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# Spatial patterns in the adaptive capacity of dryland agricultural households in South Punjab, Pakistan

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**Abstract**

Climate change and desertification continue to threaten livelihoods in drylands across the globe. This study explores the relative importance of Sustainable Livelihoods Framework components in explaining variation in the adaptive capacity of agricultural households in three districts in the drylands of south Punjab, Pakistan, and to identify spatial patterns in adaptive capacity distribution. Questionnaire generated data were analysed using Non-Linear Principal Component Analysis and spatial cluster mapping using the Global Moran's I and Anselin Local Moran's I. Natural assets were found to describe most variation among households, followed by physical, financial, human and social assets. Most households with high adaptive capacity were spatially clustered in Rahim Yar Khan, a district offering more employment opportunities and multiple income sources. Low adaptive capacity clusters were abundant in Rajanpur where respondents had negative loadings on all the principal components. Bahawalpur district lacked any significant adaptive capacity clusters. Spatial analyses can serve as a useful tool for policy makers in identifying the areas requiring government intervention to enhance adaptive capacity. The approach used here could usefully be applied to dryland regions in other parts of the world, and could help guide more targeted efforts to build adaptive capacity.

**Keywords:** Sustainable Livelihoods Framework, SLF, desertification, land use, assets, vulnerability, Asia

## 1 Introduction

Climate change and variability have the potential to intensify the poverty of a substantial number of the world's poor (Davies, 2017). At the same time, the IPCC (2019) emphasizes that climate change is projected to increase the risk of desertification in the drylands. Approximately half of the world's dryland population currently resides in South Asia (IPCC, 2019). The South Asia region continues to suffer from water scarcity (Hasnat et al., 2018;

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Khan and Shah, 2011; Zheng et al., 2018), with 12% of the region's total population living in extreme poverty (World Bank 2018, cited in IPCC, 2019a). Under shared socio-economic pathway 1 (SSP1), for global warming of 2°C, the world's dryland population is 974 million, with half of this vulnerable population being from South Asia (IPCC, 2019a). These projections mean it is paramount to understand people's ability to adapt to climate change in dryland areas, to highlight where additional efforts must be made to build adaptive capacity for the future. Without appropriate adaptive actions, climate change and desertification can lead to food insecurity, decreased livestock production, lack of livelihood options and low levels of human wellbeing (Nooghabi et al., 2019).

Adaptive capacity has been defined as "the ability of systems, institutions, humans and other organisms to adjust to potential damage, to take advantage of opportunities, or to respond to consequences" (IPCC, 2015, p. 118). Adaptive capacity plays a pivotal role in bridging the gap between resilience and vulnerability (Engle, 2011), with adaptive capacity sometimes being equated to resilience (Smit and Wandel, 2006). Elsewhere in the literature, adaptive capacity has been presented as a component of resilience (Carpenter et al., 2001), as system robustness to shifts in resilience (Gunderson, 2001), and as a collective capacity of people to manage resilience (Walker et al., 2004).

Economic resources, availability of technology, skills, information, access to institutions, infrastructure and equity, have all been regarded as key determinants of adaptive capacity (Engle, 2011), which can be shaped at both macro and micro levels. Huynh and Stringer (2018) explore community and individual vulnerability, and emphasize that differences in vulnerability at one level have a significant impact on vulnerability at other levels. Marzi et al. (2018) articulate the importance that policy makers must give to variation in adaptive capacity at lower administrative levels, while formulating national level indices through which it can be assessed.

The need for regular multidimensional assessments of adaptive capacity continues to rise in today's climate change threatened world. Communities with high levels of adaptive capacity are better able to select and implement adaptation options to cope, adjust and transform, following exposure to shocks and stresses (Brooks, 2003). Livelihood asset ownership is often closely associated with adaptive capacity (Moser, 1998). Generally, people with more assets have a higher adaptive capacity, assuming that under times of shock and stress they are able to shift between the types of assets required to adapt (Antwi-Agyei et al., 2013; Moser, 1998).

While there is a copious body of literature focused on vulnerability and adaptive capacity assessments across scales, it is not always linked to the major components that shape local livelihoods; nor is it presented spatially. Mapping patterns of adaptive capacity can help decision-makers visualise where investments are needed. Although there is a growing literature on vulnerability assessment (Nooghabi et al., 2019; Rajesh et al., 2018; Huynh and Stringer, 2018; Antwi-Agyei et al., 2013), and some researchers have sought to present the findings spatially, there remains a dearth of literature specifically regarding adaptive capacity mapping (but see Marzi et al. 2018). This study targets these gaps and advances the role of spatial mapping in vulnerability assessment. It aims to assess the role of sustainable livelihood components (human, physical, social, financial and natural assets) in shaping the adaptive capacity of dryland agricultural household communities in South Punjab, Pakistan: a region lacking detailed empirical studies, but thought to have low capacity to adapt to climate induced disasters (Malik et al., 2012). It explores the spatial variance of adaptive capacity clusters in the study area in relation to areas with different exposure to desertification. It offers a new spatial method of adaptive capacity clustering by aggregating household adaptive capacity indicators into a spatially explicit, unit-less adaptive capacity index. Focus is on adaptive capacity at the household level as this is the scale at which livelihood assets are most commonly managed.

# 2 Methodology

## 2.1 Study area and data collection

Pakistan is located in South Asia and is at high risk from natural disasters associated with the changing climate (Eckstein et al., 2019). Anjum et al. (2010) state that 90% of Pakistan's land is either arid or semi-arid, and thus vulnerable to desertification, while other researchers have highlighted the severity of aridity in the country (Mazhar et al., 2015b; Siddiqui and Javid, 2018). Drought frequency in the country is 2-3 years in every decade (Mazhar et al., 2015a). Severe droughts occurred in 1952, 1969, 1971, 2000, 2001 and 2002 (Adnan and Ullah, 2020). The dryland areas of Pakistan have witnessed a decline of 1.27 mm mean annual rainfall between 1961 and 2015 (Saifullah et al., 2018). Simultaneously, temperatures are rising, with a reported 1.6° C increase in the mean temperature of Pakistan's drylands over the last 55 years (Saifullah et al., 2018). Salinization of the Indus River is also contributing to desertification (IPCC, 2019b).

Punjab is the second largest province of Pakistan and the agricultural sector forms the backbone of its economy. South Punjab has been highlighted as the most arid part of the province (Mazhar et al., 2015b; Siddiqui and Javid, 2018). Three districts of South Punjab, namely Bahawalpur, Rahim Yar Khan and Rajanpur, situated in the dryland region (Saifullah et al., 2018), form the study area in this research (Fig. 1). The mean annual rainfall of Bahawalpur was 112.2 mm, Rahim Yar Khan 119.13mm, and the Division Dera Ghazi Khan (the broader administrative division in which Rajanpur District falls) 205.73mm in the year 2016, while the aridity index for the same year for the three districts under study was 0.04, 0.04 and 0.07 respectively (Javid, 2017).

The districts under study extend as a belt across the southern edge of Punjab, and have a high rural population: 68% in Bahawalpur, 79% in Rahim Yar Khan and 83% in Rajanpur (GoP, 2017b). The community is highly agrarian, relying on farming and livestock herding to support livelihoods (Siddiqui and Javid, 2018). Recurring vulnerability to food insecurity has been high in Rajanpur, but is considered to be medium in Bahawalpur and Rahim Yar Khan (National Disaster Management Authority (NDMA), 2017).

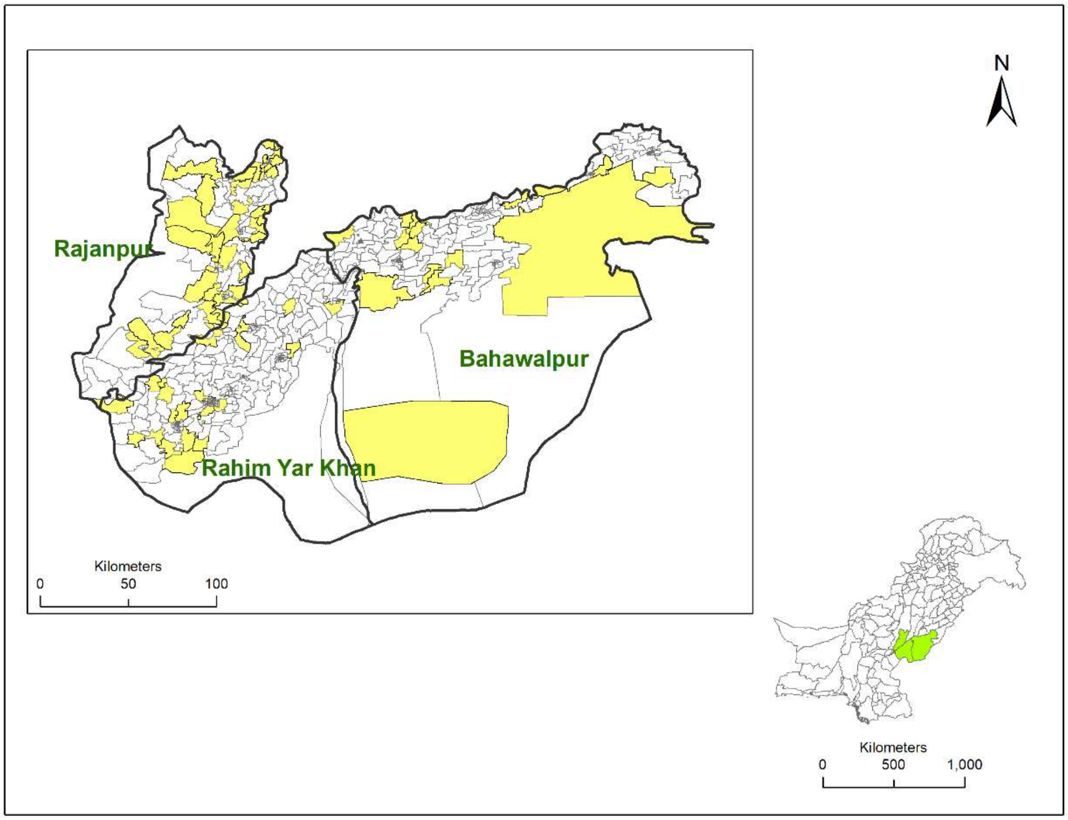


**Fig.1** The location of the study area within Pakistan (right). The left-hand panel shows the three districts of Bahawalpur (coordinates 29.3541°N, 71.6908° E), Rahim Yar Khan (28.4211°N, 70.2986°E), and Rajanpur 29.1041°N, 70.33°E) and the 66 union councils surveyed for this study (shaded yellow). Unshaded union councils were not included in the study. Data source: DIVA-GIS

The drought hazard risk is high in Bahawalpur and Rahim Yar Khan and medium in Rajanpur (NDMA, 2017). Desertification and climate change look set to aggravate the livelihoods and wellbeing of the highly agrarian population, as the region experiences high rates of evapotranspiration alongside decreasing mean annual precipitation. District Bahawalpur experienced a significant rise in potential evapotranspiration (PET) from 226mm in 1980 to 235.85mm in 2016, while Rahim Yar Khan underwent a rise in PET from 211.09mm in 2005 to 226.46mm in 2016. Similarly, a decrease in mean annual rainfall has also been recorded for the region, for e.g. Bahawalpur had 11.66mm of mean annual rainfall in 1980, which reduced to 9.23mm in 2016 (Siddiqui and Javid, 2018).

Household adaptive capacity may differ from that at other scales (e.g. collective, community or national scales (Huynh and Stringer, 2018)) but we focus on household adaptive capacity in this study. A questionnaire was designed to collect data to assess the adaptive capacity of households in the study area. The adaptive capacity indicators used are subjective although they are firmly grounded in the Sustainable Livelihoods Framework (SLF) (Scoones, 1998). The SLF is commonly used to monitor and analyse a community's wellbeing when faced with shocks. It encompasses five types of asset to present a holistic understanding of wellbeing: human assets (including education, skills, health, information, and ability to labour), social assets (such as community, group and institutional networks, and relationships of trust), natural assets (including land, water, biodiversity, wildlife, and environmental resources), financial assets (such as savings, credit, pensions, remittances, and livestock), and physical assets (which include infrastructure for water, sanitation, energy, transportation and communication, farm equipment, and household goods (TV, phone etc.)) (Ellis, 1999; Majale, 2001; McLeod, 2001; Scoones, 1998). When viewed in the context of prevailing policies, institutions and processes as per the SLF, these assets can be used to estimate a livelihood's outcomes and its associated risks (Keating et al., 2014). Nineteen indicators were selected for this study, and structured subjectively according to SLF asset categories following pilot surveys and informed by existing research (Huynh and Stringer, 2018; Nooghabi et al., 2019; Rajesh et al., 2018; Williges et al., 2017). The indicators selected, the asset they relate to, and what they are indicative of is summarised in the appendix (see Table A.1).

Union councils can be rural or urban. They are the lowest tier of the system of administrative divisions in Pakistan (Abbas et al., 2009). There are 109 union councils in Bahawalpur (GoP, 2013a), 139 in Rahim Yar Khan (GoP, 2013b), and 69 in Rajanpur (GoP, 2013c). The questionnaire was pilot tested in 14 union councils during January 2019. The process of administering the pilot survey allowed minor alterations to be made before the main questionnaire survey was administered during Feb - July 2019. Data collected during pilot testing was not included in the final sample. Final data collection was undertaken with the help of six trained field assistants fluent in the local language, Saraiki.

For the main questionnaire survey, 66 union councils were surveyed, chosen because metalled roads and political stability allowed relatively easy access: 15 from district Bahawalpur, 22 from district Rahim Yar Khan and 29 from district Rajanpur. A disproportionate stratified random sampling technique was used to select households from each district. The study area was divided into three strata based on the districts, and further sub strata on the basis of Desertification Vulnerability Index (DVI) zones (Mazhar et al., 2018). Within each sub stratum, simple random sampling was used to select the households for the survey. Effort was made for equal sample sizes to be targeted from high, medium and low DVI zones of each district. However, as the low DVI zones were mostly located in remote areas with difficult terrain, smaller populations and a harsh climate, the low DVI zone regions of Bahawalpur and Rajanpur districts were not equally represented. Slovin's formula (equation 1) was used to determine the sample size of the survey (Fikri et al., 2018; Indarti et al., 2017; Pawirosumarto et al., 2017), expressed as:

**Equation 1** $$n = N / (1 + Ne^2)$$

where n = Number of samples, N = Total population and e = Error (tolerance level).

The total population of the agricultural and livestock areas of the three districts under study according to provisional results of the 2017 census was 7,936,974 (GoP, 2017a). By placing the total population of the three districts into the equation, and using a tolerance level of 0.05, the sample size calculated was 399.

## 2.2 Computation of Adaptive Capacity

Principal component analysis (PCA) was used to identify key determinants of variation among households in adaptive capacity indicators, and to obtain object scores for each household with which an adaptive capacity index could be calculated. The adaptive capacity indicators comprise data of multiple types (nominal, ordinal and numeric) which were not always linearly related. Unlike linear PCA, which assumes a linear relationship between data, non-linear principal component analysis (NLPCA) can accommodate data relationships with different shapes. NLPCA can also analyse indicators at different levels simultaneously (Linting and van der Kooij, 2012). Therefore, NLPCA (using the Categorical Principal Component Analysis (CATPCA) tool in SPSS 25, with Varimax rotation and Kaiser normalisation) was used to reduce the 19 adaptive capacity indicators to components describing key variation in the data. The analysis was repeated iteratively following the stepwise procedure outlined by Linting and van der Kooij (2012), with different numbers of components and using different analysis levels. The steps involved in performing NLPCA, and analysis of outputs informing our decisions, is provided in Appendix A. Ultimately, an optimal solution was achieved using ordinal/ordinal spline analysis levels and five components. During analysis, two indicators were removed ('Rely on help: community' and 'Rely on help: family') because they explained little variation among households (variance accounted for (VAF) scores: 0.103 and 0.031 respectively).

The NLPCA object scores for each household on each component were used as an input variable to calculate household adaptive capacity using equations 2 and 3 adapted from Rajesh et al. (2018).

**Equation 2**

$$NSACI_j = \sum_{i=1}^{n} F_i C_{ji}$$

Where $NSACI_j$ represents a Non Standardized Adaptive Capacity Index for household $_j$. $F_i$ represents the percentage of variance explained by factor *i,* where *i* ranges from 1 to n, and n stands for the total number of factors produced by the non-linear component analysis. $C_{ji}$ is representative of the object score coefficient of household $_j$ for factor *i*. The resultant values were the input into Equation 3:

**Equation 3**

$$SACI_j = \left(\frac{NSACI_j - NSACI_{min}}{NSACI_{max} - NSACI_{min}}\right) \times 100$$

Where $SACI_j$ represents the Standardized Adaptive Capacity Index of a household. $NSACI_j$ represents the value of Non Standardized Adaptive Capacity Index (NSACI) for household $_j$. $NSACI_{min}$ represents the lowest value of NSACI and $NSACI_{max}$ is the highest value of NSACI observed among all households. The resultant values of SACI ranged from 0 to 100, with 0 representing households with least adaptive capacity and 100 representing the households with most adaptive capacity. In subsequent sections this is referred to simply as the ACI.

## 2.3 Mapping the Adaptive Capacity and its Components

The mean ACI score for households in each union council was calculated and categorized into five equal classes. The adaptive capacity of the households increased with increasing class number, i.e. class 1 showing very low adaptive capacity, to class 5 showing very high adaptive capacity.

The Global Moran's I and Anselin's Local Moran's I were applied to explore spatial clustering of household ACI scores. The Global Moran's I measures spatial autocorrelation producing a score ranging from +1 to -1, with +1 indicating clustering, 0 indicating randomness and -1 indicating dispersion (Tokarz and Novak, 2018). Our analysis revealed clustering in ACI scores (Global Moran's I: 0.09, p-value: .0663, z-score: 1.837). The Global Moran's I index was calculated using the Arc GIS spatial autocorrelation tool, with inverse distance selected to conceptualise the spatial relationship between features, and Euclidean distance selected to specify distance calculations as a straight line between points. The Anselin Local Moran's I statistic was then used to map the ACI clusters. Following the methodology of Tokarz and Novak (2018), Anselin Local Moran's I was run in ArcGIS 10.6, using the Cluster and Outlier Analysis tool.

Object score values for each component were normalized and the zonal statistics tool in Arc GIS spatial analyst was used to interpolate a single raster surface to cover the entire study area. This enabled a a larger scale spatial picture of individual components explaining variance in the ACI for the three districts under study to be obtained. The resultant principal component score maps were prepared with a standardized legend.

# 3 Results

## 3.1 Variation in household adaptive capacity

Five principal components were retained for the adaptive capacity analysis, explaining 63.82% of the variance in the data set across 17 indicators (Table 1). Indicators loading most heavily on the five components, except 'land holding' and 'relief by Government', had positive values, indicating unidirectional influence of the factors on adaptive capacity.

**Table 1** Model summary of NLPCA using Varimax rotation with Kaiser Normalization

| Component | Cronbach's Alpha | Variance Accounted For Total (Eigenvalue) | % of Variance |
|---|---|---|---|
| 1 | 0.74 | 3.08 | 18.17 |
| 2 | 0.64 | 2.41 | 14.22 |
| 3 | 0.62 | 2.01 | 11.87 |
| 4 | 0.59 | 1.98 | 11.68 |
| 5 | 0.32 | 1.33 | 7.85 |
| Total | 0.96[a] | 10.85 | 63.82 |

a. Total Cronbach's Alpha is based on the total Eigenvalue.

Indicator loadings on the five components enabled the identification of five distinct aspects of adaptive capacity that link back to the SLF asset categories (Table 2): 'natural assets' (PC 1), 'physical assets' (PC 2), 'financial assets' (PC 3), 'human assets' (PC 4) and 'social assets' (PC 5).

**Table 2** Varimax rotated component loadings, with Kaiser normalization from a five-dimensional NLPCA on 17 indicators of adaptive capacity, analyzed on ordinal/ordinal spline analysis levels. Component loadings where values >0.40 are shown in bold.

| **Indicators of Adaptive Capacity** | **Principal Components** | | | | |
|---|---|---|---|---|---|
| | Natural assets | Physical assets | Financial assets | Human assets | Social assets |
| | **1** | 2 | 3 | 4 | 5 |
| Number of crops cultivated by household | **0.95** | 0.04 | 0.14 | 0.08 | -0.02 |
| Area cultivated by household | **0.94** | 0.05 | 0.15 | 0.11 | -0.01 |
| Land Holding | **-0.89** | -0.07 | -0.11 | -0.13 | 0.03 |
| Garden area | **0.55** | 0.03 | -0.27 | 0.06 | 0.30 |
| Number of appliances at home | 0.01 | **0.76** | 0.26 | 0.21 | -0.17 |
| Type of house | 0.09 | **0.71** | 0.11 | -0.13 | 0.18 |
| Sources of information | -0.02 | **0.71** | -0.08 | 0.32 | -0.28 |
| Number of basic facilities available | 0.12 | **0.71** | 0.01 | -0.24 | 0.13 |
| Number of livestock | 0.15 | 0.05 | **0.76** | 0.11 | -0.03 |
| Household earning members | 0.08 | -0.07 | **0.68** | **0.46** | -0.02 |
| Total owned farming equipment | 0.28 | 0.16 | **0.45** | -0.09 | **0.42** |
| Relief provided by Government | 0.05 | -0.17 | **-0.43** | 0.28 | 0.04 |
| Number of livelihood activities | 0.15 | 0.03 | -0.06 | **0.68** | 0.12 |
| Household Non-labour force | 0.04 | -0.27 | 0.20 | **0.67** | -0.06 |
| Household educated members | 0.10 | 0.28 | 0.09 | **0.65** | 0.12 |
| Community Connectedness | -0.01 | -0.11 | -0.10 | 0.13 | **0.76** |
| Monthly Income | -0.01 | 0.22 | **0.52** | 0.17 | **0.53** |

## 3.2 Spatial patterns of adaptive capacity

The spatial pattern of mean household ACI scores for union councils (Fig. 2) suggests high adaptive capacity clusters are limited to north-eastern Rajanpur, and northern and south western Rahim Yar Khan.

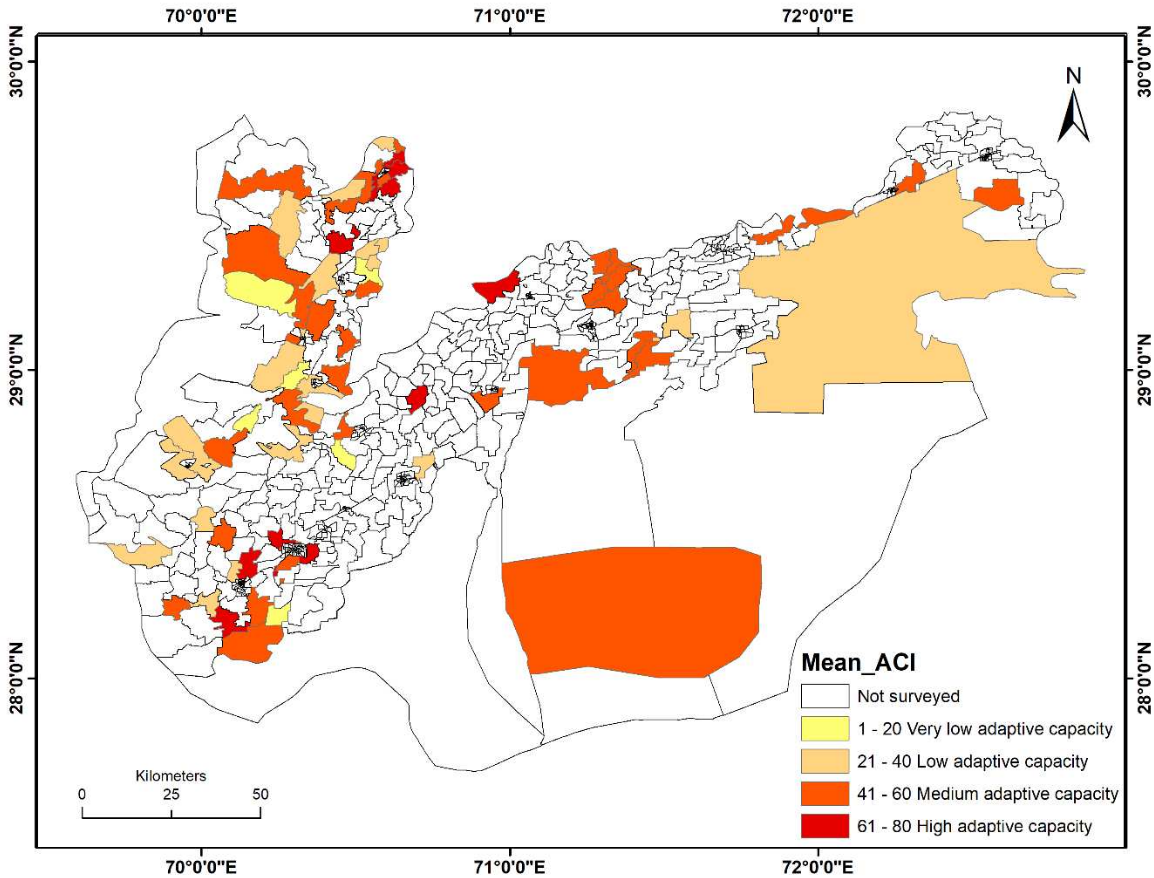


**Fig. 2** Mean Adaptive Capacity Index (ACI) of surveyed households located within each union council in south Punjab, Pakistan. The numbers represent classes calculated based on normalized ACI scores.

Most of the very low mean union council household ACI scores are also limited to Rajanpur. The mean household ACI scores of Bahawalpur's surveyed union councils indicate low to medium adaptive capacity.

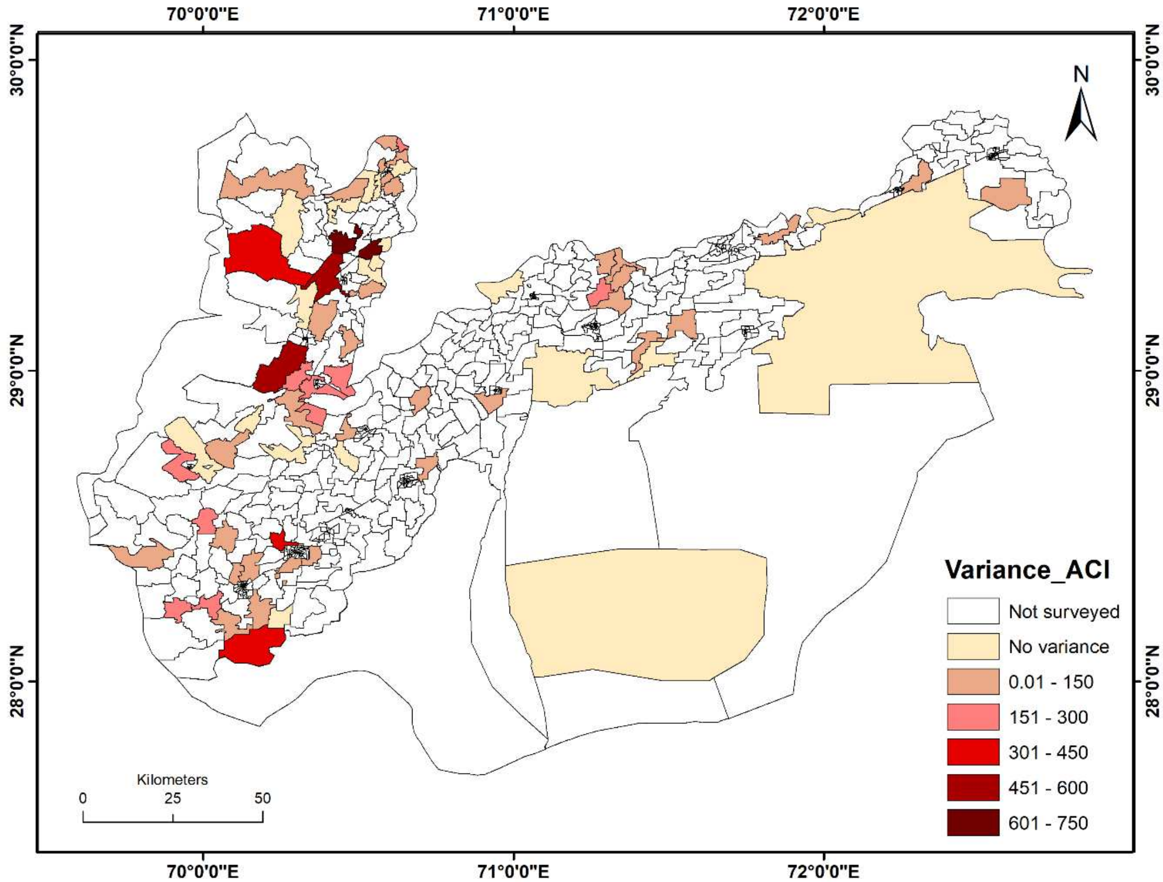


**Fig. 3** Variance of the Adaptive Capacity Index (ACI) among surveyed households in each union council in south Punjab, Pakistan. Only one household was surveyed in Union councils with no variance. The legend shows ranges of classes, independent of units, where greater numbers on the scale represent greater variance in adaptive capacity within those union councils, and vice versa.

The variance of ACI among the households under study (fig. 3) present maximum variance in the medium to high mean ACI union councils of District Rajanpur.

The results of the mean adaptive capacity mapping verify and support the Anselin Local Moran's I spatial adaptive clustering results, since all the low adaptive capacity clusters existed within union councils falling in low and very low mean adaptive capacity classes (Fig. 4). Similarly, all the high adaptive capacity clusters were found in the union councils with high or medium mean adaptive capacity.

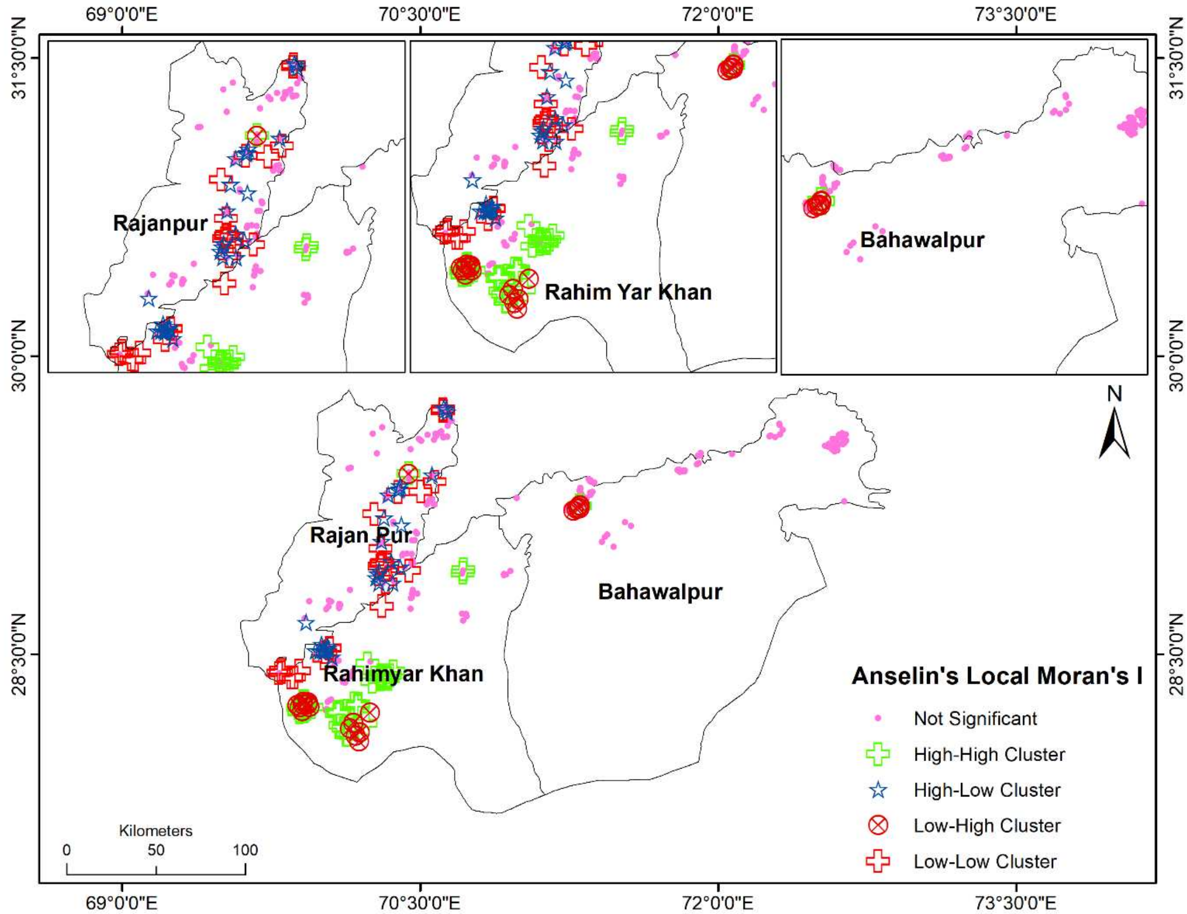


**Fig. 4** Adaptive capacity clusters identified using the Anselin Local Moran's I, where High-High and Low-Low clusters represent households with high adaptive capacity that are in close proximity to each other, and households with low adaptive capacity located in close proximity to other low adaptive capacity households, respectively. A High-Low outlier represents a high adaptive capacity household surrounded by low adaptive capacity households, while a Low-High adaptive capacity outlier represents a low adaptive capacity household surrounded by high adaptive capacity households. The left inset map shows finer detail for Rajanpur, central top inset map shows West Rahim Yar Khan's clusters of adaptive capacity, while the top right inset map provides finer detail for North Bahawalpur's adaptive capacity clusters. The bottom map presents the relative location of the three districts under study.

The spatial pattern of household ACI scores suggests most high adaptive capacity clusters are located in Rahim Yar Khan, with clusters found in the south east of the district (Fig. 4). Rajanpur has the bulk of the low adaptive capacity clusters, which are scattered along the eastern edge of the district, followed by Rahim Yar Khan. There is one high but no low adaptive capacity clusters in Bahawalpur.

The high-high adaptive capacity clusters in Rahim Yar Khan coincide with high positive object scores on principal components (Fig. 5) representing financial, human and social assets, while Rajanpur's high-high adaptive capacity clusters coincide with high positive scores for natural and social assets, and Bahawalpur's high-

high cluster with natural and physical assets. Low-low adaptive capacity clusters in Rajanpur coincide with low values on all the principal components. In Rahim Yar Khan low adaptive capacity clusters coincide with low values on all the principal components except PC5 (representing social assets), indicating households located in low adaptive capacity clusters areas have relatively low access to natural, physical, financial, human and sometimes social assets, and that access to social assets alone may not be sufficient to elevate adaptive capacity.

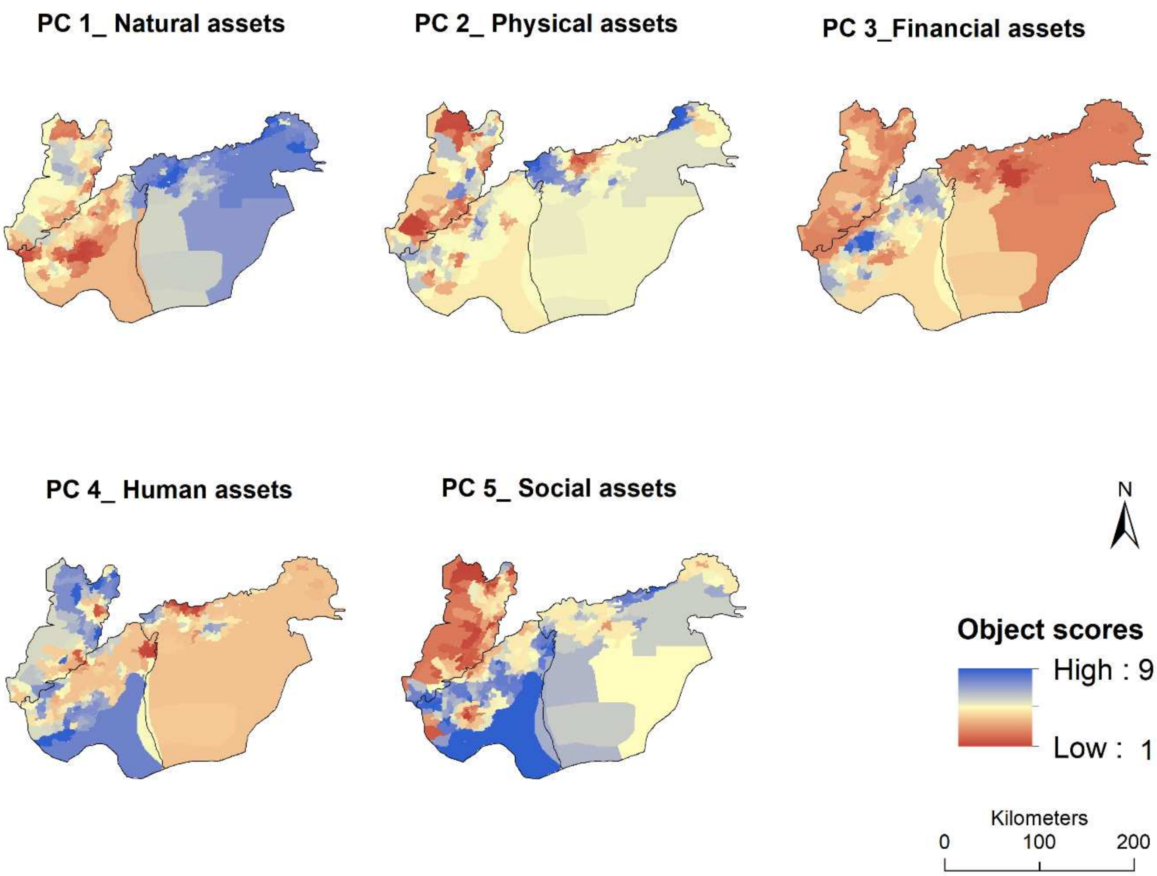


**Fig. 5** Spatial variation in household object scores on each of the principal components. Object scores reflect the scoring of households for indicators that loaded heavily on each component (see Table 2). Locations with high object scores indicate households have higher adaptive capacity in that region for the component in question and vice versa. For example, dark blue areas on map PC1 show regions where households have higher adaptive capacity linked to natural assets, such as the number and areas of crops cultivated, whereas dark blue areas on map PC2 shows regions where household have higher adaptive capacity linked to physical assets such as the number of appliances, facilities and type of housing.

## 4 Discussion

The results identify strong socio-economic and spatial patterns in terms of adaptive capacity in South Punjab, Pakistan. Adaptive capacity is lowest in Rajanpur's eastern area, a zone where households achieved low scores on components describing natural, physical and financial assets, whereas the highest adaptive capacity clusters were limited to southern Rahim Yar Khan. The principal component describing 'natural assets' explained most variation in the data set (18.17%), indicating that household ability to access the natural assets that can contribute to adaptive capacity varied more than access to other SLF assets described by the other components. The positively loaded indicators on this component are 'number of crops cultivated', 'area cultivated by household', and 'garden area', while the variable highly negatively loaded on this component is 'land holding'. This negative high loading can be explained by the field observation, that households owning smaller land holdings cultivated greater areas than those with a larger land holding. Cultivation is more manageable at a smaller scale, due to the constraints posed by water deficits and salinity over larger areas. Interestingly, it was observed and later confirmed through the field survey, that the high adaptive capacity clusters, especially in Bahawalpur and Rajanpur, coincided with high scores on natural assets, as the respondents were found to be cultivating most of the land they owned and were practicing crop rotation. On the contrary, low adaptive capacity clusters in Rajanpur and Rahim Yar Khan that align with low scores on natural assets, showed respondents owned less land, were relying on monocrop cultivation, or were not practicing cultivation at all. Our finding regarding the importance of natural assets is supported by Williges et al. (2017), who state that this asset is especially important in adaptive capacity assessments of farming communities, since their dependence on land underpins their livelihoods. This finding is therefore not unexpected in such a highly agrarian study area.

The second most important livelihood component explaining variation in adaptive capacity of the dryland agricultural household community of the study area describes 'physical assets'. The position of households on this component reveals information about the relative difference in levels of adaptive capacity, based on the number of appliances, sources of information, better housing, and access to basic facilities. Williges et al. (2017), while elaborating indicators of physical assets, mention that access to water supply, sanitation and farm assets etc. have a strong influence on adaptive capacity of a household, while other studies also consider the importance of physical assets for enabling households to respond to climate stresses, such as extreme temperatures (Nunes, 2018).

The NLPCA analysis suggests that 'financial', 'human' and 'social' assets explain less variation in adaptive capacity among households than 'natural' and 'physical' assets. The level of bonding within the community to fight against natural disasters is a key social asset that can elevate adaptive capacity, and similar arguments in other studies (Deressa et al., 2009; Huai, 2016; Pretty, 2003) emphasize that socially well-connected households are often better placed to cope with climatic hazards. Engle and Lemos (2010) acknowledge that social assets are an important factor for the adaptive capacity of a region because interactions between associations, networking, and stakeholder involvement all contribute towards adaptive capacity enhancement. This is exemplified by Pandey et al. (2017) who compared the vulnerability of

Himalayan communities to climate change, considering temperature and precipitation. They found that households with less social coherence and which lacked cooperation and inter-dependability, had lower adaptive capacity. On the contrary, other households had better networks and relied on each other in times of extreme events. In our study area high positive scores for social assets coincided with clusters of both high and low adaptive capacity. However, results indicate that where adaptive capacity was high, households also scored highly for access to at least one other asset type.

A key novel contribution of this study is that it spatially presents the pattern of outliers among the clusters of adaptive capacity. It also shows which union councils have the least adaptive capacity. These are the areas where resources are limited, and households have low scores on all the principal components. Fig. 4 can therefore help in identifying union councils that could be targeted for government intervention to help boost the adaptive capacity of the dryland agricultural household community. This finding is in agreement with the wider literature (Munjoma, 2013; Sujakhu et al., 2019) which suggests that failure of governments to intervene in areas at risk results in a substantial increase in people exposed to chronic vulnerability, which continues to make the situation worse.

The spatially explicit adaptive capacity maps made the relation between spatial patterns of overall adaptive capacity starkly apparent at union council level. The approach supports calls by Marzi et al. (2018) who emphasize that for effective ACI to be constructed at national level, variability in ACI scores at lower administrative levels needs to be monitored. The ACI maps produced in the current study demonstrate that the High-High adaptive clusters are located in the high and medium adaptive capacity union councils of Rahim Yar Khan, and that households in these areas have good access to financial assets, which contributed to their high adaptive capacity. One of the reasons for High-High adaptive capacity clustering in Rahim Yar Khan might be the availability of employment opportunities and multiple income sources of households, as reported by Ahmad and Afzal (2019). Also, the farming community in Rahim Yar Khan is well aware of the challenges posed by climate change and is willing to invest in proper climate change adaptation programmes in order to boost agricultural production, which enhances their adaptive capacity (Ahmed et al., 2015). Low-Low adaptive capacity clusters are only present in Rajanpur's eastern strip, extending from union council Kot Janu in the northeast to union council Ghari Dhodo in the southeast of the district. The object scores of the households in the low adaptive capacity clusters exhibit negative loadings on all principal components, indicating they have relatively poor access to all assets. This highlights the urgency for government to support these households in strengthening assets and ultimately their adaptive capacity. These results are consistent with the findings of Ahmad and Afzal (2019), who conclude that households in Rajanpur are more vulnerable and have lower capacity to adapt to floods, compared to households in Rahim Yar Khan.

High-Low outliers, i.e. some high adaptive capacity households surrounded by many low adaptive capacity households, were mostly located in Rajanpur, further supporting the finding that Rajanpur is the district with least adaptive capacity in the study area and continues to be the district requiring urgent government intervention. Similarly, most of the Low-High outliers were limited to district Rahim Yar Khan, and some to Bahawalpur. Most of Bahawalpur district did not have significant adaptive capacity clusters, thus hinting towards a reasonably uniform pattern of adaptive capacity. The mean adaptive capacity also supports this finding, since most of the union councils surveyed in Bahawalpur had medium mean adaptive capacity while only two union councils surveyed in Bahawalpur had low mean adaptive capacity.

Aggregation of NLPCA components into an index to undertake adaptive capacity mapping does not produce an absolute measure of adaptive capacity, rather it generates patterns of adaptive capacity relative to the households surveyed. Secondary data collected by government bodies might have helped to identify indicators of adaptive capacity that best represent the actual situation of the community of the region, enhancing the reliability of the results under the SLF headings and providing more information to explain the relative relationships. However, this paper is the first to assess adaptive capacities of the dryland agricultural household community in this part of Pakistan, so the limited available secondary data could not be used to triangulate our findings. The poor road network in the region limited access to all parts of the study area too, meaning that the more remote households, including those at high altitude, were not surveyed. This was especially the case in unstable, tribal areas where there were safety and security concerns during data collection. It is possible that households in these areas have low adaptive capacities, particularly given governance and accessibility challenges. Thus further research is required to ascertain the kinds of support they might need and how their adaptive capacity compares to that of households in the rest of the district. Given these areas are also less densely populated, it is not anticipated that this will have a substantial bearing on the results.

Overall, this study has provided a practical tool to identify the communities with least adaptive capacity among sampled union councils and offers policy makers a useful guide to better design strategies to boost community adaptive capacity. Given the challenges of climate change and desertification in the study area, this is increasingly important. The proposed methodology can be extended and applied to gauge the adaptive capacity of communities elsewhere in Pakistan, South Asia, as well as in other areas globally. The findings have clear policy implications, identifying clusters of lowest and highest adaptive capacity, providing policy makers with concise information to be fed into more practical and targeted climate adaptation policies and efforts to combat desertification. At the same time, if adaptive capacity can be improved more generally in areas where it is lacking, it can reduce the vulnerability of households to other risks and threats, beyond those considered in this paper.

## 5 Conclusion and Recommendations

Adaptive capacity continues to be of paramount significance in national policies on climate change, as it helps communities to prepare to manage risks by building their resilience. This study explored the dominant livelihood assets determining how adaptive capacity varied among respondents in South Punjab, Pakistan, and revealed spatial patterns in adaptive capacity in the region. Nineteen subjective sustainable livelihood based indicators guided the assessment of adaptive capacity. NLPCA, Global Moran's I and Anselin's Local Moran's I were used to show that adaptive capacity of households in Bahawalpur, Rahim Yar Khan and Rajanpur is related to SLF asset categories in the region, and that adaptive capacity presents spatially distinct patterns. Respondents in the study were dependent on farming and livestock herding for their living, both of which are climate and land dependent. It is therefore suggested that policy makers promote the adoption of off-farm income sources in the region, so as to reduce the sensitivity of livelihoods to environmental shocks and stresses. Simultaneously, the existing irrigation network can be strengthened by ensuring regular supply of water to the fields, while feasibility assessments could consider revival of the Government of Punjab's Salinity Control and Reclamation Programme (SCARP) if further investigations show it to be economically viable. Ultimately, improved natural capital, supported by other assets, could help people to be more resilient in this dryland region of South Punjab, Pakistan.

Research on adaptive capacity assessment can be improved through more intensive sampling and extending the regular tracking of adaptive capacity from local to regional level. The ACI might be calculated for communities in low adaptive capacity areas on a more regular basis, so that the long-term implications of any coping strategies or policy interventions could be identified and assessed. The approach used here could therefore be utilised for monitoring and evaluation purposes. The ACI spatial clustering presented in this paper could serve as a benchmark in adaptive capacity assessments as it offers a unique method of analysing mixed types of data and could provide valuable insights in other dryland areas and climatic zones.

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