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ORIGINAL PAPER

Has Pakistan learned from disasters over the decades? Dynamic resilience insights based on catastrophe progression and geo-information models

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Abstract

Since the last two decades, Pakistan has been often cited among the top ten countries most vulnerable to climate change and disasters, such as intense flooding, extreme heat, and droughts, among others. However, the unavailability of nationwide administrative-scale assessments from a space–time perspective hinders disaster resilience building in Pakistan. In this context, the key purpose of this study is to evaluate the spatial and temporal disparities in community disaster resilience (CDR) in Pakistan during 2004–2014—the period covering two of the most devastating disasters in Pakistan in recent history. Eventually, the dynamic nature of resilience is empirically demonstrated through the catastrophe progression method, and regions, where resilience increased/decreased, are identified using geo-information models, such as the Moran's Index and the local indicators of Spatial Association (LISA). It is evident that CDR in the earlier, middle and final periods during 2004–2014 vary significantly (95% confidence). With inconsistent resilience distribution across Pakistan during 2004–2014, some noteworthy regional disparities are also found. For instance, while the overall lowest resilience is found for the areas in Balochistan province, the regions that became less resilient during the studied period are spread across Pakistan with notable concentrations in southern districts. Such place-based information is a crucial stepping-stone to initiating and formulating effective plans and resilience enhancement strategies in Pakistan. Furthermore, based on the pioneering analysis presented here, this study acts as a baseline for disaster resilience in Pakistan in terms of spatial–temporal heterogeneities along with pinpointing the significant areas for gradual or immediate attention—facilitating priority intervention areas.

Keywords Disaster risk reduction · Spatial analysis · Geographic information systems (GIS) · Resilience mapping · Spatial statistics · Resilient Pakistan

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1 Introduction

In the last two decades, with a rise in the frequency of intense hazards and sometimes the prolonged duration of disasters, such as earthquakes, floods, heatwaves, and drought, the world has faced deadly consequences. Geographically, thousands have been killed and millions are displaced along with billions of financial losses in Asia due to weather-related extremes and climate change-associated disasters over the past few decades (Franziska et al. 2022; IPCC 2021). In recent decades, for instance, more than 200 million people have suffered annually due to the outcomes of natural hazards, such as poverty, food scarcity, infectious disease outbreak, and social instability (McGlade et al. 2019; UNISDR 2005). Even though governments prioritize disaster management activities aiming at the reduction, mitigation, and recovery issues, the majority of the disaster combating costs are utilized for post-disaster recovery-related activities (Ostadtaghizadeh et al. 2015).

While the post-disasters effects can be handled through proper planning and policies implementation for better resource allocation, the impacts can severely be reduced by analysing the ability of communities to handle or resist the impacts of disaster beforehand (Ostadtaghizadeh et al. 2015; Sharifi 2016). This is where disaster resilience comes in place, which according to Isdr et al. 2005, is "*the ability of a particular community to deal with internal or external shocks without compromising long-term stability*". Similarly, while the definition of community resilience could be field-specific (Sajjad and Chan 2019), the National Institute of Standards and Technology of the United States defines it as the inherent capability of communities to prepare for anticipated/expected hazards, adapt to fluctuating situations, and endure and recover rapidly from disturbances. Such intrinsic characteristics lead to performing better in the future when facing similar calamities. Thus, by the definition of community resilience, less resilient communities are more likely to face substantial damages from disaster and vice versa (Mayer 2019). This situation shows that the proportions of people living in less resilient communities are prone to the aftermath of disasters. Hence, for the well-being of such community residents, the government and policymakers require up-to-date resilience information at different national scales with considerable temporal intervals (Tiernan et al. 2019). Such information is essential to prepare better action plans and strategies for resilience building and enhancement, thus, ultimately being able to withstand and adapt to various disasters in the face of global environmental changes (Ostadtaghizadeh et al. 2015). However, when addressing community resilience, studies often pay less attention to the temporal context (Cutter et al. 2014; Frazier et al. 2013; Marto et al. 2018; Sajjad 2021). One of the most important critiques of resilience measurement is the lack of a dynamic approach to measuring collective spatial–temporal disparities in community resilience (Cutter and Derakhshan 2018). Such temporal and spatial resilience evaluations allow for assessing the effectiveness of previous policies and resilience enhancement measures taken at different stages following disaster events (Frazier et al. 2013). The exclusive emphasis of current literature on assessing resilience only spatially represents a considerable research gap.

Developing countries, particularly in Asia and Africa, are among the most vulnerable to the impacts of climate change (IPCC 2021). For example, the World Risk Report 2022 indicates that eight out of the top ten most at-risk countries in the world (80% of the top ten) are in Asia (Franziska et al. 2022). Pakistan—a developing nation in South Asia with ~ 220 million people—is no exception as the country is often cited among the most vulnerable to climate change impacts globally. While vulnerable conditions can result in huge damages even though there is a low exposure, Pakistan has been subjected

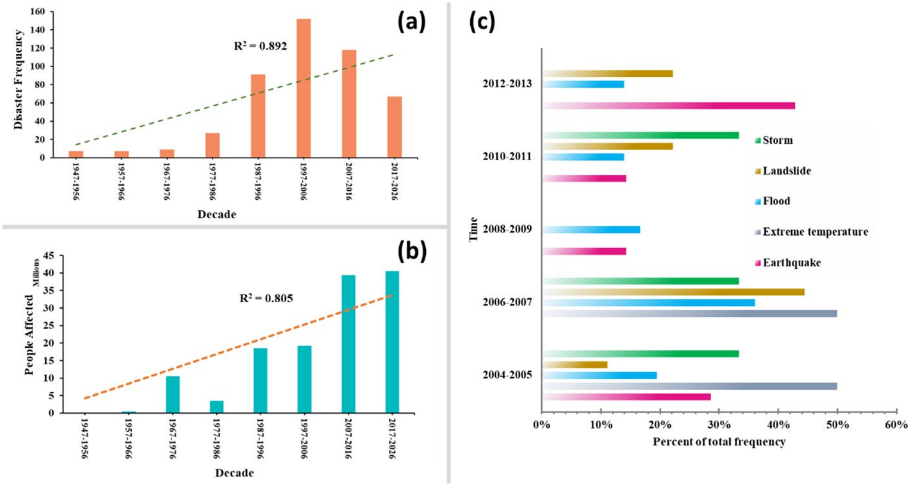

Fig. 1 Inter-decadal variations in (**a**) disaster frequency and (**b**) affected people in Pakistan since its creation in 1947. The dash lines in both graphs represent the overall linear trends for disaster frequency (**a**) and people affected (**b**). Figure (**c**) represents the frequency (presented as percentage) of different major type of disasters for six 2-year periods during 2004–2014—the study period for this research. The data are retrieved from the international country-level disasters database (EM-DAT: www.emdat.be)

to frequent disasters over the past few decades including the devastating earthquake in 2005 and the floods in 2010. For example, the inter-decadal variations in disaster frequency and affected people in Pakistan since its creation in 1947 show significant increasing trends, indicating rising risks for the population, infrastructure, and economy (Fig. 1a and b). In terms of major disasters, it is observed that floods, landslides, and earthquake are the major events impacting Pakistan during 2004–2014 (Fig. 1c).

In Pakistan, the effects of previous disasters were more lethal because of the poor economy, lack of awareness, weak emergency management and disaster preparedness, and lack of institutional coordination (Haq et al. 2012; Memon et al. 2015, 2020). The earthquake of 2005 damaged the majority of northern areas in Pakistan including Muzaffarabad, Balakot, and several other areas in the North–West Frontier Province. A 7.6 magnitude earthquake was recorded and resulted in the deaths of 80,000 people with more than 4 million people affected (World Bank 2005). Similarly, the flood of 2010, which resulted due to the overflowing of the Indus River, resulted in the loss of more than 2,000 lives, affected 20 million people, and 1.6 million houses were destroyed resulting in more than 1 million homeless people (van derSchrier et al. 2018).

Recently, the floods of 2020 in Pakistan due to excessive monsoon rainfall impacted more than 2.4 million people (Patel 2020). Despite the on-time effective rescue missions initiated by the provincial governments in Pakistan, the lack of GIS-based multi-temporal field data resulted in a delay in exact damage assessment (Cristina and Trannin 2013; OCHA 2020). Similarly, the 2022 flooding affected more than 33 million people, damaged nearly 1.2 million houses, and killed more than1200 people (Smriti 2022). With its continuous history of such calamities, Pakistan still suffers considerable damage due to environmental disasters. Primarily, the ill-equipped and un-informed disaster planning and management are to be blamed, which are further aided by the lack of

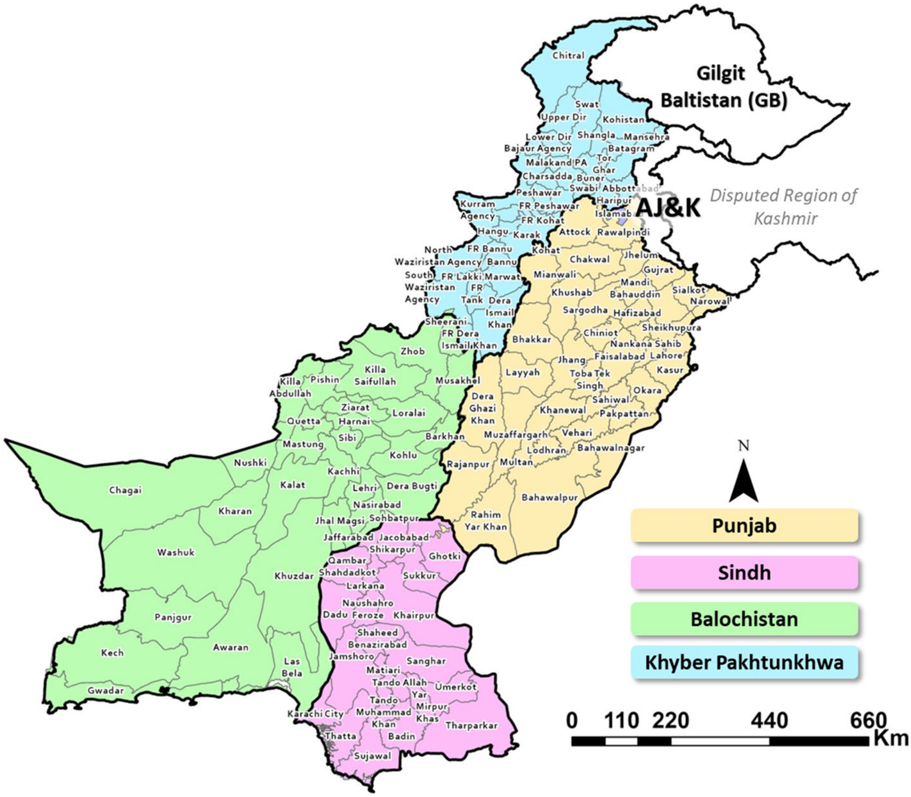

Fig. 2 Map of Pakistan showing provinces' and districts' distribution. The analysis in this study is conducted for all of these districts (based on data availability), and districts are labelled to provide geographical references

resources, political interference, poor data infrastructure, and lack of interest and awareness. (Cheema 2022; Mayer 2019; Sajjad 2021; Tariq and van deGiesen, 2012).

After the above-mentioned notable events, many studies focused on disaster assessment to evaluate the extent and duration of post-disaster effects and to provide recommendations and references for effective disaster management in Pakistan with nearly all of them being localized investigations (Haq et al. 2012; Memon et al. 2015; Sajjad et al. 2020a, b; Sayama et al. 2012). For example; Sajjad et al. (2020a, b) performed a damage assessment over Chenab plain region in Pakistan using Remote Sensing (RS) and Geographic Information Systems (GIS), Memon et al. (2015) performed a damage assessment after the 2012 flood, Cheema (2022) presented the state of disaster management in Pakistan based on pre and post-2005 earthquake management approaches, and Ainuddin and Routray (2012a, b) presented the situation regarding community resilience in two very localized regions in Balochistan, Pakistan. The map presented in Fig. 2 reflects the administrative divisions in Pakistan (i.e. provinces and districts) to provide geographical references to the areas mentioned above.

However, there are few, if any, national-level high-resolution (i.e. district/administrative scale) studies to drive efforts in terms of resilience building in the country to tackle natural hazards more effectively. For instance, Sajjad (2021) highlighted the absence of a national resilience baseline in Pakistan, which hinders informed planning and decision-making in terms of priority interventions regarding resilience management. In connection to this, the present study profiles (assesses and maps) spatial–temporal disparities in the community disaster resilience (CDR) in Pakistan along with addressing the critique of dynamic resilience investigation by providing the district-level temporal resilience changes and their patterns in Pakistan at a national scale. For this purpose, the data on 20 resilience variables for six different periods (2004, 2006, 2008, 2010, 2012, and 2014) are utilized and evaluated through geo-information modelling and the catastrophe progression method to illustrate the dynamic nature of CDR across Pakistan. While the findings will provide important insights into the varying nature of CDR in space and time, the study will deliver important information to set a spatial–temporal baseline of disaster resilience in Pakistan.

2 Materials and methods

In this section, we provide a brief description of the basic procedure for calculating the community disaster resilience index. This resilience index is inspired by the baseline resilience indicators for communities (Cutter et al. 2010), which is based on several reasonably justified indicators ($n=20$) within social, institutional, and economic domains of community resilience (Gillespie-Marthaler et al. 2019; Sajjad 2021; Sharifi, 2016b). Such an estimation of CDR adheres to the conceptual underpinnings of the Disaster Resilience of Place (DROP) model (Cutter et al. 2008), a place-based paradigm for assessing community resilience to disasters. This approach takes resilience as an inherent characteristic in communities, which is assumed to exist before any natural catastrophic event takes place.

For this spatial–temporal CDR analysis, we follow Sajjad (2020) and collect the data on resilience indicators for six periods including the years 2004, 2006, 2008, 2010, 2012, and 2014. The unit of analysis adopted in this study is the district, which is a key administrative level in Pakistan where most of the planning and resource allocation decisions take place. To avoid the modifiable areal unit problem, the vector shapefile for these units is obtained from the United Nations Office for the Coordination of Humanitarian Affairs (UN-OCHA: https://data.humdata.org/). While it would have been ideal to perform the analysis on all the districts in Pakistan, the unavailability of data on the variables used for resilience estimation resulted in the final inclusion of 116 districts. The excluded districts included regions from the Federally Administered Tribal Area (now part of Khyber Pakhtunkhwa province since 2018) due to unstable security conditions in the area during the analysis period along with Azad Jammu & Kashmir and Gilgit Baltistan provinces. Furthermore, it is noted that the reliability of these indicators to represent the abstract of overall CDR is evaluated through Cronbach's alpha, and the resultant value (0.56) shows an intermediate level of interconnections among the employed 20 variables, which is expected in socio-economic aspects (Cui and Li 2019). While the selected indicators are presented in Fig. 2, readers are encouraged to see Sajjad (2020) for a full description of these variables and the justification for their selection. Given the nature of assessments and the data, a geospatial repository is established for storage, retrieval, and analyses. The indicator data are selected and cleaned using a spreadsheet from Microsoft Office. These spreadsheets are later appended to the vector shapefile of the districts to transform the data into a spatial environment. Afterwards, we conducted the ANOVA test to investigate if there are any significant variations between different periods during 2004–2014. Furthermore, to identify different pairs that are significantly different at $p=0.05$, the post hoc Tukey HSD test is employed.

The CDR in this study is evaluated using the catastrophe progression technique, which is well known for its utilization to describe continuous processes that are undergoing changes over time, such as the resilience of systems (i.e. communities from a System-of Systems view point) after the occurrence of any disaters (Krueger et al. 2019; Wang et al. 2017). This inherent characteristic of communities refers to the dynamic behavious of several aspects within communities in the face of disturbances, shocks absorption abilities, and adaptation, as well as reorganization, to sustain the system functionality (here communities exposed to disasters; Holling and Gunderson 2002). The application of catastrophe progression technique can be traced in several disciplines including social and behaviourial sciences, ecology, and health systems among many others (Pincus and Metten 2010; Tian et al. 2019; Wang et al. 2021). While the method has been discussed as a comprehensive technique to evaluate changes in order to describe a system's resilience (Li et al. 2018a, b; Li et al. 2018a, b), to the best of our knowledge, it has not been applied to explore community disaster resilience, which this study intends to do.

To compute the CDR index, we developed the catastrophe progression-technique-based algorithm using *MATLAB*, a multi-paradigm programming language and numeric computation environment developed by MathWorks (www.mathworks.com). The algorithm's basic input is the raw data of all the indicators, which is extracted from a number of sources including the Development Statistics, the Pakistan Bureau of Statistics (available at: www.pbs.gov.pk/), national/provincial Statistical Year Books for corresponding years, and the Provincial Multiple Indicator Cluster Surveys (available at: www.bos.gop.pk/). It should be noted that the studied period (i.e. 2004–2014) is based on the availability of the data. While the data for later years (e.g. 2016 and onwards) are being compiled in collaboration with UNICEF (www.unicef.org), we focus on the utilization of the available data and make the best use of it in the context of a spatial–temporal CDR baseline setting in Pakistan at the district level. Using the developed algorithm, we initially classify the data in the framework based on the intended resilience indicators. In the following stage, we positively and negatively normalize the indicator data since certain indicators have a positive influence, while others have a negative contribution to CDR—higher values of variables reduce CDR, such as poverty (Cutter and Derakhshan 2018; Sajjad et al. 2019). Following that, we employ different catastrophic models under the catastrophic progression method. These models include butterfly, swallowtail, cusp, and fold (Scheffer and Carpenter 2003). Given the hierarchical nature of the technique, the applied models are selected based on the number of indicators in different customized sub-systems, and the overall schematic of different employed models is presented in Fig. 3. The computations are made for each studies period between 2004 and 2014. It is noted that the normalization of all the indicators is carried out prior to their utilization for the computation of resilience index. For this purpose, the minimum–maximum normalization is used following Sajjad (2021). Through this normalization, the values for each variable are distributed between 0 and one—making the overall indicator data dimensionless. After the normalization of the data, the catastrophe fuzzy membership functions of each indicator are calculated as follows (Xiao-jun et al. 2014):

The fold catastrophe (for one indicator) is given as:

$$x_{\mathrm{a}} = a^{1/2} \tag{1}$$

The cusp catastrophe (for two indicators) is given as Eq. 2:

$$x_{\mathrm{a}} = a^{1/2}, \quad \text{and} \quad x_{\mathrm{b}} = b^{1/3} \tag{2}$$

The swallowtail catastrophe (for three indicators) is given as Eq. 3:

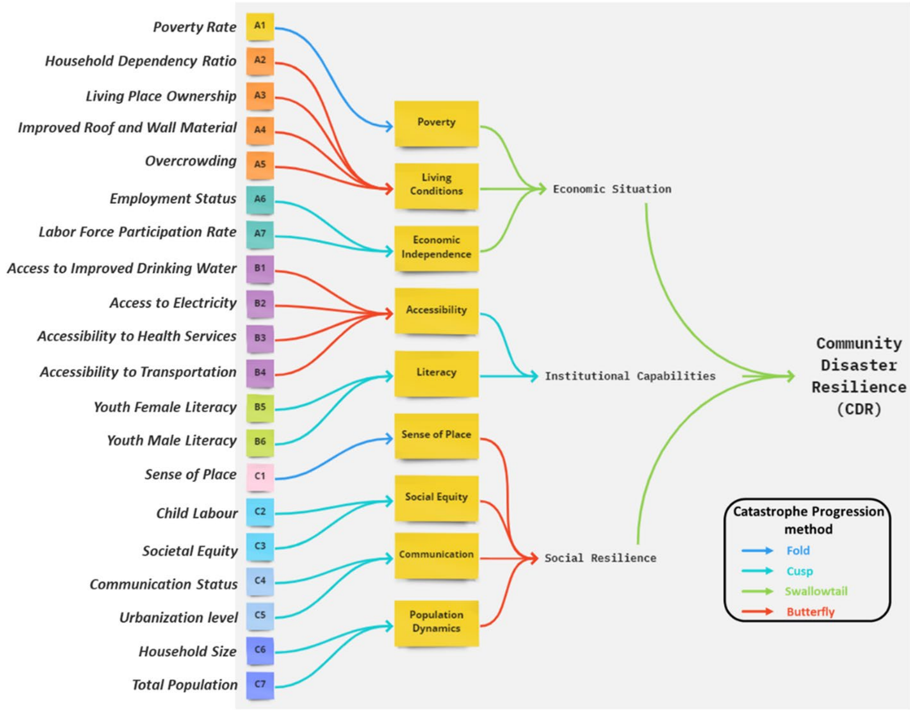

Fig. 3 Schematic for overall workflow and Catastrophe Progression model application

$$x_a = a^{1/2}, x_b = b^{1/3}, \quad \text{and} \quad x_c = c^{1/4} \tag{3}$$

The butterfly catastrophe (for four indicators) is given as Eq. 4:

$$x_a = a^{1/2}, x_b = b^{1/3}, x_c = c^{1/4}, x_d = d^{1/5} \tag{4}$$

where $a, b, c, andd$ represent the control variables.

In our calculation, we apply the comparative principle. According to this principle, the control variables can fill up the deficiency of each other. Therefore, their mean value can be used for the system such as:

The fold catastrophe (for one indicator) is given as Eq. 5:

$$x = x_a \tag{5}$$

The cusp catastrophe (for two indicators) is given as Eq. 6:

$$x = \frac{x_a + x_b}{2} \tag{6}$$

The swallowtail catastrophe (for three indicators) is given as Eq. 7:

$$x = \frac{x_a + x_b + x_c}{3} \tag{7}$$

The butterfly catastrophe (for four indicators) is given as Eq. 8:

$$x = \frac{x_a + x_b + x_c + x_d}{4} \tag{8}$$

From this analysis, the resultant catastrophe degrees of sub-systems vary between zero and one, where values closer to one represent higher degree of resilience for a particular area (district in our case). The results are presented using thematic maps, and 1 standard deviation is used to reflect the geographic distribution of resilience in each district in comparison with overall resilience across the study area (Pakistan).

2.1 Comparing resilience over time

Statistical analysis is applied to evaluate if there are any significant differences between CDR of several periods. For this purpose, the method of analysis of variance (ANOVA) at $p = 0.05$ is used to statistically compare the means of all the periods (i.e. 2002, 2004, 2006, 2008, 2010, 2010, 2012, and 2014). For additional exploration, the post hoc Tukey–Kramer test, using all pairwise comparisons, is used to examine statistically significant differences between the disaster resilience means during different periods. Such assessment reveals insights regarding different pairs that are significantly different (e.g. 2004 vs 2006, 2006 vs 2008, and so on). The null hypothesis (Ho) of the cross-period analysis assumes that the average resilience scores of different periods across Pakistan are not significantly different ($p = 0.05$). The alternative hypothesis (Ha), on the other hand, assumes that they are different. This analysis contributes to an understanding of the temporal dynamism of disaster resilience in Pakistan.

2.2 Modelling geographical disparities

For geographical distribution modelling, the data are stored in ArcGIS's spatial data repository. A data table containing information about CDR is connected to a vector layer of administrative units (i.e. districts) to create the final shapefile. This shapefile is further utilized in ArcGIS to perform spatial assessments, such as general distributions and patterns in CDR to highlight regions that are high or less resilient. Firstly, a comprehensive thematic map is developed to generate geographic references regarding the state of CDR, which enables effective communication of the overall resilience across Pakistan. While this assessment provides spatially relative information on the resilience status of different regions, mapping provides decision-makers with a spatial reference for prioritization during decision-making and resource allocation. In terms of temporal evaluation, the change is computed for different periods by subtracting the value of CDR for corresponding periods, such as subtracting the values of 2004 from 2014 provided us with the change during 2004–2014 (CDRIΔ). Table 1 presents different analysis combinations in terms of temporal assessment and provides information on codes that are utilized from this point forward. The resultant changes (i.e. loss or gain in resilience) are comprehensively mapped to provide geographical references in terms of improvements or reductions in CDR across the study area.

Moreover, two well-accomplished geographic distribution techniques are utilized to examine the CDR from a spatial statistical standpoint. In order to determine whether there is any overall spatial clustering in terms of temporal changes, a global Moran's I-based spatial autocorrelation technique is first employed (Getis and Ord, 1992; Sajjad et al. 2020a, b) using ArcGIS Pro. software from the Environmental Systems Research Institute (ESRI:

Table 1 Different combinations for change analysis and codes utilized this point forward

Serial	Code	Description
1	CDRIΔ6	Change in CDR from 2004 to 2006
2	CDRIΔ8	Change in CDR from 2006 to 2008
3	CDRIΔ10	Change in CDR from 2008 to 2010
4	CDRIΔ12	Change in CDR from 2010 to 2012
5	CDRIΔ14	Change in CDR from 2012 to 2014
6	CDRIΔ	Overall change in CDR from 2004 to 2014

www.esri.com). According to the analysis's null hypothesis, the attribute values (in this example, CDR change values) are distributed randomly across the study area. This analysis delivers a z-score, a Moran's Index value (varying between -1 and 1), and a p value to determine the significance of the outcome. If the subsequent p value is significant at $p = 0.05$, we must reject the null hypothesis. This condition suggests that spatial clustering is evident in the data. The intensity of this global autocorrelation is determined through the value of Moran's Index. For example, while the value 0 suggests an absence of spatial association, a value closer to $+1$ or -1 signifies a clear positive or strong negative global relationship, respectively, for the evaluated data (i.e. the changes in resilience for different periods). Such evaluation provides insights into the geographic clustering of loss and/or gain in CDR, which can potentially indicate the collective situation of particular regions dealing with repetitive disasters.

Furthermore, to highlight the clusters of higher resilience change, we use the Local Indicators of Spatial Association (LISA) technique using ArcGIS Pro. software from the Environmental Systems Research Institute (ESRI: www.esri.com). This analysis helps to identify coldspots (regions that became resilient over the analysis period), hotspots (regions with a larger reduction in resilience—becoming less resilient), and spatial outliers, if any, at $p = 0.05$ (Frigerio and DeAmicis 2016; Ord and Getis 1995). The outliers here describe the areas where a district with resilience gain is contained by various other areas that became less resilient during the studies period or vice versa. It is noted that because our data are in vector polygons representing the administrative unit, the contiguity-based weight matrix is employed to identify different aforementioned spatial patterns (ESRI 2016).

3 Results

3.1 Catastrophe progression-based current state of CDR across Pakistan

The results of the CDR of 2014 in Pakistan at the district level are illustrated in Fig. 4, and the mapping is carried out using one standard deviation representing how much the value of each local region (district) varies from the overall mean. In general, the findings show good resilience scores for the northeastern districts of Pakistan (upper Punjab and Khyber Pakhtunkhwa—KPK), representing relatively resilient areas. On the other hand, the least resilience scores are observed for southwestern areas of Pakistan, such as the districts of Balochistan province. The most resilient districts are located primarily around the upper Punjab region including Lahore, Islamabad, Rawalpindi, Sialkot, Faisalabad, and Multan (>0.50 standard deviation). Overall, the CDR score shows satisfactory results for KPK

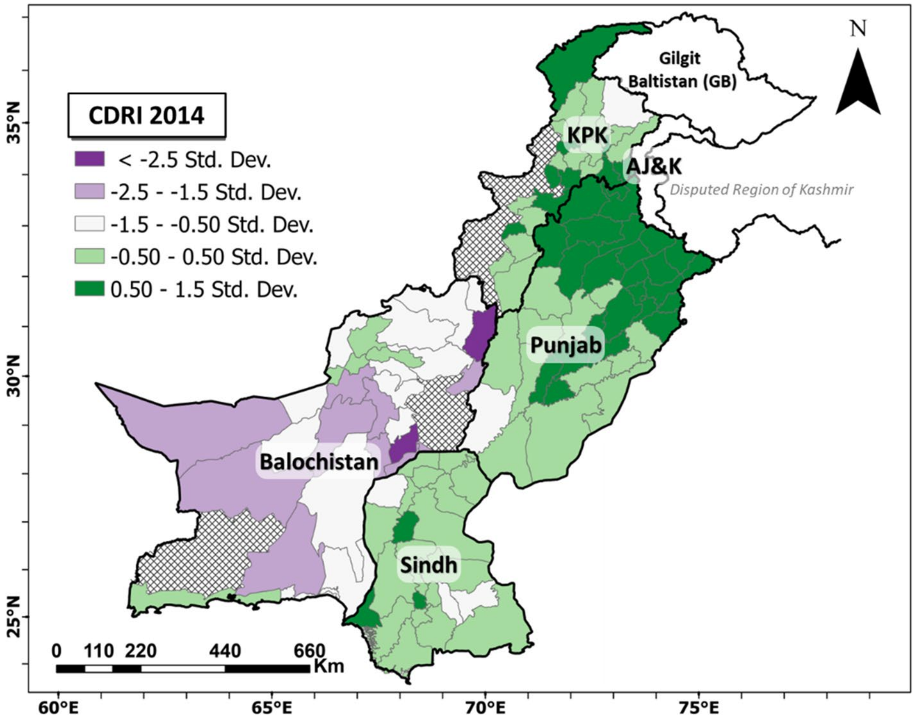

Fig. 4 Distribution of community disaster resilience (CDRI) in Pakistan in 2014 based on the Catastrophe Progression method. The results are presented using one standard deviation reflecting how much the value of each region differs from the overall mean across Pakistan

and Sindh provinces (values > −0.50 standard deviation) among which the districts with the highest economic development including Karachi in Sindh and Peshawar in KPK show the highest CDR scores (> 0.50 standard deviation values). On the contrary, Balochistan province shows the worst resilience situation (values < −1.5 standard deviation values) as compared with other regions of Pakistan with Musakhel and Nasirabad districts having the least CDR scores (values < −2.5 standard deviation).

3.2 Spatial–temporal change in CRD

While the overall multi-scale CDRI evaluation is important to prioritize local to regional areas prone to the impacts of various disasters, its temporal characteristics are equally important to assess the effectiveness of policies and countermeasures taken by the representative bodies during that time interval. The results from post hoc Tukey HSD test are presented in Table 2. Given the lower *p* value corresponding to the *F* statistic, the results suggest that there are groups with statistically significant differences (95% confidence), which is also evident from the larger value of the *F* statistic (24.088, Table 2). From the Tukey HSD test, it is evident that the resilience in 2004 tends to be significantly different than in 2010, 2012, and 2014 (at least 95% confidence, Table 2—bold values). Similarly, while the community resilience in 2006 significantly varies from 2012 and 2014, the situation in 2008 seems to be significantly different than in 2014. Finally, the resilience in 2014

Table 2 Results from ANOVA based on Tukey–Kramer all-pairs test for community disaster resilience in different years between 2004 and 2014

Source	Sum of squares	Degrees of freedom	Mean square	*F* statistic	*p* value
Categories	0.059	5	0.012	24.088	< 0.01
Error	0.330	678	0.001		
Total	0.389	683			

Post-hoc Tukey honestly significant difference (Hsd) test results

Comparison pairs	Tukey HSD Q-statistic	Tukey HSD *p* value	Tukey HSD remarks
2004 vs 2006	1.025	0.900	Insignificant
2004 vs 2008	3.968	0.058	Insignificant
2004 vs 2010	**4.054**	**0.049**	***p* < .05**
2004 vs 2012	**6.464**	**0.001**	****p* < .01**
2004 vs 2014	**7.493**	**0.001**	**** *p* < .01**
2006 vs 2008	2.943	0.299	Insignificant
2006 vs 2010	3.028	0.267	Insignificant
2006 vs 2012	**5.439**	**0.002**	****p* < .01**
2006 vs 2014	**8.518**	**0.001**	****p* < .01**
2008 vs 2010	0.086	0.900	Insignificant
2008 vs 2012	2.496	0.489	Insignificant
2008 vs 2014	**11.461**	**0.001**	****p* < .01**
2010 vs 2012	2.411	0.525	Insignificant
2010 vs 2014	**11.547**	**0.001**	****p* < .01**
2012 vs 2014	**13.957**	**0.001**	****p* < .01**

The bold represents statistically significant comparison pairs

*95% confidence, **99% confidence

is evidently different from 2010 and 2012. Conclusively, the situation regarding community resilience in the earlier, middle, and final periods of the studied time varies significantly (95% confidence). The next step is to identify regions where the temporal resilience changes happened (i.e. increased or decreased) during 2004–2014.

The evaluated spatial distributions of CDRI changes during 2004–2014 with a 2-year time interval are presented in Fig. 5. To begin with, the CDRI change during 2004–06 (CDRIΔ6) in Sindh and Balochistan provinces showed the least resilience scores, reflecting that most of the districts in these provinces became less resilient over the studies period. This might be attributed to Tsunami in late December of 2004 in Karachi and the moderate drought in some districts of Balochistan between 2004 and 2006. For spatial–temporal changes between 2006 and 2008 (CDRIΔ8), nearly all the districts in Balochistan showed declining resilience (values < -2.5 standard deviation). Punjab province in terms of CDRIΔ8 also experienced declining resilience scores with northwestern districts having values < -2.5 standard deviation.

In terms of the change during 2008–2010 (CDRIΔ10), the overall resilience score of districts in Balochistan improved, whereas districts in KPK showed a decline (values < -2.5 standard deviation). In the proceeding period (i.e. between 2010 and 2012—CDRIΔ12), most of the districts in Balochistan and Sindh provinces experienced lowering

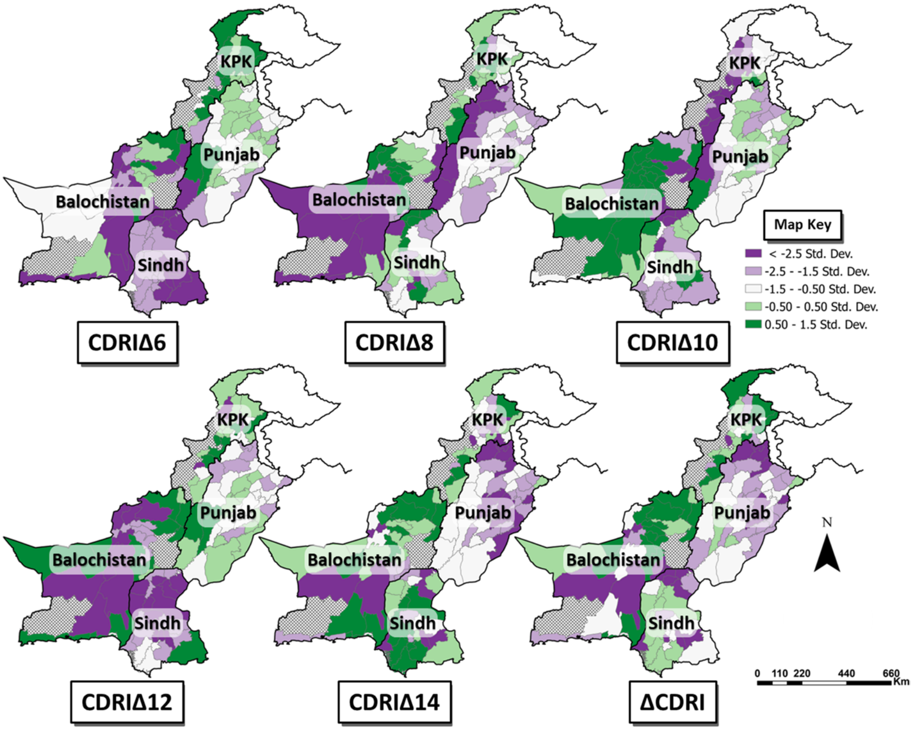

Fig. 5 Distribution of spatial–temporal trends and patterns in CDRI in Pakistan between 2004–2014. The purple and green shades represent regions that became less resilient or more resilience, respectively, during each period

resilience (values < -2.5 standard deviation) with some segregated areas from Punjab and KPK. Notably, the resilience of some of these districts improved during the next period (i.e. during 2012–2014—CDRIΔ14) in Balochistan and Sindh with Punjab province witnessing the decline. For instance, the regions in upper Punjab (northeastern) showed reasonably declining resilience scores with values < -2.5 standard deviation. Finally, on a long-term basis (i.e. temporal changes between 2004 and 2014—ΔCDRI), the results show that the overall CDRI for almost 50 percent of the districts in Pakistan declined with Punjab being the most prominent followed by Balochistan, Sindh, and KPK (i.e. the districts with CDRI values < -2.5 standard deviation).

Another important insight regarding temporal change is the degree to which resilience has changed over time in a longet run (i.e. during 2004–2014). To evaluate this, we estimated the percent change in CDR during 2004–2014, which leads us to highlight regions with the largest decline in community resilience. For instance, Fig. 6 represents the regions where the largest decline in resilience is observed during the studied period. It is evident that most of the districts with overall resilience decline belong to Balochistan with 17 out of the top-25 (~70%) in terms of percent change in CDR. Three districts each from KPK and Sindh provinces are among the top 25. From Punjab, there is only one district (Attock, 7% decrease in CDR) among the top 25 that became less resilient during 2004–2014. Comparatively, Gawadar district from Balochistan observed the largest decline in resilience (16%) followed by Kachhi and Jaffarabad with a 10% and 9% decline, respectively (Fig. 6).

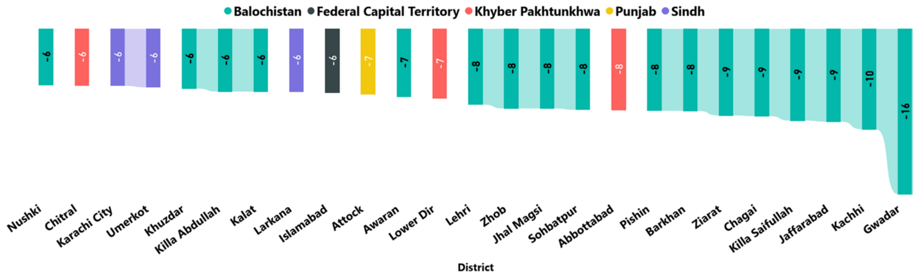

Fig. 6 Top-25 districts in different provinces in terms of percent change in CDR during 2004–2014. The districts are arranged in ascending order (left to right) to show the temporal variations and the values are in percent. It is noted that the negative (−) sign with values represents the decline in resilience

At the provincial level, Abbottabad from KPK province observed an 8% decline during 2004–2014. All three districts from Singh (i.e. Larkana, Umerkot and Karachi) experienced a 6% decline in CDR. On the federal level, the capital territory (Islamabad city) also observed a decline in CDR by 6%. Conclusively, it is observed that Punjab province performed comparatively better in terms of maintaining CDR even after the two calamitous events including the 2005 earthquake and the 2010 floods.

3.3 Global patterns of temporal changes in resilience

The global spatial association is carried out to check the clustered, dispersed or random patterns in the temporal changes in CDR. Such evaluation provides insights into the geographical equity in terms of resource allocation for resilience building. Based on the resultant positive Moran's I index values, it is evident that all the periods, such as 2-year intervals and long-term variations (CDRIΔ), show clustered patterns (95% confidence) with varying intensities of geographical associations (Table 3). This situation reflects that changes in resilience are spatially concentrated in some particular regions across Pakistan. Among different temporal segments, Moran's I values for CDRI show that CDRIΔ10 has the highest spatial clustering with Moran's index values equal to 0.48 followed by CDRIΔ6 (Moran's Index value = 0.46). On the other hand, the lowest spatial clustering is found for CDRIΔ14 with Moran's I equal to 0.15 (95% confidence). Similarly, there is a weak spatial association observed for the long-term change (CDRIΔ) with Moran's Index value of 0.19.

3.4 Local patterns of temporal changes in resilience

While the long-term changes in resilience are helpful to grasp the overall state of resilience in the face of several disasters (as presented in Fig. 6), short-term evaluations are particularly helpful to gauge the success of implemented policies and actions after a disaster. Furthermore, pinpointing areas with statistically significant concentration resilience dynamics (increase or decrease) provides a road map for further in-depth investigations. In this context, results from LISA analysis show localized cold and hotspots of multi-temporal resilience in Pakistan (Fig. 7). It should be note that the figure represents statistically significant patterns in "change-in-resilience" and not the general spatial distribution. Hence, the results should be interpreted as such. It is evident that for each given time

Table 3 Results from the spatial association analysis of temporal changes in CDR in Pakistan using the Global Moran's I model

Resilience change	Moran's index	z-score	*p* value	Global spatial pattern
CDRIΔ	0.19	3.42	< .01	Clustered
CDRIΔ14	0.15	2.83	< .01	Clustered
CDRIΔ12	0.26	4.59	< .01	Clustered
CDRIΔ10	0.48	8.15	< .01	Clustered
CDRIΔ8	0.28	4.77	< .01	Clustered
CDRIΔ6	0.46	7.79	< .01	Clustered

interval, Balochistan and Sindh show high severity of hotspot areas. In CDRIΔ6, CDRIΔ8, and CDRIΔ12 hotspots are clustered primarily around Sindh and Balochistan, whereas in CDRIΔ10 and CDRIΔ14 these regions show relatively high coldspots (relatively higher resilient). For Punjab, no prominent spatial clustering is observed, whereas for KPK coldspots areas are present for CDRIΔ6 and CDRIΔ8. Additionally, for CDRIΔ10, KPK shows hotspots in Northern areas, which reflects the clustering of the least resilient areas.

4 Discussion

Climate change has accelerated the intensity and frequency of disasters ranging from floods, cyclones, and droughts, but the aftereffects vary at regional, national, and local scales. The Sendai Framework for Disaster Risk Reduction and the agenda of SDGs, such as SDG-13, climate actions and improving localized community resilience, place particular emphasis on enhancing the disaster resilience of communities (Kelman 2015; Peduzzi 2019). Generally, developed nations can deal with the devastating impacts of disasters more efficiently than developing and under-developed countries because of resilience building at earlier stages of disaster risk preparations through informed planning, decision-making, and resource allocation (Marto et al. 2018).

Pakistan has faced numerous disasters in the past, including floods, earthquakes, and droughts (Khoshnazar et al. 2023; UNDP Pakistan 2021), which highlighted the need for better disaster risk reduction (DRR) strategies and preparedness along with a need for greater investment in DRR and resilience-building measures, particularly at the local level. In 2018, the National Disaster Management Authority (NDMA) of Pakistan developed a National Disaster Risk Reduction Policy to align with the Sendai Framework (National Disaster Management Authority 2018). The policy aims to reduce the country's vulnerability to disasters by building resilience at all levels of society. Pakistan has also developed a National Action Plan on DRR that outlines the country's approach to implementing the Sendai Framework (Government of Pakistan 2019). The plan includes initiatives to improve early warning systems, enhance community-based disaster risk management, and promote disaster risk reduction in development planning. Despite these efforts, Pakistan faces some challenges in implementing the Sendai Framework. Limited resources, lack of capacity building, and weak institutional frameworks are among the key issues (UNDP Pakistan 2021). In addition, there is a need for better coordination among various stakeholders and greater involvement of local communities in disaster risk reduction efforts. Given the fact that climate change is a major challenge that poses significant risks to the

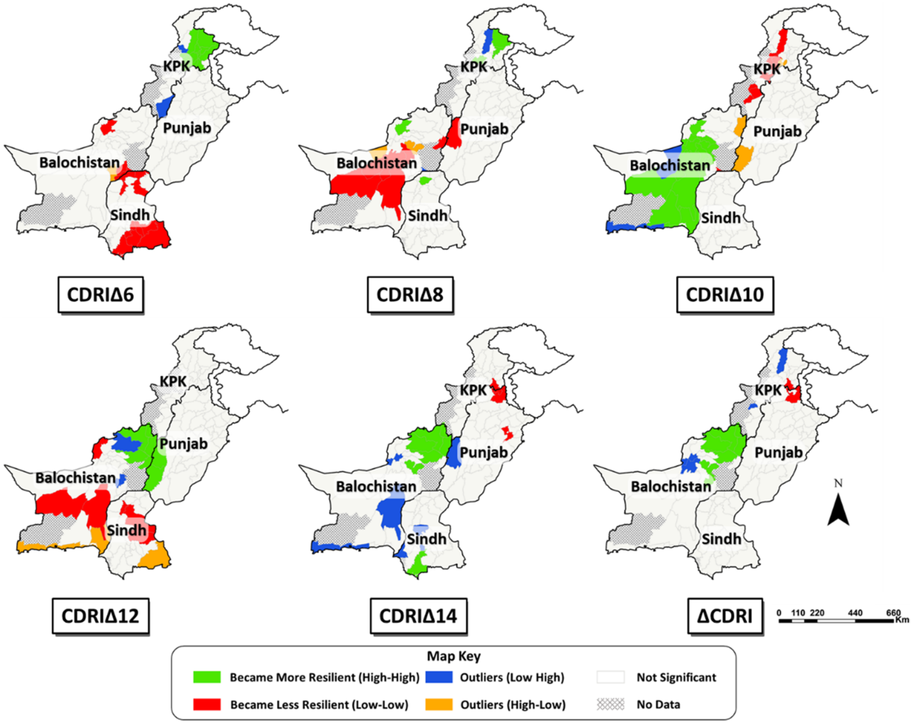

Fig. 7 LISA-based clustering of CDRI change across space and time in Pakistan during 2004–2014

country's economy, environment, and social fabric, Pakistan has taken several actions to improve the state of SDG-13 (Climte Actions). For instance, Pakistan has taken several steps to adapt to the impacts of climate change, including the development of a national climate change policy, the establishment of a climate change ministry, and the implementation of several climate adaptation projects. However, there are still significant gaps in adaptation measures, particularly in vulnerable communities (Government of Pakistan 2017; Ministry of Climate Change 2019).

In this study, the community disaster resilience (CDR), its temporal trends, and spatial patterns are identified during 2004–14 to support effective resilience building in Pakistan. For instance, the southern regions of the country are less resilient as compared with the northern ones, providing empirical evidence on the spatial inequalities in disaster resilience across Pakistan. Under such conditions, the less resilient districts particularly from Balochistan province are at greater risk of natural hazards, which are becoming more frequent and intense under climate change. Hence, to avoid these hazards from becoming disasters, there is a direct need to integrate resilience information in disaster risk planning and management practices in Pakistan. The current study provides crucial intel regarding this kind of integration. For example, the mapped resilience from this study could potentially be utilized in combination with hazard intensity and frequency information to get risk distributions in the study area. Given the frequent occurrence of flooding in Balochistan province over the past two decades, these regions need special attention from responsible authorities. Our results on the overall spatial distribution of resilience can progressively support such initiatives (Fig. 5).

Furthermore, the multi-temporal disaster resilience profiling in Pakistan, as presented in this study, will contribute towards setting a baseline for informed decision-making in the context of disaster management policies. At the same time, such assessments further allow transparency of past government initiatives and efforts during a disaster onset. For instance, the temporal shifts in the resilience (Fig. 5) scores provide proxy evidence on the initiatives taken at several stages during the studied period. Moving forward, the identified clusters of changes (Fig. 7) in Pakistan should be a matter of serious concern as they reflect no improvement in overall resilience despite experiencing several disasters. As multi-scale and multi-temporal resilience investigations help in proper resource allocation to the least resilient areas, especially after a disaster (Sharifi 2016), the findings from this study, such as spatial–temporal dynamics of resilience, serve this purpose reasonably.

The findings from this study also help to identify the state of resilience in Pakistan in 2014 after experiencing several disasters including the 2005 earthquake and floods of 2008, 2010, and 2014. For example, the situation of the 25 most resilient districts in 2014 as compared with 2004 is presented in Fig. 8. It is evident that the majority of these districts became less resilient in 2014 relative to 2004.

This study covers the existing gap in disaster resilience assessment in Pakistan; being the first of its kind in the context of multi-temporal national scale evaluation in the country. The CDR for most of the periods between 2004 and 2014 indicates Balochistan province to be the least resilient than other neighbouring provinces, while Punjab province is the most resilient. However, a large number of districts in Punjab experienced a decline in resilience between 2004 and 2014. The low CDR resilience scores for districts in Balochistan put this region disproportionally at higher risk of disasters and the findings are in line with existing local scale studies (e.g. Ainuddin and Routray 2012a, b). The findings on temporal changes and their spatial distribution (Figs. 5 and 6) highlight a reduction in resilience for Balochistan and Sindh, whereas Punjab showed overall better performance except for CDRIΔ8 and CDRIΔ14. In both these years, flood severely affected the region (the flood of 2006 and 2012 affected nearly 452,000 peoples). Besides, the continuous decline in CDRI for districts of Balochistan and Sindh also reflects a lack of efforts by concerned departments. This lower resilience situation could be attributed to inadequate disaster management infrastructure, lack of resilience awareness, and poor performance in terms of institutional and economic aspects (Sajjad 2021). Connectedly, the flood of 2010 which occurred due to excessive monsoon rainfall and the floods of 2012–14 (annually) affected the southern region of Pakistan primarily Balochistan and Sindh—providing smaller windows for recoveries from previous disasters and to work on improvements in the context of community resilience.

4.1 Fostering resilience-informed disaster management in Pakistan

Even though the Pakistani government has acknowledged the gravity of the situation following numerous disasters that occurred simultaneously and caused enormous damage in the past few decades, building resilience in a long-term perspective still needs special attention from local, provincial, and national authorities. The findings from both, spatial and temporal, assessments from this study could potentially support initiatives in this regard as they provide place-based information for improvements in resilience. As recently highlighted in the "*Disaster Management Reference Handbook of Pakistan (DMRH-Pak)*",

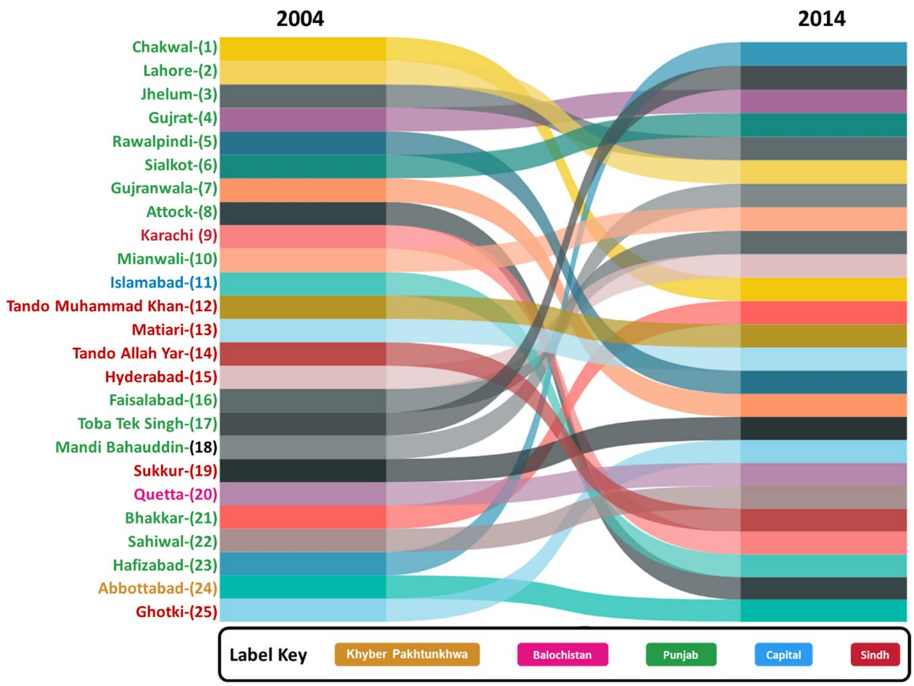

Fig. 8 Temporal change between 2004 and 2014 in the CDR of the 25 most resilient districts in 2004. The numbers in parenthesis (left axis) represent the ranks of districts according to CDR in 2004, and the label key reflects the province of corresponding districts using different colours

one of the key challenges to building a disaster-resilient Pakistan is the lack of capabilities in terms of informed resource allocation and adaption of modern tools to explore the state of resilience for effective interventions (CFE-DM 2021). Notably, the DMRH-Pak recommends profiling detailed hazards and risk evaluations as a future outlook in Pakistan to cope with disasters in the face of climate change. Hence, this study should be considered an important contribution towards this recommendation. Moving forward, the information on hazards can be integrated with the estimated resilience to map risks at the district level in Pakistan. On an important note, the dependency syndrome of local governments on provincial and national authorities for risk management interventions results in confusion regarding responsibilities and resource exploitation to manage disasters. Hence, empowering local authorities, particularly in the districts with the least resilience and significant reduction in CDR, will support resilience building and enhancement in the country.

However, there is a long way to go regarding this based on location-specific information, such as the one provided in this study. For example, there have been fragments of areas where resilience has been declining over the studied period—making them more susceptible to the impacts of disasters. This study outlines various major interventions to provide better policy-making and implementation ultimately for better resource allocation contributing to a resilient Pakistan. For example, the results of this study including multi-temporal resilience mapping, change analysis and pinpointing regions with significant change through cluster analysis contribute towards the prioritization of areas requiring immediate or gradual measures through appropriate actions. From a broader policy perspective, the findings could be used as part of the risk preparedness and management efforts from the national, provincial, and local disaster management authorities in Pakistan to put forth a holistic and more inclusive picture of "at-risk communities" in the country. Such integrated products regarding disaster risks (i.e. based on hazard, vulnerabilities and resilience—(Sajjad and Chan (2019)) can serve the purpose to deliver risk-based references and knowledge to be incorporated into local, provincial, and national risk mitigation plans. Likewise, the maps produced in this study can be utilized to communicate the state of resilience, its spatial–temporal changes, and identification of regions where resilience reduced significantly to authorities at different scales, which can help overcome the challenge of lack of awareness among institutions and communities (CFE-DM 2021).

4.2 Current limitations and the way forward

In Pakistan, the scope of disaster resilience is still in progressing stage, with only a handful of studies addressing the issues related to the emerging disaster resilience field. Though the current study contributes significantly in the context of resilience planning and enhancement in Pakistan, there are still a few limitations which could be addressed in future studies. For example, the variable data required for the estimation of CDR are not updated on regular basis. The seriousness of this issue is reflected by the fact that no national-level information on the variables at the scale of this assessment is available for current years—making 2014 the latest year. Hence, while the study does a reasonably significant job in terms of establishing a spatial–temporal baseline regarding community resilience dynamics in Pakistan, the recent dynamics of resilience after experiencing the 2014 and 2018 floods could not be captured in the present assessment. Hence, future studies should be conducted whenever the latest data becomes available. Furthermore, while provincial-level decentralized data management is recommended, the establishment of a federal centralized data platform (i.e. integrated spatial and non-spatial data management) should be encouraged to facilitate in the context of spatial data infrastructure in the country. However, there are several challenges to this initiative, such as institutional obstacles resulting from a lack of a national data policy, unclear stakeholder responsibilities, ineffective inter-organizational synchronization, a lack of a data-sharing policy, and unstable organizational alliances (Ali et al. 2021). Furthermore, as discussed earlier the assessed resilience should be integrated with several hazard maps to compute and map risks across Pakistan—presenting a comprehensive situation—which can facilitate further in terms of disaster management practices.

5 Conclusions

Enhancing disaster resilience is one of the most important objectives of hazard risk reduction and climate change adaptation, which is also recognized by the Sendai Framework for Disaster Risk Reduction and Sustainable Development Goal-13 (climate actions and strengthening community resilience). However, managing and enhancing resilience to cope with the looming uncertainties under climate change prerequisite its measurement in space and time. In this regard, the present study leverages the catastrophe progression method in integration with geo-information modelling techniques to assess and map spatial–temporal inconsistencies in the CDR along with exploring the geographies of temporal changes at the district level across Pakistan. Such first-of-its-kind evaluation in Pakistan is essential to provide progressive key references to community leaders, as well as decision and policymakers, to monitor spatial and temporal dynamics of disaster resilience for each district. For example, the study captures and explores the inherent resilience and its spatial–temporal dynamics within places at the individual district level. Furthermore, it allows them to assess how the less and/or highly resilient regions compare to neighbouring districts in the study area. Such insights are particularly useful to highlight where improvements in terms of resilience are possible. For example, Balochistan sharing ~ 70% of the districts among the top-25 areas that experienced the highest percent change in terms of CDR decline should be a matter of utmost concern for relevant authorities—given the current 2022 flood impacts Pakistan (i.e. 1,163 deaths, ~ 2 million house damages, and ~ 33 million people affected[1]).

Furthermore, the assessments as such are important to emergency preparedness in addition to providing a foundation for resilience planning and enhancement on a long-term basis. The results of this study have significant policy development ramifications that will help Pakistan create a disaster response strategy. Given the temporal and geographical distributions of CDR at district level in Pakistan, it is aptly demonstrated that the one-size-fits-all notion to manage (plan and enhance) resilience could be ineffective. This is primarily because such an approach disregards the uniqueness of places and willingness of communities to improve their resilience to the coming disasters in the face of climatic and environmental changes. Hence, the higher-resolution district-level CDR insights, as presented in this study, could provide a road map for adaptation actions, resulting in resilient communities in Pakistan.

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Declarations

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

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