range of functionalities. We used the length of the longest common sub-
277 sequence (LCS) between two sequences x and y , and derived a dissimilarity measure expressed by the
278 formula:

$$279 \quad d(x,y) = A(x,x) + A(y,y) - 2A(x,y)$$

280 where $d(x,y)$ corresponds to the distance between x and y , $A(x,y)$ is the length of the longest common
281 subsequence between x and y . If $A(x,y)=0$, the dissimilarity between the two sequences is maximal. If
282 $A(xx)=A(yy)=A(x,y)$, x and y are identical.

283 Then we performed an agglomerative hierarchical clustering (AHC) in order to group the farms with
284 the most similarities. The AHC successively groups the closest farms into clusters, which then are
285 grouped into larger clusters of higher rank based on their factorial coordinates (Omran et al. 2007).
286 We used the Ward's minimum-variance aggregation method for minimizing intra-cluster variance and
287 maximizing variance between clusters (Kaufman and Rousseeuw 2009). AHC is represented by a

288 dendrogram which illustrates the classification obtained at each successive rank of the analysis. The
289 number of farm types of each AHC clustering was chosen to enable a sound interpretation of results
290 and adequate differentiation between types of crop categories choice for each season (Baccar et al.,
291 2018).

292 For each type, we also calculated via descriptive statistics the distribution of crop categories. For
293 visualization of each type by season, among the wide range of possibilities available in the TraMineR
294 package, we plotted the time series across years of the proportion of each state within the group of
295 farms belonging to the type. These plots, considered globally, allow to highlight the dominant states
296 across the farms within the considered type, and also to visualize year to year variations in the
297 proportion of dominant states across farms. Finally, we calculated an index of crop category diversity,
298 as the percentage of states comprising more than one crop category within a given farm for the same
299 season across years. Please note that this is not a biodiversity index, as there can be a large diversity
300 of crop species (with similar water requirements) within a single crop category (Table S1), but rather
301 an indicator of the prevalence of decisions of simultaneously implanting crops with different water
302 requirements within a same farm.

303

304 ***2.3.2 Correlation between water availability and types of crop categories choice***

305

306 For each farm type, we conducted correlation analyses between the year to year variations of crop
307 categories and indicators of water availability, using the R FactoMineR package (Lê et al., 2008). In
308 addition, we performed correlations between the diversity index and water availability in order to
309 assess if diversification is a tactical adaptation to water variability.

310 We assumed that observed groundwater levels and rainfall can be used as proxies for water
311 availability. For groundwater availability, we averaged, for each farm and year, the groundwater levels
312 observed during the first 2 months of the season and the previous month, assuming that decisions of
313 crop category are made during this 3-month period. For rainfall, we tested independently the monthly
314 rainfall for the first two months of the season and for the last two months of the previous season for
315 the considered year, and only the months for which significant correlation between rainfall and crop
316 categories choice were found were retained in the analysis.

317 ***2.3.3 Pathways of crop categories choice across seasons***

318

319 The annual pathway of each farm was obtained by grouping the crop category choices according to
320 the three seasons. We then gathered together farms with the same pathway and ranked these
321 pathways according to their frequency. Finally, we interpreted the most frequent pathways as
322 reflecting different general strategy across farms, with specific tactical adjustments linked with year-
323 to-year variations in water availability.

324

325 **3. Results**

326

327 ***3.1. Characterization of water resource availability***

328

329 Yearly rainfall (Figure S2) shows a large year-to-year variation, with the occurrence of severe drought
330 years (2012, 2016, 2017) and an exceptionally rainy year (2018). Average monthly rainfall exceeds
331 monthly PET for 5 to 6 months (Figure S3), which explains why two cycles of rainfed crops are possible
332 in the region. The rainiest months (August and October) are also the ones displaying the largest
333 variability, suggesting that crop water stress can occur even during the core of the rainy season. In
334 Summer, rainfall is almost absent while PET is the highest, therefore crops can only be grown with
335 irrigation.

336 Groundwater levels for the 188 farms across the 10-year monitoring period illustrate the dynamic
337 behavior of the aquifer (Figure 2), with large seasonal water table level variations, and marked
338 interannual trends - with a general downward trend from 2010 to 2018 followed by a dramatic increase
339 in 2018 and 2019, leading to an average groundwater level slightly shallower at the end than at the
340 beginning of the period. This highlights the fact that hard rock aquifers are highly dynamic, and that a
341 few years of good groundwater recharge can completely offset the progressive decline observed
342 during dry and average years. Although the standard deviation remained quite large throughout the
343 period (about 13 m), reflecting the large spatial variability of groundwater levels, all the wells followed
344 the same general trend, suggesting a good connectivity of the aquifer within the catchment. In
345 addition, groundwater levels displayed large seasonal variations linked with groundwater recharge. On
346 seasonal average (Figure S4), groundwater level was the deepest in Kharif with high interannual
347 variability.

348 Pump yields were very sensitive to variations in groundwater table level (Figure 3), with a steep
349 decrease of discharge rates with decreasing groundwater level in the first 20 m below ground, and a
350 moderate decrease below this threshold. This high sensitivity of well yields to groundwater table level

351 suggests that the large interannual and seasonal variations of water table level observed during the
352 study period have induced large variations in water availability for irrigation both in the short and long
353 term. However, for a given range of groundwater level depth, pump yields can differ largely across
354 borewells (see standard deviation in Figure 3).

355 **3.2. Seasonal choices of crop categories**

356

357 **3.2.1. Kharif season**

358

359 In Kharif season, we identified four types of farms with a relatively even distribution between types.
360 Each type had a specific pattern and a dominant crop category (Table 2). K1 was dominated by irrigated
361 long-cycle crops (LC) but irrigated short-cycle crops (SC) were also very frequent. K2 was largely
362 dominated by SC. K3 was dominated by fallow (NC) but the distribution of crop categories was more
363 even. K4 was largely dominated by rainfed crops (R). Time series shows that the proportion of states
364 for each group of farms varies a lot from one year to the other for all types (Figure 4a). The diversity
365 index show significant difference between farm types (Figure 4b). In particular, for the K1 type, very
366 high value of diversity index indicates that while LC were dominant throughout the studied period,
367 they were most of the time cultivated in combination with other crop categories, mostly SC. This
368 suggests that cultivating simultaneously crops with different water requirement is a general strategy
369 for this farm type. To the contrary, the other three types displayed smaller values for the diversity
370 index (decreasing from K2 to K4), the general strategy is rather to cultivate crops with the similar water
371 requirement in a given year, but possibility shifting for a crop category to another from one year to the
372 other.

373 Average groundwater table levels were not significantly different between farm types (Figure 4c), and
374 therefore our hypothesis that groundwater availability drives the general strategy for crop category
375 choice was not validated.

376 However crop category choices displayed large year-to-year variations, which were partly explained
377 by variations in water availability (Table 3). Variations in groundwater availability affected farm types
378 differently: it was negatively correlated with the decision to leave the plot fallow (NC) for K1 and K2
379 and with the decision to grow R for K4, and positively with the decision to grow LC for K2 and K4. The
380 amount of rainfall in April, which is critical for land preparation at the end of the dry season, showed
381 strong correlations with crop category choices: it was strongly correlated with the decision to grow LC
382 for all farm types and to grow SC for K3 and K4. The diversity index displayed only weak correlations
383 with groundwater level (K3) and April rains (K3 and K4), which suggests that the decision to grow or

384 not different crop categories simultaneously on the same farm in Kharif season was more a general
385 strategy than a tactical adaptation to the conditions at the time of the sowing decision.

386 **3.2.2. Rabi season**

387

388 In the Rabi season, there were only a few occurrences of LC as they are mostly planted in Kharif season
389 in the region. We identified two types of farms (Table 2): R1 was largely dominated by SC while R2 was
390 slightly dominated by NC with an almost equal proportion of R.

391 Time series shows that the proportion of states across farms varied less across years than during the
392 Kharif season, especially in the case of R1 (Figure 5a). The diversity index (Figure 5b) was low for both
393 farm types and mostly driven by the combination of SC and R. As for kharif season, the average
394 groundwater table level was not significantly different between the two types, suggesting that
395 groundwater availability was not a driving factor of the general strategy (Figure 5c).

396 In Rabi season, year to year variations of crop category choices were mostly not correlated with the
397 variations in groundwater availability, except for the decision to cultivate or not in the case of R1 farms
398 (Table 3). The occurrence of good rains in the month preceding the crop category choice decision (July)
399 influenced differently farmers of the R1 type, who cultivated more frequently LC – although it
400 remained marginal - and the farmers of R2 type, who cultivated more frequently rainfed crops. In both
401 cases, the intensity of July's rains was correlated with the diversification index, suggesting that a
402 replenished soil water reservoir at the beginning of the Rabi season was an opportunity for trying
403 different crop categories, but mostly in combination. In the case of R2, the amount of rainfall in the
404 early Rabi season (August) was strongly correlated with fallow (negatively) and rainfed crops
405 (positively), suggesting that this factor was crucial in determining the crop category choice. In the case
406 of R1, the largely dominant crop category choice SC was not correlated with rainfall nor with
407 groundwater availability, suggesting that for the farmers belonging to this type, growing SC in Rabi
408 season was a general strategy, unaffected by the conditions at the time of the decision.

409

410 **3.2.3. Summer season**

411

412 During the summer season, since LC are rarely planted and rainfed crops are barely possible, the
413 decision was mainly limited to an alternative between short-cycle irrigated crops (SC) and fallow (NC),
414 although other categories were marginally present. We identified 2 types of farms (Table 2) with
415 similar populations: S1 dominated by SC and S2 dominated by NC.

416 The time series of crop category choices (Figure 6a) displayed strong variations in some years, mostly
417 due to the alternance between fallow and irrigated short-cycle crops. For example, for the S1 type,
418 fallow became the dominant choice in years such as 2013, 2016, and 2017. As expected, the diversity
419 Index was extremely low (Figure 6b), due to the limited range of options available in this season. Again,
420 the average groundwater table level was not significantly different between the two types, suggesting
421 that, similarly to the other seasons, the amount of groundwater available was not a determining
422 general strategies of crop category choice (Figure 6c).

423 For S1 farms, the variations in year-to-year decisions to grow SC or leave the land fallow was strongly
424 correlated with groundwater table levels at the beginning of the season, and more weakly with the
425 rainfall amount in the preceding month (Octobre) that replenish the soil reservoir for Summer crops
426 (Table 3). No significant correlations were found between crop category choice and water availability
427 for S2 farms.

428

429 **3.3. Typology of farm strategic pathways**

430

431 Five annual pathways of successive seasonal types represented 73% of the surveyed farms (Figure 7).
432 We find that these pathways can be interpreted in terms of general strategies followed by farmers to
433 selected crop categories. Each pathway is characterized by different factors governing tactical
434 decisions for each season. These main pathways, presented by decreasing frequency, are the
435 following:

436 **Pathway A** (K2, R1, S1) corresponds to a strategy of **specialization in irrigated short-cycle crops in the**
437 **three seasons**. This strategy was by far the most frequent, and it was probably driven by the awareness
438 among farmers of the high risk of investing in long-cycle crops in the context of unreliable groundwater
439 availability. The tactical decisions were strongly influenced by the variations of groundwater
440 availability and rainfall patterns, with an increase of long-cycle crops in Kharif and short-cycle crops in
441 Summer during the favorable years.

442 **Pathway B** (K3, R2, S2) corresponds to a strategy of **abandonment of agriculture**, as the dominant
443 choice in all seasons was clearly fallow land. The tactical decisions were not influenced by variations in
444 groundwater availability, but these farmers seized the opportunity of favorable rainfall years to
445 increase the proportion of irrigated crops (LC and SC) in Kharif and of rainfed crops in Rabi.

446 **Pathway C** (K1, R1, S1) corresponds to a strategy of **high water use over the three seasons**, with
447 priority given to irrigated long-cycle crops in Kharif and irrigated short-cycle crops in Rabi and Summer.

448 Compared the Pathway A, these farmers appear to be ready to accept the risk of large losses in the
449 case of failure of LC crops. Their tactical decisions appear to be little influenced by year to year
450 variations in groundwater availability: rainfed crops were always present in Kharif and Rabi, but their
451 proportion was not increased when groundwater availability decreased. However, they increased SC
452 in Summer when groundwater levels were shallow and when they are too deep, the preferred
453 alternative to the dominant crop category choice was fallow in all seasons. Interestingly, this strategy
454 was characterized by a large diversification of crop categories in Kharif, to make the best use of the
455 available land and water and probably as a strategy of risk management.

456 **Pathway D (K2, R1, S2)** corresponds to a strategy of **specialization in irrigated short-cycle crops only**
457 **in the two rainy seasons**. The only difference with pathway A is that these farmers mostly preferred
458 not to grow any crops during the dry Summer season and seem more risk averse to crop failure in the
459 dry season. Year-to-year variations in groundwater level or rainfall before the Summer season had no
460 significant impact on this choice. Given the large water requirement of irrigated crops in Summer, this
461 strategy is probably the most reasonable in terms of water resource management.

462 **Pathway E (K4, R2, S2)** corresponds to a **constrained specialization in rainfed agriculture**. The
463 dominant crop category choice is rainfed crops in Kharif, and fallow in Rabi and Summer. Unlike for
464 the pathway B, the tactical decisions in Kharif are not only influenced by the variations in yearly rainfall
465 patterns but also by variations in groundwater availability, with a substitution of rainfed crops by
466 irrigated long-cycle crops when conditions are favorable.

467

468 **4. Discussion**

469

470 Our study, based on the monitoring of crop categories choice, climate and groundwater over 10 years
471 in a population of smallholder's irrigated farm in a small watershed, showed that farmers develop a
472 diversity of strategies, and that the choice a given strategy was not based on the average availability
473 of groundwater. However, within each strategy, some tactical choices resorted to adaptations to water
474 availability variations.

475 **4.1. Large temporal variability of water availability**

476 During the 10-years monitoring period, the hydrosystem was characterized by large variability of yearly
477 rainfall and large variations of groundwater levels, both seasonally and across years. This situation,
478 typical in the region since the 2000's, was probably quite different from the conditions prevailing a few
479 decades ago, at the onset of the development of groundwater irrigation in the region. At that time,

480 groundwater levels were shallower (about 5m), and their seasonal and interannual variations were
481 smaller (Sekhar et al., 2004). In the 1980's and 90's, with much more reliable access to the
482 groundwater resource, through open wells or shallow borewells, the first irrigators focused mostly on
483 a long cycle crop, namely sugarcane, which was ubiquitous in the region (Fischer et al., 2022). We
484 observed that, contrary to the widespread perception of a continued decline in groundwater levels
485 (e.g., Bhattarai et al. 2021), increased groundwater withdrawals in the region have instead resulted in
486 a large variability in groundwater levels. We showed that a decrease in groundwater level was
487 associated with a decrease in borewell yields (Figure 3), implying that over the past decade, availability
488 of groundwater for irrigation had become highly unreliable. However, the large standard deviation of
489 borewell yields for a given water table level depth, especially at shallow depth, which reflects the
490 spatial variability of aquifer properties at short-distances in this hard rock aquifer, implies that
491 groundwater level depth is only a rough approximation of groundwater availability at the farm level.

492

493 ***4.2 Diversity of irrigating Farmer's strategies is not linked with the quantity of groundwater available*** 494 ***in their farms***

495

496 We showed that statistical analysis of the patterns of crop categories, using sequence analysis (SA) and
497 Agglomerative Hierarchical Clustering (AHC) methods, can reveal the different strategies implemented
498 by irrigated farmers in building cropping systems using a range of crops with different water
499 requirements.

500 We highlighted five main general strategies based on specific mobilization of the range of crop
501 categories with different water requirement available to farmers, that included cultivating long-cycle
502 crops in combination with other crop categories, specializing in short-cycle crops in two or three
503 seasons, specializing in rainfed crops or abandoning agriculture. This result shows that farmers
504 strategic options appears quite more diverse than suggested by previous studies in the same region,
505 which summarize the farmer's alternative as "to chase water and not adapt to changing conditions" or
506 "quit" agriculture (Patil et al., 2019 ; Blakeslee et al., 2020).

507 Interestingly, and contrary to our initial hypothesis, we found that the average groundwater level
508 depth in the farm was a not significantly different between the different farm types. Even if it is
509 possible that this was in part due to the fact that groundwater level only a rough proxy of the amount
510 of groundwater available in a given farm, we can still conclude that farmer's decision to opt for a given
511 cropping strategy is mostly driven by other factors.

512 Among the possible factors, we can speculate that available capital is probably one of the most
513 important. This was the object of many studies, which highlighted the inequality in the groundwater
514 economy in India (Sarkar, 2011; Modak, 2018) and around the world (Ameur et al., 2017). For example,
515 in our case study, the farmer following the pathway D dominated by irrigated long-cycle crops were
516 capable of assuming the high investment in inputs, labour and equipment specific to this type of crops
517 (Fischer et al., 2022), but more importantly they were able to wait one year after planting to generate
518 an income – or bear the risk of a crop failure. It is also possible that they were capable of maintaining
519 this strategy even during drought years because they had invested in micro irrigation, making their
520 cropping systems less sensitive to variations in groundwater availability compared to their neighbours.
521 By comparison, the pathways A and C, dominated by irrigated short-cycle crop, are less capital-
522 intensive and these crops can provide a quick return on investment. It is worth noting that in the
523 region, the capacity to invest in agriculture is not solely depending on the capital available in the
524 household, as contracting loans is a common practice. According to a 2016 survey, interests on the
525 loans taken by irrigating smallholders amounted to around 30% of the value added created on irrigated
526 farms (Fischer, 2022). However, indebted farmers face high risks given the high rate of crop failure in
527 such a context (Taylor, 2013) and when they are unable to repay their loans, they have to hand over
528 their land to their creditor (Sadanandan, 2014, Fischer et al., 2022). This mechanism is central to the
529 Indian 'agrarian crisis' that has been in news media since the 2000s (Sadanandan, 2014). Irrigating
530 farmers with no investment capacity – because they cannot access new loans or because they are risk
531 averse - might be the ones following the pathways B (abandoning agriculture) and E (rainfed crops),
532 cultivating irrigated crops only when the risk of failure is minimal. It is possible that this strategy is
533 viable because the important job demand induced by the development of irrigation in the region
534 allows these farmers to work off-farm to supplement their income (Fischer et al., 2022).

535

536 ***4.3 Tactical choices can be driven by variations in water availability***

537

538 While our results showed that the choice of farmer's strategy was not significantly linked with
539 groundwater availability, we found that in several cases, year-to variations in water availability – rain
540 or groundwater - were correlated with year-to-year variations in crop category choice (Table 3), which
541 we can interpret as tactical decisions to adapt to variable water resources.

542 Interestingly, we found that these tactical decisions were often specific to the general strategy of the
543 farm type. For example, the correlation between the tactical decision to leave the farm fallow and the
544 groundwater level was very significant in some cases (for example for the farmers following the water

545 intensive pathway B) but not significant for others. Similarly, the tactical decision to grow more long-
546 cycle crops in Kharif season was strongly correlated with groundwater level only for the type K2, while
547 it was correlated with April rainfall for all the Kharif types. Decision to grow more rainfed crops was
548 negatively correlated with groundwater availability only for the type K4 in Kharif, and positively
549 correlated with rainfall only for the type R2 in Rabi.

550 It is not so surprising that in many cases, no correlations were found between crop category choice
551 variations and variations in water availability, considering how complex decision-making of crop choice
552 is. The first possible reason is that for some farms, water availability is not a limiting factor for deciding
553 crop choice. It can be for example because they have an exceptionally good pump yield, their plot size
554 is small, the water holding capacity of their soil is high, or they are using micro irrigation techniques.
555 Other possible reasons can be that even if a crop with large water requirement is technically possible
556 in a given year, farmers might decide to rather grow other crop categories, or even leave the farm
557 fallow, for a wide range of reasons, linked for example to evolution of prices, market opportunities or
558 labour availability. Finally, we based our categorization of crop species on large differences in seasonal
559 water requirement, but we are well aware that within these categories, differences exist between crop
560 species that might also be accounted for by farmers while taking their final decisions.

561 Therefore, in this context, the fact that we were still able to identify clear correlations between water
562 availability and some tactical decisions suggests that crop water requirement is clearly identified and
563 sometimes used by farmers as a primary criteria in their tactical decision-making process. This also
564 implies that farmers (at least some of them) empirically estimate the seasonal water balance of their
565 cropping systems at seasonal scale to take tactical decisions, and therefore providing them science-
566 based tools to refine this estimation could help them taking better decisions.

567

568 ***4.4. The importance of crop diversity***

569

570 Our results highlighted that in the Berambadi watershed, the capacity of farmers to adopt a large
571 diversity of crop categories with different water requirement led to a diversity of irrigated farming
572 systems. This diversity was large between farm types, but also within some of the farm types, for which
573 cultivating different crop categories at the same time is a strong characteristic of their strategy (Figure
574 4b). Such strategies are probably possible thanks to the very large range of crop species that can be
575 cultivated in this region – diversity that we have not analyzed in our study. Such diversity is perhaps a
576 specificity of the study area, which is characterized by a rather favorable climate (Fischer et al., 2022)
577 and multiple market opportunities, as it is located near the border of three Indian states, with a long

578 tradition of intense exchange of people, knowledge, and goods between them (Hooge et al., 2022). It
579 could also be specific to the structure of Indian smallholder farms, dominated by 'patronal farms'
580 relying mainly on hired manual labour for most of the technical operations of their cropping systems,
581 and little on crop-specific equipment (Aubron et al., 2022), allowing greater flexibility in crop choices.

582 While the critical role of crop diversity for coping with future unpredictable changes is increasingly
583 acknowledged (Østergård et al., 2009; Darnhofer, 2010; Kumar et al., 2020, Alletto et al., 2022), the
584 adaptive capacity of farmers is often restricted by market and regulatory pressures (e.g. Duker et al.,
585 2020; Sutcliffe et al., 2021). In our study site, participatory workshops with stakeholders, including
586 policymakers, extension services and NGOs (Baccar et al., 2021), revealed that while climate change
587 impact was considered a serious issue, the envisaged solutions concerned primarily water access (e.g.
588 farm pond) or water use efficiency (e.g. drip irrigation), and little crop diversification. In a global
589 context characterized by a trend towards a global homogenization of crop species and varieties grown
590 across regions, driven by the industrialization of agriculture (Khoury et al., 2014; Martin et al., 2019),
591 preserving the heterogeneity and diverse strategies of millions of smallholder farmers is essential
592 (Altieri and Nicholls, 2017). We believe that policies designed to protect water resources (e.g.
593 restrictions, quotas, pricing) (Leenhardt et al., 2010) or to support agricultural production and farmer's
594 livelihood, should include maintaining or increasing farmer's adaptive capacity in terms of crop choice
595 as a one of their main target.

596

597 ***4.5. The way forward for understanding and modelling farmers' strategies***

598

599 The methodology proposed in this here, based on the analyses of choices of functional crop categories
600 characterized by different seasonal water requirement, allowed to identify different cropping systems
601 strategies among small irrigated farmers, a category often considered as homogeneous in farmers
602 typologies (Robert et al., 2017a; Fischer et al., 2022). To go further and understand the factors driving
603 the observed differentiation of farmer's strategies, we would require an analysis of the different
604 technical and socio-economic factors at stake, such as farm size and assets, available capital, access to
605 market, know-how, etc. (Baccar et al., 2017). Designing socio-economic surveys based on such a
606 typology would allow to assess the relative importance of individual cognitive factors (Yuan et al., 2021;
607 Zobeidi et al., 2022), availability of water resources and farm households characteristics in driving the
608 differentiation of farmer's strategies. Indeed, as pointed out recently, farm typologies based on socio-
609 economic surveys do not always reflect the typologies of agricultural practices, and only the
610 combination of both can help tailoring the design of agricultural policies and extension services to the
611 need of different farmers (Berre et al., 2022)

612 Importantly, it would be critical to assess the environmental impacts and the sustainability of the
613 different strategical pathways followed by irrigators (Leenhardt et al., 2012b). In other words, while
614 we observed that farmers resorted to different strategies and tactics to cope with a water-stressed
615 context, we did not assess their relative success. Such an evaluation could be done by building
616 scenarios representing the different pathways we have revealed in this study and assessing them with
617 farm level models representing the biophysical, economic and decision processes within these systems
618 (e.g. Robert et al., 2018), in order to evaluate their impact on the water resources and the economic
619 viability of the farms.

620

621

622 **4 Conclusion**

623

624 This study showed that analyzing time-series of choices of functional crop categories based on water
625 requirement allowed to highlight diverse strategies and some specific tactical decisions to cope with
626 unreliable water availability used by smallholding farmers in a small watershed in South India. We
627 identified five main strategies followed by farmers ranging from intensive use of water to
628 abandonment of agriculture, and the strategies are not static and show adaptations over the years.
629 We believe that such a diversity, which was possible because of the wide range of crops that can
630 possibly be cultivated in the area, is a main lever for building the resilience of these farming systems.

631 One of the implications of this result is that modelling the impact of climate change on groundwater
632 resources and agricultural production in such a system must account for the diversity of small irrigating
633 farmer's strategies and tactics to face unreliable water resources. Another implication is that
634 maintaining or increasing the opportunities for farmers to cultivate a wide range of crops is likely to
635 increase their resilience and adaptive capacity and therefore should become a primary objective of
636 policy makers in charge of agricultural or environmental regulations.

637

638 **Acknowledgements**

639 The study was funded by the project ATCHA ANR-16-CE03-0006, and the SNO M-TROPICS
640 (<https://mtropics.obs-mip.fr/>), itself supported by the University of Toulouse, IRD and CNRS-INSU and
641 by the SUJALA III project (Karnataka Watershed Development Department and World Bank). We thank
642 the farmers of the Berambadi catchment for all the support and information provided. Comments by
643 Valérie Viaud improved an earlier version of this manuscript. This work is dedicated to the memory of
644 P. Giriraj (1975-2022).

645

646 **Author contributions**

647 M.B., H.R., M.S., J.E.B., M.W. and L.R. designed the study. M.S. and L.R. secured funding. M.S.
648 conceived and coordinated the field monitoring. P.G. and S.M. carried out the field surveys. M.B., H.R.
649 and P.C. carried out data analyses. M.B., H.R., M.W. and L.R. interpreted the results. M.B. wrote the
650 first draft of the paper. All authors reviewed and approved the final manuscript.

651

652 **Declaration of Competing Interest**

653 The authors declare that they have no known competing financial interests or personal relationships
654 that could have appeared to influence the work reported in this paper.

655

656 **References**

- 657 Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). Crop evapotranspiration-Guidelines for
658 computing crop water requirements-FAO Irrigation and drainage paper 56. Fao, Rome, 300(9),
659 D05109.
- 660 Alletto, L., Vandewalle, A., & Debaeke, P. (2022). Crop diversification improves cropping system
661 sustainability: An 8-year on-farm experiment in South-Western France. *Agricultural Systems*,
662 200, 103433. <https://doi.org/10.1016/j.agry.2022.103433>
- 663 Altieri, M. A., & Nicholls, C. I. (2017). The adaptation and mitigation potential of traditional agriculture
664 in a changing climate. *Climatic Change*, 140(1), 33-45. [https://doi.org/10.1007/s10584-013-](https://doi.org/10.1007/s10584-013-0909-y)
665 [0909-y](https://doi.org/10.1007/s10584-013-0909-y)
- 666 Ameer, F., Kuper, M., Lejars, C. & Dugué, P. (2017). Prosper, survive or exit: Contrasted fortunes of
667 farmers in the groundwater economy in the Saiss plain (Morocco). *Agric. Water Manag.* 191,
668 207–217. <https://doi.org/10.1016/j.agwat.2017.06.014>.
- 669 Anuraga, T.S., Ruiz, L., Kumar, M.S.M., Sekhar, M., Leijnse, A. (2006). Estimating groundwater recharge
670 using land use and soil data: a case study in South India. *Agric. Water Manag.* 84:65–76.
671 <http://dx.doi.org/10.1016/j.agwat.2006.01.017>
- 672 Aubron, C., Bainville, S., Philippon, O., & Dorin, B. (2022). Neither corporate, nor family: the Indian
673 “patronal” farm. *Front. Sustain. Food Syst.* 6:850545. <https://10.3389/fsufs.2022.850545>.
- 674 Babaeian, F., Delavar, M., Morid, S., & Srinivasan, R. (2021). Robust climate change adaptation
675 pathways in agricultural water management. *Agricultural Water Management*, 252, 106904.
676 <https://doi.org/10.1016/j.agwat.2021.106904>
- 677 Baccar, M., Bouaziz, A., Dugué, P., & Le Gal, P. Y. (2017). Shared environment, diversity of pathways:
678 dynamics of family farming in the Saïs Plain (Morocco). *Regional environmental change*, 17(3),
679 739-751. <https://doi.org/10.1007/s10113-016-1066-4>
- 680 Baccar, M., Bouaziz, A., Dugué, P., Gafsi, M., & Le Gal, P. Y. (2018). The determining factors of farm
681 sustainability in a context of growing agricultural intensification. *Agroecology and sustainable*
682 *food systems*, 43(4), 386-408. <https://doi.org/10.1080/21683565.2018.1489934>
- 683 Baccar, M.; Bergez, J.-E.; Couture, S.; Sekhar, M.; Ruiz, L.; Leenhardt, D. (2021). Building Climate Change
684 Adaptation Scenarios with Stakeholders for Water Management: A Hybrid Approach Adapted
685 to the South Indian Water Crisis. *Sustainability*, 13, 8459. <https://doi.org/10.3390/su13158459>
- 686 Barbiero, L., Kumar, M.S.M., Violette, A., Oliva, P., Braun, J.J., Kumar, C., Furian, S., Babic, M., Riotte,
687 J., Valles, V. (2010). Ferrollysis induced soil transformation by natural drainage in vertisols of
688 sub-humid South India. *Geoderma* 156:173–188.
689 <http://dx.doi.org/10.1016/j.geoderma.2010.02.014>.

690 Berre, D., Adam, M., Koffi, C. K., Vigne, M., & Gautier, D. (2022). Tailoring management practices to
691 the structure of smallholder households in Sudano-Sahelian Burkina Faso: Evidence from
692 current practices. *Agricultural Systems*, 198, 103369.
693 <https://doi.org/10.1016/j.agry.2022.103369>

694 Bhattarai, N., Pollack, A., Lobell, D. B., Fishman, R., Singh, B., Dar, A., & Jain, M. (2021). The impact of
695 groundwater depletion on agricultural production in India. *Environmental Research Letters*,
696 16(8), 085003. <https://doi.org/10.1088/1748-9326/ac10de>

697 Biarnès, A., Bailly, J. S., Mekki, I., & Ferchichi, I. (2021). Land use mosaics in Mediterranean rainfed
698 agricultural areas as an indicator of collective crop successions: Insights from a land use time
699 series study conducted in Cap Bon, Tunisia. *Agricultural Systems*, 194, 103281.
700 <https://doi.org/10.1016/j.agry.2021.103281>

701 Blakeslee, D., Fishman, R., Srinivasan, V. (2020). Way Down in the Hole: Adaptation to Long-Term
702 Water Loss in Rural India. *Am. Econ. Rev.* 110, 200–224.
703 <https://doi.org/10.1257/aer.20180976>

704 Boisson, A., Guihéneuf, N., Perrin, J., Bour, O., Dewandel, B., Dausse, A., ... & Maréchal, J. C. (2015).
705 Determining the vertical evolution of hydrodynamic parameters in weathered and fractured
706 south Indian crystalline-rock aquifers: insights from a study on an instrumented site.
707 *Hydrogeology Journal*, 23(4), 757-773. <https://doi.org/10.1007/s10040-014-1226-x>

708 Braun JJ, Desclotres M, Riotte J, Fleury S, Barbiéro L, Boeglin JL, Violette A, Lacarce E, Ruiz L, Sekhar
709 M, Mohan Kumar M.S., Subramanian S and Dupré B. (2009). Regolith mass balance inferred
710 from combined mineralogical, geochemical and geophysical studies: Mule Hole gneissic
711 watershed, South India. *Geochimica and Cosmochimica Acta*, 73, 935-961.
712 <http://dx.doi.org/10.1016/j.gca.2008.11.013>

713 Brouwer, C., & Heibloem, M. (1986). *Irrigation water management: Irrigation water needs*. Rome: Food
714 and Agriculture Organization. <http://www.fao.org/docrep/S2022E/S2022E00.htm#>

715 Buvaneshwari S, Riotte J, Sekhar M, Mohan Kumar MS, Sharma AK, Duprey JL, Audry S, Giriraj PR,
716 Yerabham P, Moger H, Durand P, Braun JJ and Ruiz L . (2017). High spatial variability of nitrate
717 contamination in the hard rock aquifer of an irrigated catchment: Implications for water
718 resource assessment. *Science of the Total Environment*. 579, 838-847
719 <http://dx.doi.org/10.1016/j.scitotenv.2016.11.017>

720 Buvaneshwari, S., Riotte, J., Sekhar, M., Sharma, A. K., Helliwell, R., Kumar, M. M., Bran, J.J. & Ruiz, L.
721 (2020). Potash fertilizer promotes incipient salinization in groundwater irrigated semi-arid
722 agriculture. *Scientific reports*, 10(1), 1-14. <https://doi.org/10.1038/s41598-020-60365-z>

723 Collins, L., Loveless, S. E., Muddu, S., Buvaneshwari, S., Palamakumbura, R. N., Krabbendam, M., ... &
724 MacDonald, A. M. (2020). Groundwater connectivity of a sheared gneiss aquifer in the Cauvery

725 River basin, India. *Hydrogeology Journal*, 28(4), 1371-1388. [https://doi.org/10.1007/s10040-](https://doi.org/10.1007/s10040-020-02140-y)
726 [020-02140-y](https://doi.org/10.1007/s10040-020-02140-y)

727 Darnhofer, I., Bellon, S., Dedieu, B., Milestad, R. (2010). Adaptiveness to enhance the sustainability of
728 farming systems. A review. *Agron. Sustain. Dev.* 30, 545–555.
729 <https://doi.org/10.1051/agro/2009053>

730 Dogliotti, S., W. A. H. Rossing, and M. K. Van Ittersum. (2003). ROTAT, a tool for systematically
731 generating crop rotations. *European Journal of Agronomy* 19.2: 239-250.
732 [https://doi.org/10.1016/S1161-0301\(02\)00047-3](https://doi.org/10.1016/S1161-0301(02)00047-3)

733 Duker, A. E. C., Mawoyo, T. A., Bolding, A., de Fraiture, C., & van der Zaag, P. (2020). Shifting or drifting?
734 The crisis-driven advancement and failure of private smallholder irrigation from sand river
735 aquifers in southern arid Zimbabwe. *Agricultural Water Management*, 241, 106342.
736 <https://doi.org/10.1016/j.agwat.2020.106342>

737 Dupuis, A., Dadouchi, C., & Agard, B. (2022). Predicting crop rotations using process mining techniques
738 and Markov principals. *Computers and Electronics in Agriculture*, 194, 106686.
739 <https://doi.org/10.1016/j.compag.2022.106686>

740 Dury, J., Schaller, N., Garcia, F., Reynaud, A., & Bergez, J. E. (2012). Models to support cropping plan
741 and crop rotation decisions. A review. *Agronomy for sustainable development*, 32, 567-580.
742 <https://doi.org/10.1007/s13593-011-0037-x>

743 Elzinga, Cees H. (2008). Sequence analysis: Metric representations of categorical time series. Technical
744 Report, Department of Social Science Research Methods, Vrije Universiteit, Amsterdam.

745 Fischer, C., Aubron, C., Trouvé, A., Sekhar, M., & Ruiz, L. (2022). Groundwater irrigation reduces overall
746 poverty but increases socioeconomic vulnerability in a semiarid region of southern India.
747 *Scientific Reports*, 12(1), 1-16. <https://doi.org/10.1038/s41598-022-12814-0>

748 Fishman, R. M., T. Siegfried, P. Raj, V. Modi, and U. Lall (2011), Over-extraction from shallow bedrock
749 versus deep alluvial aquifers: Reliability versus sustainability considerations for India’s
750 groundwater irrigation, *Water Resour. Res.*, 47, W00L05, doi:10.1029/2011WR010617.

751 Gabadinho, A., Ritschard, G., Mueller, N. S., & Studer, M. (2011). Analyzing and visualizing state
752 sequences in R with TraMineR. *Journal of statistical software*, 40(4), 1-37.
753 <https://doi.org/10.18637/jss.v040.i04>

754 Gaillardet, J., Braud, I., Gandois, L., Probst, A., Probst, J. L., Sanchez-Pérez, J. M., & Simeoni-Sauvage,
755 S. (2018). OZCAR: The French network of critical zone observatories. *Vadose Zone*
756 *Journal*, 17(1), 1-24. <https://doi.org/10.2136/vzj2018.04.0067>

757 Goddard, W. & Melville, S. (2004) “Research Methodology: An Introduction” 2nd edition, Blackwell
758 Publishing

759 Gomez, C., Dharumarajan, S., Féret, J. B., Lagacherie, P., Ruiz, L., & Sekhar, M. (2019). Use of sentinel-
760 2 time-series images for classification and uncertainty analysis of inherent biophysical
761 property: Case of soil texture mapping. *Remote Sensing*, 11(5), 565.
762 <https://doi.org/10.3390/rs11050565>

763 Hooge R., Landy F., Nous, C & Ruiz L., (2022) Consolidation d'une paysannerie émiettée... ou
764 accaparement de terres par des estates (Inde du Sud) ? *Etudes rurales*, 209, 162-185.
765 <https://doi.org/10.4000/etudesrurales.28942>

766 Howden, S. M., Soussana, J. F., Tubiello, F. N., Chhetri, N., Dunlop, M., & Meinke, H. (2007). Adapting
767 agriculture to climate change. *Proceedings of the national academy of sciences*, 104(50),
768 19691-19696. <https://doi.org/10.1073/pnas.0701890104>

769 IPCC, 2022. *Climate Change 2022: Impacts, Adaptation and Vulnerability*. Working Group II
770 Contribution to the IPCC Sixth Assessment Report

771 Kaufman L, Rousseeuw PJ (2009) *Finding Groups in Data: An Introduction to Cluster Analysis*, John
772 Wiley.

773 Khoury, C. K., Bjorkman, A. D., Dempewolf, H., Ramirez-Villegas, J., Guarino, L., Jarvis, A., ... & Struik, P.
774 C. (2014). Increasing homogeneity in global food supplies and the implications for food
775 security. *Proceedings of the national Academy of Sciences*, 111(11), 4001-4006.1
776 <https://doi.org/10.1073/pnas.1313490111>

777 Kumar, S., Mishra, A. K., Pramanik, S., Mamidanna, S., & Whitbread, A. (2020). Climate risk,
778 vulnerability and resilience: Supporting livelihood of smallholders in semiarid India. *Land Use*
779 *Policy*, 97, 104729. <https://doi.org/10.1016/j.landusepol.2020.104729>

780 Labeyrie, V., Renard, D., Aumeeruddy-Thomas, Y., Benyei, P., Caillon, S., Calvet-Mir, L., M. Carrière, S.,
781 Demongeot, M., Descamps, E., Braga Junqueira, A., Li, X., Locqueville, J., Mattalia, G., Miñarro,
782 S., Morel, A., Porcuna-Ferrer, A., Schlingmann, A., Vieira da Cunha Avila, J., Reyes-García, V.,
783 2021. The role of crop diversity in climate change adaptation: insights from local observations
784 to inform decision making in agriculture. *Curr. Opin. Environ. Sustain.* 51, 15–23.
785 <https://doi.org/10.1016/j.cosust.2021.01.0069>.

786 Landy, F., Ruiz, L., Jacquet, J., Richard-Ferroudji, A., Sekhar, M., Guétat-Bernard, H., Oger-Marengo, M.,
787 Venkatasubramanian, G., & Noûs, C. (2021). Commons as Demanding Social Constructions:
788 The Case of Aquifers in Rural Karnataka. *International Journal of Rural Management*, 17(1) 27-
789 54. <https://doi.org/10.1177/0973005220945428>

790 Lê, S., Josse, J. & Husson, F. (2008). FactoMineR: An R Package for Multivariate Analysis. *Journal of*
791 *Statistical Software*. 25(1). pp. 1-18

792 Le Goix, R., Giraud, T., Cura, R., Le Corre, T. & Migozzi, J. (2019), "Who sells to whom in the suburbs?
793 Home price inflation and the dynamics of sellers and buyers in the metropolitan region of Paris,
794 1996-2012", PLoS ONE. Vol. 14(3). e0213169.

795 Leenhardt, D., Angevin, F., Biarnes, A., Colbach, N., Mignolet, C., 2010. Describing and locating cropping
796 systems at a regional scale. *Agronomy for Sustainable Development*, 30, 131-138
797 <https://doi.org/10.1051/agro/2009002>

798 Leenhardt, D., Therond, O., and Mignolet, C., (2012a). Quelle représentation des systèmes de culture
799 pour la gestion de l'eau sur un grand territoire ?. *Agronomie, Environnement & Sociétés*,
800 Association Française d'Agronomie (Afa), 2012, 2 (2), pp.77-89. [https://hal.inrae.fr/hal-](https://hal.inrae.fr/hal-02648041)
801 [02648041](https://hal.inrae.fr/hal-02648041)

802 Leenhardt, D., Therond, O., Cordier, M. O., Gascuel-Oudou, C., Reynaud, A., Durand, P., ... & Moreau,
803 P. (2012b). A generic framework for scenario exercises using models applied to water-resource
804 management. *Environmental Modelling & Software*, 37, 125-133.
805 <https://doi.org/10.1016/j.envsoft.2012.03.010>

806 Levitt M. 1969. Detailed molecular model for transfer ribonucleic acid. *Nature* 224:759–763.
807 <https://doi.org/10.1038/224759a0>

808 Levenshtein V. 1966. Binary codes capable of correcting deletions, insertions, and reversals. *Soviet*
809 *PhysicsDoklady* 10:707–710

810 Lin, B. B. (2011). Resilience in agriculture through crop diversification: adaptive management for
811 environmental change. *BioScience*, 61(3), 183-193. <https://doi.org/10.1525/bio.2011.61.3.4>

812 Martin, A. R., Cadotte, M. W., Isaac, M. E., Milla, R., Vile, D., & Violle, C. (2019). Regional and global
813 shifts in crop diversity through the Anthropocene. *PLoS One*, 14(2), e0209788.

814 Mas, J.-F., Nogueira de Vasconcelos, R. & Franca-Rocha, W. (2019), "Analysis of High Temporal
815 Resolution Land Use/Land Cover Trajectories", *Land*. Vol. 8(2), pp. 30.

816 Mendelsohn, R. O., & Massetti, E. (2020). The use of cross-sectional analysis to measure climate
817 impacts on agriculture: theory and evidence. *Review of Environmental Economics and Policy*.

818 Modak, T. S. From public to private irrigation: Implications for equity in access to water. *Rev. Agrar.*
819 *Stud.* 8(1), 28–61 (2018).

820 Moniruzzaman, S. (2015). Crop choice as climate change adaptation: Evidence from Bangladesh.
821 *Ecological Economics*, 118, 90-98. <https://doi.org/10.1016/j.ecolecon.2015.07.012>

822 Nowak, B., Michaud, A., & Marliac, G. (2022). Assessment of the diversity of crop rotations based on
823 network analysis indicators. *Agricultural Systems*, 199, 103402.
824 <https://doi.org/10.1016/j.agsy.2022.103402>

825 Omran M, Engelbrecht A, Salman A (2007) An overview of clustering methods. *Intelligent Data Analysis*
826 11:583–605.

827 Østergård, H., Finckh, M. R., Fontaine, L., Goldringer, I., Hoad, S. P., Kristensen, K., ... & Wolfe, M. S.
828 (2009). Time for a shift in crop production: embracing complexity through diversity at all levels.
829 Journal of the Science of Food and Agriculture, 89(9), 1439-1445.
830 <https://doi.org/10.1002/jsfa.3615>
831

832 Patil, V. S., Thomas, B. K., Lele, S., Eswar, M., & Srinivasan, V. (2019). Adapting or Chasing Water? Crop
833 Choice and Farmers' Responses to Water Stress in Peri-Urban Bangalore, India. Irrigation and
834 Drainage, 68(2), 140-151. <https://doi.org/10.1002/ird.2291>

835 Risbey, J., Kandlikar, M., Dowlatabadi, H. et al. Scale, context, and decision making in agricultural
836 adaptation to climate variability and change. Mitigation and Adaptation Strategies for Global
837 Change 4, 137–165 (1999). <https://doi.org/10.1023/A:1009636607038>

838 Robert, M., Thomas, A. & Bergez, J.E. (2016a) Processes of adaptation in farm decision-making models.
839 A review. Agron. Sustain. Dev., 36:64. <http://dx.doi.org/10.1007/s13593-016-0402-x 7>.

840 Robert M., Dury j., Thomas A., Therond O., Sekhar M., Badiger S., Ruiz L., Bergez J.E. (2016b) CMFDM:
841 A methodology to guide the design of a conceptual model of farmers' decision-making
842 processes. Agricultural Systems. 148, 86-94. <http://dx.doi.org/10.1016/j.agsy.2016.07.010>

843 Robert, M., Thomas, A., Sekhar, M., Badiger, S., Ruiz, L., Willaume, M., Leenhardt, D., Bergez, J.-E.,
844 (2017a). Farm Typology in the Berambadi Watershed (India): Farming Systems Are Determined
845 by Farm Size and Access to Groundwater. Water 9 (1), 51. <https://doi.org/10.3390/w9010051>

846 Robert, M., Thomas, A., Sekhar, M., Badiger, S., Ruiz, L., Raynal, H., & Bergez, J. E. (2017b). Adaptive
847 and dynamic decision-making processes: A conceptual model of production systems on Indian
848 farms. Agricultural Systems, <https://doi.org/10.1016/j.agsy.2016.08.001>

849 Robert, M., Thomas, A., Sekhar, M., Raynal, H., Casellas, É., Casel, P., ... & Bergez, J. E. (2018). A dynamic
850 model for water management at the farm level integrating strategic, tactical and operational
851 decisions. Environmental modelling & software, 100, 123-135.
852 <https://doi.org/10.1016/j.envsoft.2017.11.013>

853 Sadanandan, A. (2014) Political economy of suicide: Financial reforms, credit crunches and farmer
854 suicides in India. J. Dev. Areas 48(4), 287–307

855 Salmon-Monviola, J., Durand, P., Ferchaud, F., Oehler, F., & Sorel, L. (2012). Modelling spatial dynamics
856 of cropping systems to assess agricultural practices at the catchment scale. Computers and
857 electronics in agriculture, 81, 1-13. <https://doi.org/10.1016/j.compag.2011.10.020>

858 Salonen, J., Möttönen, J., Tikanmäki, H. & Nummi, T. (2020), "Using sequence analysis to visualize and
859 validate model", International Journal of Microsimulation. Vol. 13(2), pp. 61-78.

860 Sekhar, M., Rasmi, S. N., Sivapullaiah, P. V., & Ruiz, L. (2004). Groundwater flow modeling of Gundal
861 sub-basin in Kabini river basin, India. *Asian Journal of Water, Environment and Pollution*, 1(1-
862 2), 65-77.

863 Sekhar, M.; Javeed, Y.; Bandyopadhyay, S.; Mangiarotti, S.; Mazzega, P. (2011) Groundwater
864 management practices and emerging challenges: Lessons from a case study in the Karnataka
865 State of South India. In *Groundwater Management Practices*; CRC Press: Boca Raton, FL, USA,
866 p. 436.

867 Sekhar, M.; Riotte, J.; Ruiz, L.; Jouquet, J.; Braun, J.J. (2016) Influences of Climate and Agriculture on
868 Water and Biogeochemical Cycles: Kabini Critical Zone Observatory. *Proc. Indian Natl. Sci.*
869 *Acad.*, 82, 833–846.

870 Shah, T., 2009. Climate change and groundwater: India’s opportunities for mitigation and adaptation.
871 *Environ. Res. Lett.* 4, 035005. <https://doi.org/10.1088/1748-9326/4/3/035005>

872 Sarkar, A. Socio-economic implications of depleting groundwater resource in Punjab: A comparative
873 analysis of diferent irrigation systems. *Econ. Pol. Wkly.* 46(7), 59–66 (2011).

874 Sharma, A., Hubert-Moy, L., Buvaneshwari, S., Sekhar, M., Ruiz, L., Bandyopadhyay, S., Corgne, S.,
875 (2018) Irrigation History Estimation Using Multitemporal Landsat Satellite Images: Application
876 to an Intensive Groundwater Irrigated Agricultural Watershed in India. *Remote Sens.* 10, 893.
877 <https://doi.org/10.3390/rs10060893>

878 Shiferaw, B., Reddy, V. R., & Wani, S. P. (2008). Watershed externalities, shifting cropping patterns and
879 groundwater depletion in Indian semi-arid villages: The effect of alternative water pricing
880 policies. *Ecological Economics*, 67(2), 327-340.

881 Silberer, G. (2012) Analyzing Sequences in Marketing Research. In *Quantitative Marketing and*
882 *Marketing Management: Marketing Models and Methods in Theory and Practice*;
883 Diamantopoulos, A., Fritz, W., Hildebrandt, L., Eds.; Gabler Verlag: Wiesbaden, Germany, pp.
884 209–224.

885 Srinivasan, V.; Thompson, S.; Madhyastha, K.; Penny, G.; Jeremiah, K.; Lele, S. (2015) Why is the
886 Arkavathy River drying? A multiple-hypothesis approach in a data-scarce region. *Hydrol. Earth*
887 *Syst. Sci.*, 19, 1905–1917

888 Sutcliffe, C., Knox, J., & Hess, T. (2021). Managing irrigation under pressure: how supply chain demands
889 and environmental objectives drive imbalance in agricultural resilience to water shortages.
890 *Agricultural Water Management*, 243, 106484. <https://doi.org/10.1016/j.agwat.2020.106484>

891 Taylor, M. (2013) Liquid Debts: credit, groundwater and the social ecology of agrarian distress in
892 Andhra Pradesh, India. *Tird World Q.* 34(4), 691–709.
893 <https://doi.org/10.1080/01436597.2013.786291>.

894 Tripathi, A., Mishra, A.K., 2017. Knowledge and passive adaptation to climate change: An example from
895 Indian farmers. *Clim. Risk Manag.* 16, 195–207. <https://doi.org/10.1016/j.crm.2016.11.002>

896 Upcott, E. V., Henrys, P. A., Redhead, J. W., Jarvis, S. G., & Pywell, R. F. (2023). A new approach to
897 characterising and predicting crop rotations using national-scale annual crop maps. *Science of*
898 *the Total Environment*, 860, 160471. <https://doi.org/10.1016/j.scitotenv.2022.160471>

899 van Zonneveld, M., Turmel, M. S., & Hellin, J. (2020). Decision-making to diversify farm systems for
900 climate change adaptation. *Frontiers in Sustainable Food Systems*, 4, 32.
901 <https://doi.org/10.3389/fsufs.2020.00032>

902 Wyns, R., Baltassat, J. M., Lachassagne, P., Legchenko, A., Vairon, J., & Mathieu, F. (2004). Application
903 of proton magnetic resonance soundings to groundwater reserve mapping in weathered
904 basement rocks (Brittany, France). *Bulletin de la Société géologique de France*, 175(1), 21-34.

905 Yuan, S., Li, X., & Du, E. (2021). Effects of farmers' behavioral characteristics on crop choices and
906 responses to water management policies. *Agricultural Water Management*, 247, 106693.
907 <https://doi.org/10.1016/j.agwat.2020.106693>

908 Zhang, C., Di, L., Lin, L., Li, H., Guo, L., Yang, Z., ... & Yang, A. (2022). Towards automation of in-season
909 crop type mapping using spatiotemporal crop information and remote sensing data.
910 *Agricultural Systems*, 201, 103462. <https://doi.org/10.1016/j.agsy.2022.103462>

911 Zobeidi, T., Yaghoubi, J., & Yazdanpanah, M. (2022). Farmers' incremental adaptation to water scarcity:
912 An application of the model of private proactive adaptation to climate change (MPPACC).
913 *Agricultural Water Management*, 264, 107528. <https://doi.org/10.1016/j.agwat.2022.107528>

914

915 **List of Tables and Figures**

916 **Table 1:** Different states observed in the survey for individual farms. A state is the aggregation of the
917 different crop categories sown or planted on the same farm in the same season of the same year

918 **Table 2:** Percentage of occurrence of each of the four crop categories short cycle (SC), long cycle (LC),
919 rainfed crop (R), and fallow (NC) for each farm type. Percentage is expressed as the total count of each
920 crop category in each farm type – including states with more than one crop category – divided by the
921 total number of states for this farm type in this season.

922 **Table 3:** Correlations between crop choices and monthly rainfall or groundwater availability for each
923 season and each farm type.

924 **Figure 1:** Map of the Berambadi watershed with location of monitored farms (red dots)

925 **Figure 2:** Monthly average and standard deviation of groundwater depth (in meter below ground) for
926 the 188 monitored borewells with continuous data over the study period (2010-2019)

927 **Figure 3:** Borewell yields (L/s) vs water table depth (in meter below ground). We plotted the average
928 and standard deviation of 18 class intervals of groundwater table depths (for each class N=9).

929 **Figure 4:** Typology of crop sequences in Kharif season a) time series across years of the proportion of
930 each state within the group of farms belonging to the each of the four farm types (see table 1 for
931 explanation of states acronyms), b) box plot of the Diversity index by farm type, and c) box plot of
932 groundwater levels by farm type.

933 **Figure 5:** Typology of crop sequences in Rabi season a) time series across years of the proportion of
934 each state within the group of farms belonging to the each of the two farm types (see table 1 for
935 explanation of states acronyms), b) box plot of the Diversity index by farm type, and c) box plot of
936 groundwater levels by farm type.

937 **Figure 6:** Typology of crop sequences in Summer season a) time series across years of the proportion
938 of each state within the group of farms belonging to the each of the two farm types (see table 1 for
939 explanation of states acronyms), b) box plot of the Diversity index by farm type, and c) box plot of
940 groundwater levels by farm type.

941 **Figure 7:** Five main farm annual pathways of types across the three seasons, with the percentage of
942 farms following each pathway.

943

944 **Supplementary material**

945 **Table S1:** Crop categories, crop species and cultural cycles observed in the Berambadi watershed. The
946 main season(s) for sowing or planting of each crop species are noted K (Kharif), R (Rabi) and S
947 (Summer). Seasons noted into brackets are possible but less frequent.

948 **Figure S1:** Data curation steps

949 **Figure S2.** Annual rainfall (mm) for the studied period (histogram) and long-term average annual
950 rainfall over the 2004-2019 period (solid line) at the Maddur weather station.

951 **Figure S3:** Monthly average rainfall (bars, red for Kharif, green for Rabi and blue for Summer) with
952 standard deviation over the study period (2010-2019) and Penman potential evapotranspiration (blue
953 curve), in mm/month, at the Maddur weather station.

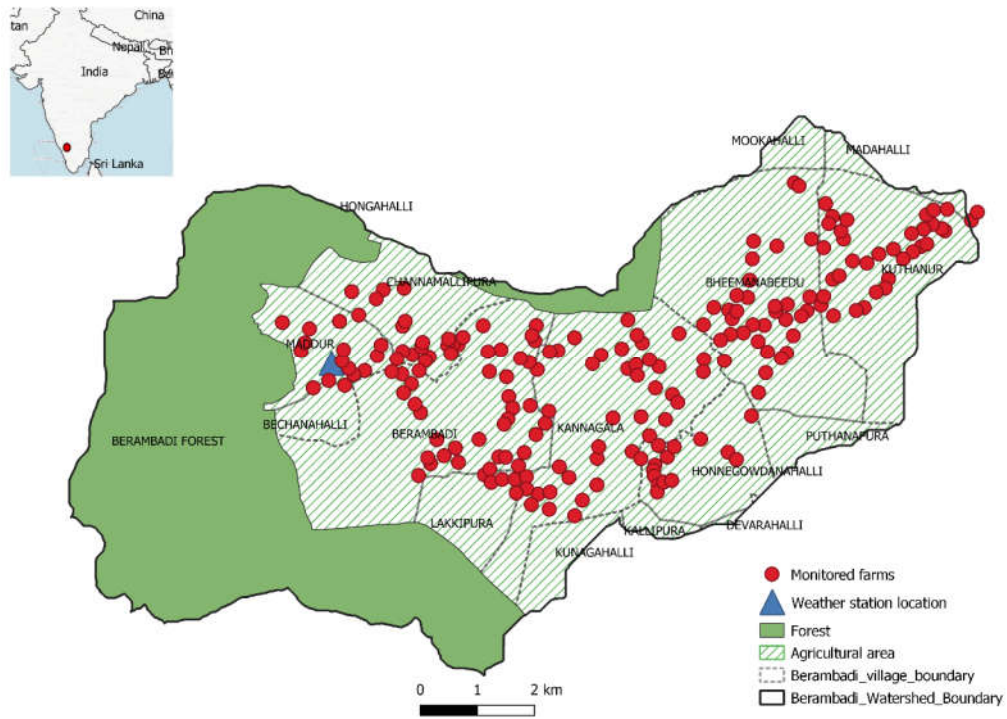
954 **Figure S4:** Box plot of average groundwater depth (in meter below ground surface) for each season

955

956

957 **Figure 1:** Map of the Berambadi watershed with location of monitored farms (red dots)

958

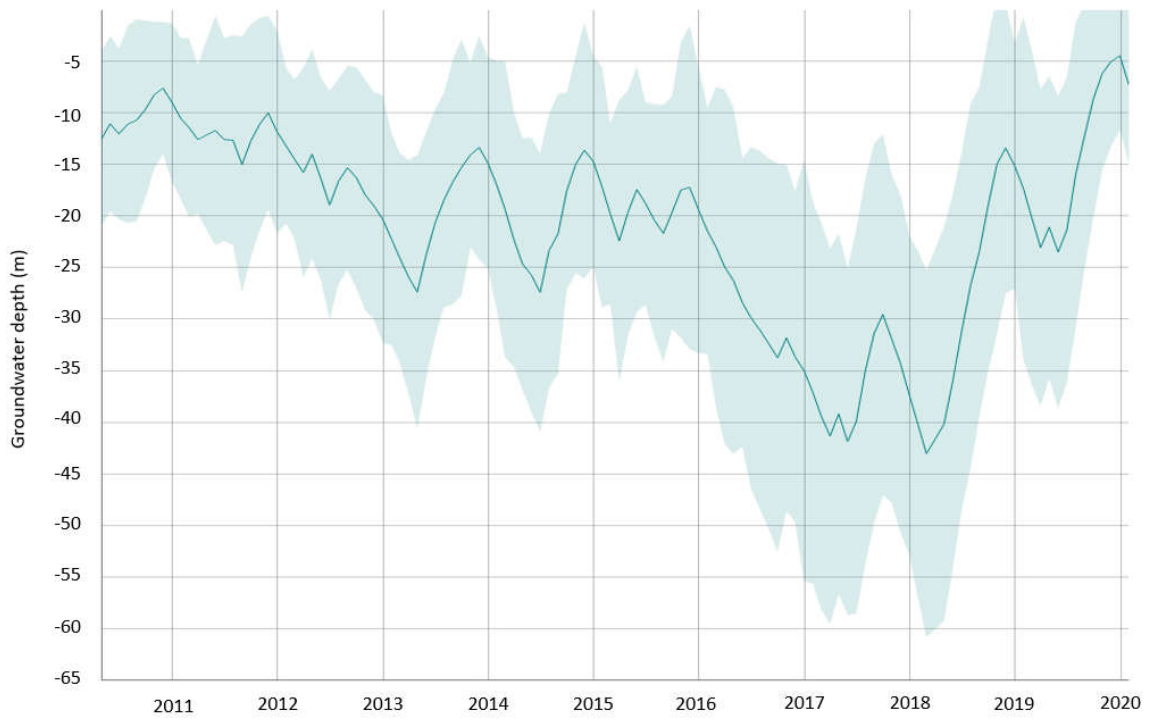


959

960

961

962 **Figure 2:** Monthly average and standard deviation of groundwater depth (in meter below ground) for
963 the 188 monitored borewells with continuous data over the study period (2010-2019)



964

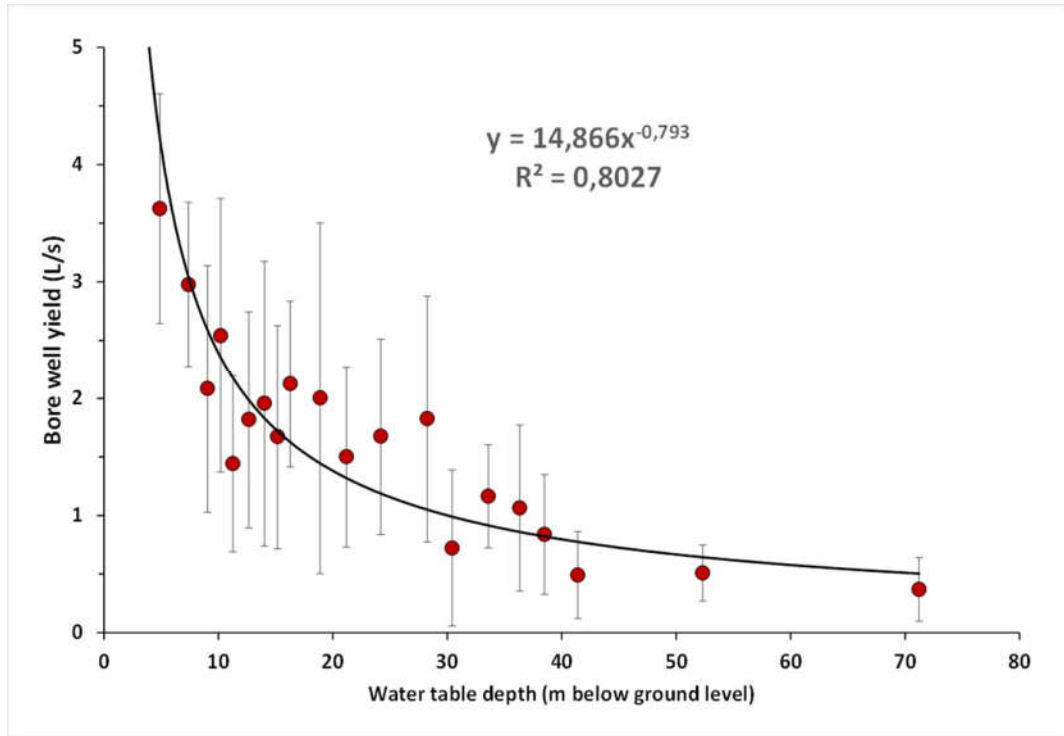
965

966 **Figure 3:** Borewell yields (L/s) vs water table depth (in meter below ground). We plotted the average
967 and standard deviation of 18 class intervals of groundwater table depths (for each class N=9).

968

969

970



971

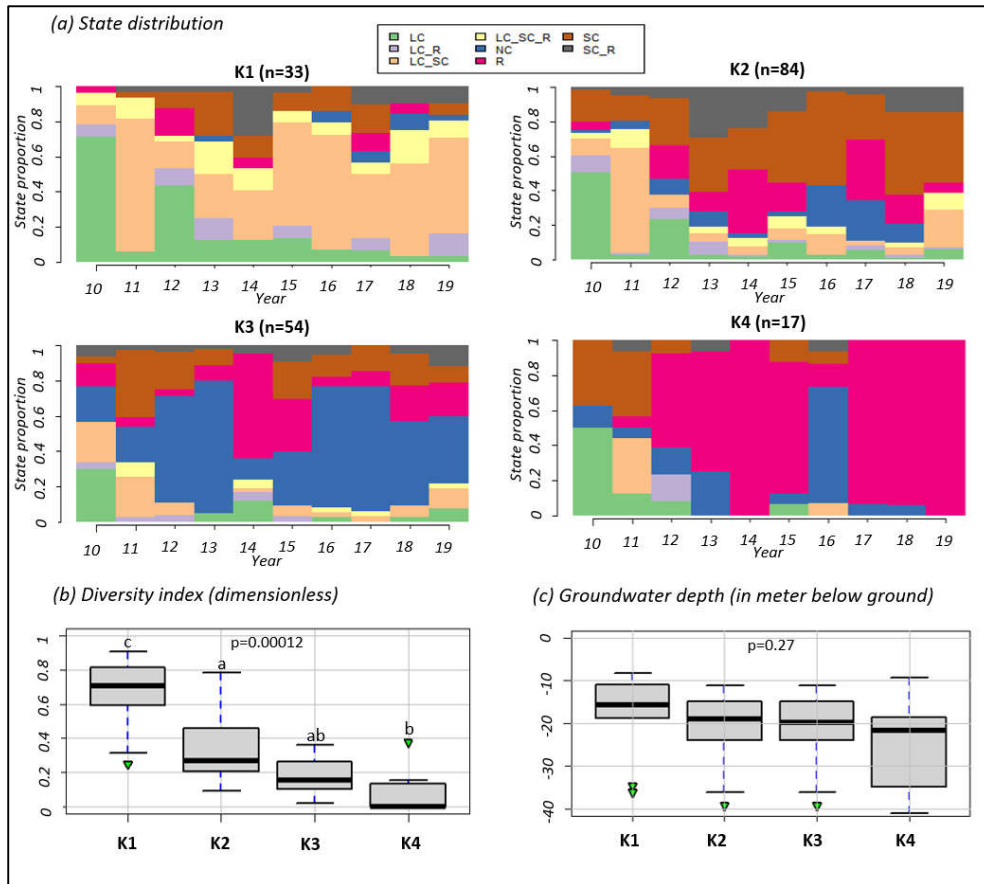
972

973

974 **Figure 4:** Farm typology for the Kharif season a) Time series across years of the proportion of each
 975 state within the group of farms belonging to the each of the four farm types (see table 1 for explanation
 976 of states acronyms), b) box plot of the Diversity index by farm type, and c) box plot of groundwater
 977 levels by farm type.

978

979



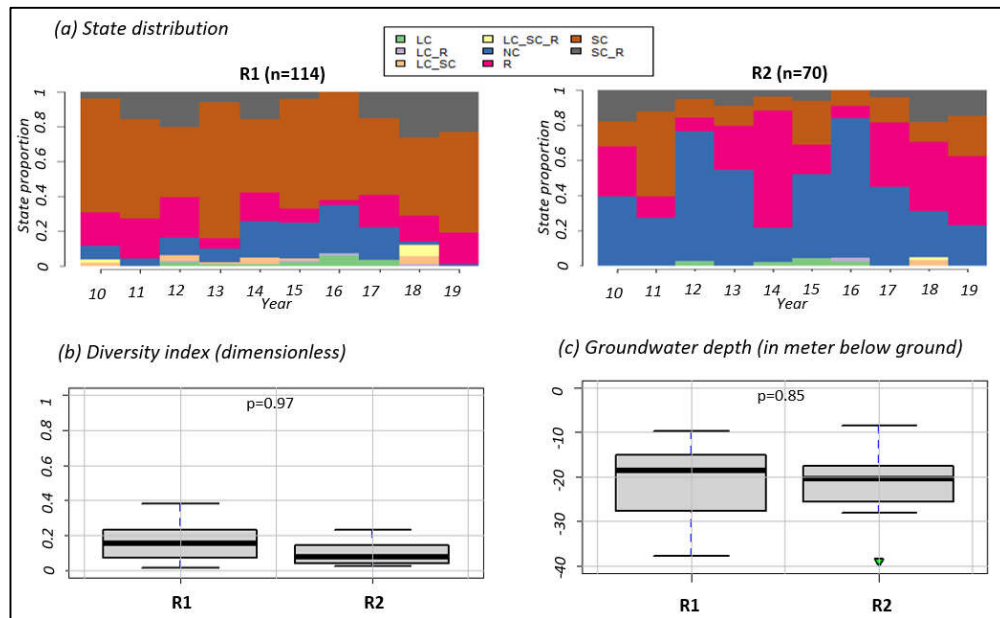
980

981

982 **Figure 5:** Farm typology for the Rabi season a) Time series across years of the proportion of each state
 983 within the group of farms belonging to the each of the two farm types (see table 1 for explanation of
 984 states acronyms), b) box plot of the Diversity index by farm type, and c) box plot of groundwater levels
 985 by farm type.

986

987



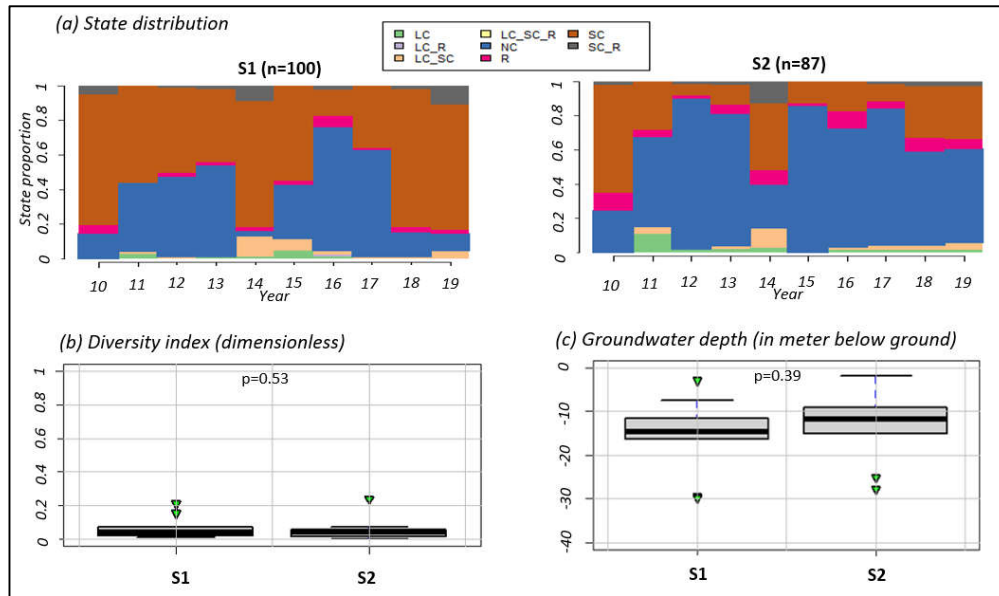
988

989

990

991 **Figure 6:** Farm typology for the Summer season a) Time series across years of the proportion of each
992 state within the group of farms belonging to the each of the two farm types (see table 1 for explanation
993 of states acronyms), b) box plot of the Diversity index by farm type, and c) box plot of groundwater
994 levels by farm type.

995

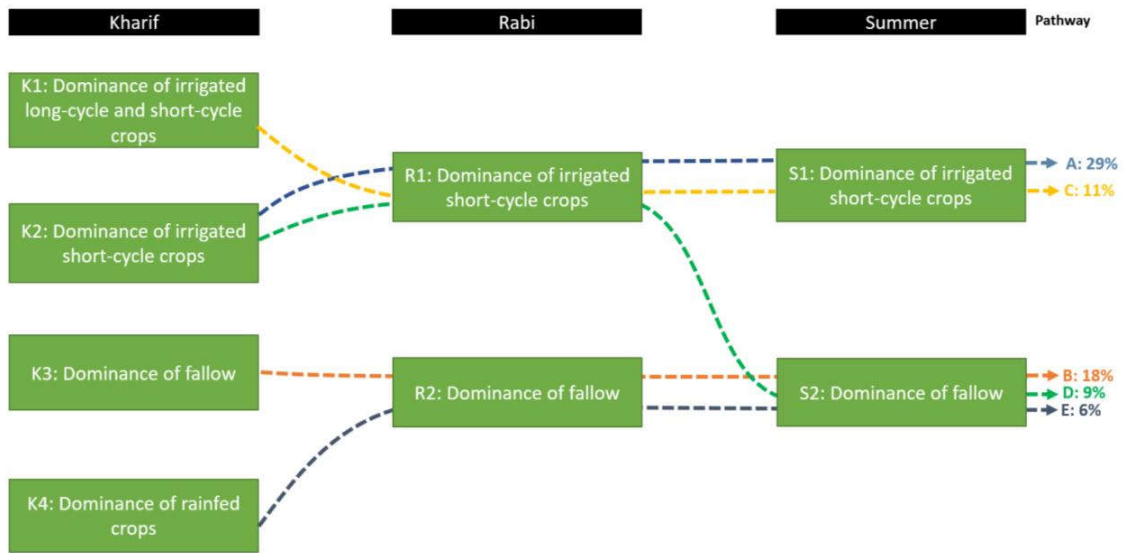


996

997

998 **Figure 7:** Five main farm annual pathways of types across the three seasons, with the percentage of
 999 farms following each pathway.

1000



1001

1002

Table 1: Different states observed in the survey for individual farms. A state is the aggregation of the different crop categories sown or planted on the same farm in the same season of the same year

States	
Code	Crop categories
LC	Long cycle irrigated crops only
LC_R	Long cycle irrigated crops and rainfed crops
LC_SC	Long and short cycle irrigated crops
LC_SC_R	Long cycle and short cycle irrigated crops and rainfed crops
NC	Fallow (no crop)
R	Rainfed crops only
SC	Short cycle irrigated crops only
SC_R	Short cycle irrigated crops and rainfed crops

Table 2: Percentage of occurrence of each of the four crop categories short cycle (SC), long cycle (LC), rainfed crop (R), and fallow (NC) for each farm type. Percentage is expressed as the total count of each crop category in each farm type – including states with more than one crop category – divided by the total number of states for this farm type in this season.

Season	Farm Type (number of Farms)		Crop category			
			LC	SC	R	NC
Kharif	K1 (n=33)	Mean	76%	69%	27%	3%
		[min, max]	[53%,96%]	[18%,94%]	[7%,47%]	[0%,9%]
	K2 (n=84)	Mean	32%	62%	34%	9%
		[min, max]	[10%,76%]	[33%,92%]	[7%,68%]	[0%,24%]
	K3 (n=54)	Mean	18%	31%	26%	44%
		[min, max]	[4%,57%]	[11%,72%]	[11%,74%]	[12%,76%]
	K4 (n=17)	Mean	13%	16%	64%	14%
		[min, max]	[0%,50%]	[0%,75%]	[0%,100%]	[0%,67%]
Rabi	R1 (n=114)	Mean	4%	71%	29%	12%
		[min, max]	[0%,12%]	[59%,85%]	[4%,49%]	[1%,28%]
	R2 (n=70)	Mean	2%	18%	37%	44%
		[min, max]	[0%,5%]	[8%,48%]	[9%,71%]	[20%,80%]
Summer	S1 (n=100)	Mean	4%	62%	6%	34%
		[min, max]	[0%,13%]	[20%,94%]	[0%,13%]	[3%,71%]
	S2 (n=87)	Mean	5%	30%	9%	61%
		[min, max]	[0%,15%]	[8%,65%]	[2%,21%]	[24%,88%]

Table 3: Correlations between crop choices and monthly rainfall or groundwater availability for each season and each farm type.

Adaptive choice	Kharif			Rabi			Summer			
	Farm type	Water availability		Farm type	Water availability			Farm type	Water availability	
		GW	Rain April		GW	Rain July	Rain August		GW	Rain Octobre
	K1			R1			S1			
NC		-0,87**	-		-0,88***	-		-0,79**	-	
LC		-	0,62.		-	0,58.		-	-	
SC		-	-		-	-		0,66*	0,71.	
R		-	-		-	-		-	-	
Divers. ¹		-	-		-	0,57.		-	-	
	K2			R2			S2			
NC		-0,58.	-		-	-		-0,70*	-	
LC		0,76*	0,81**		-	-		-	-	
SC		-	-		-	-		-	-	
R		-	-		-	0,72*		0,70*	-	
Divers. ¹		-	-		-	0,63*		-	-	
	K3									
NC		-	-							
LC		-	0,59.							
SC		-	0,62.							
R		-	-							
Divers. ¹		0,57.	0,59.							
	K4									
NC		-	-							
LC		0,72.	0,82**							
SC		-	0,69*							
R		-0,56.	-							
Divers. ¹		-	0,6.							

****p-value<0.001 ; ***0.001<p-value<0.01 ; **0.01<p-value<0.05 ; *0.05<p-value<0.1 ; >0.1; We retained only the months showing significant correlation with cropping pattern. ¹Diversification: at least two crop categories are grown on the farm at the same time (LC_R or LC_SC or SC_R or LC_SC_R)

Supplementary materials

Table S1: Crop categories, crop species and cultural cycles observed in the Berambadi watershed. The main season(s) for sowing or planting of each crop species are noted K (Kharif), R (Rabi) and S (Summer). Seasons noted into brackets are possible but less frequent.

Crop category	Common name	botanical name	Main season(s) for sowing or planting	Cycle duration (months)
Rainfed Crops (R)				
	Chickpea	<i>Cicer arietinum</i>	R	4
	Cowpea	<i>Vigna unguiculata</i>	R	4
	Cotton	<i>Gossypium sp.</i>	K (R)	5
	Finger millet	<i>Eleusine coracana</i>	R (K)	4
	Groundnut	<i>Arachis hypogaea</i>	K or R	4
	Horse gram	<i>Macrotyloma uniflorum</i>	R	4
	Indian bean	<i>Lablab purpureus</i>	R	4
	Maize	<i>Zea mays</i>	K or R (S)	4
	Marigold	<i>Tagetes erecta</i>	K (R)	4
	Pigeon pea	<i>Cajanus cajan</i>	K	5
	Sorghum	<i>Sorghum bicolor</i>	K or R	4
	Sunflower	<i>Helianthus annuus</i>	K (R)	4
	Tobacco	<i>Nicotiana tabacum</i>	K	5
Short-cycle irrigated crops (SC)				
	Beans	<i>Phaseolus vulgaris</i>	K or R or S	3
	Beetroot	<i>Beta vulgaris</i>	K or R or S	3
	Brinjal	<i>Solanum melongena</i>	K or R or S	4
	Chili	<i>Capsicum annum</i>	K or R or S	4
	Cabbage	<i>Brassica oleracea</i>	K or R or S	3
	Carrot	<i>Daucus carota</i>	K or R or S	3
	Cauliflower	<i>Brassica oleracea</i>	K or R or S	3
	Garlic	<i>Allium sativum</i>	K or R or S	3
	Ladyfingers	<i>Abelmoschus esculentus</i>	K or R or S	3
	Onion	<i>Allium cepa</i>	K (S)	3
	Potato	<i>Solanum tuberosum</i>	K or R	4
	Pumpkin	<i>Cucurbita pepo</i>	R (K)	4
	Sweet potato	<i>Ipomoea batatas</i>	K	4
	Tomato	<i>Solanum lycopersicum</i>	K or R or S	4
	Watermelon	<i>Citrullus lanatus</i>	K or S	3
Long-cycle irrigated crops (LC)				
	Banana	<i>Musa acuminata</i>	K (S)	12
	Turmeric	<i>Curcuma longa</i>	K	9
	Sugarcane	<i>Saccharum officinarum</i>	K (R, S)	12

Figure S1: Data curation steps

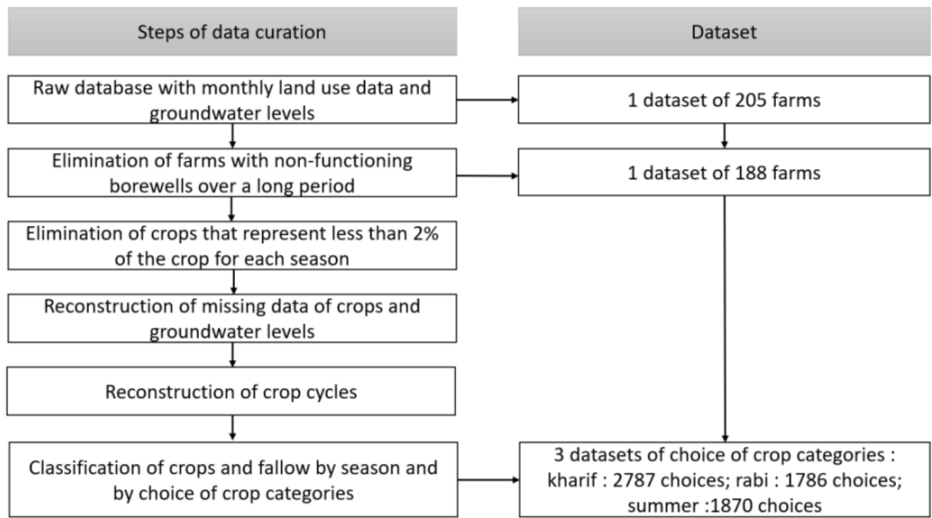


Figure S2. Annual rainfall (mm) for the studied period (histogram) and long-term average annual rainfall over the 2004-2019 period (solid line) at the Maddur weather station.

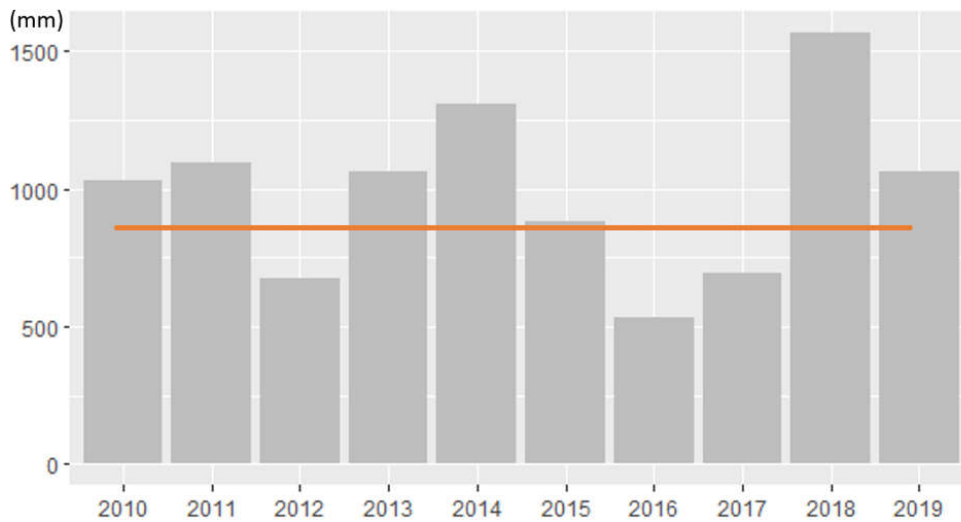


Figure S3: Monthly average rainfall (bars, red for Kharif, green for Rabi and blue for Summer) with standard deviation over the study period (2010-2019) and Penman potential evapotranspiration (blue curve), in mm/month, at the Maddur weather station.

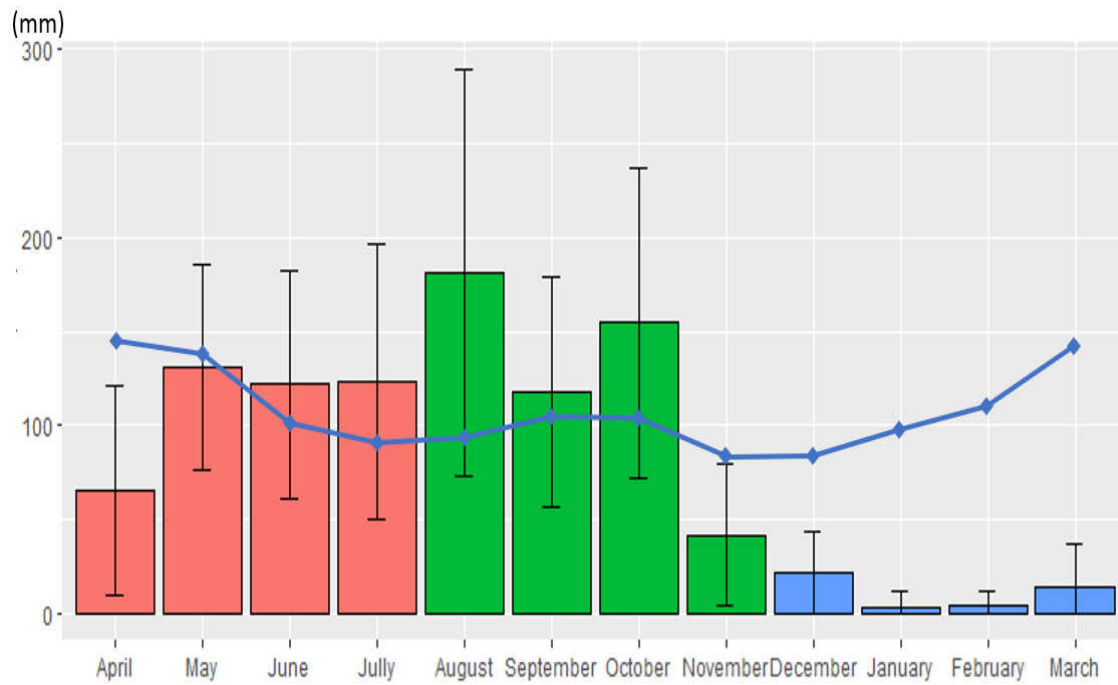


Figure S4. Box plot of average groundwater depth (in meter below ground surface) for each season

