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On the emergence of a predicted climate change signal: When and where it could appear over Pakistan

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ABSTRACT

Emergence of climate change signal attributed to change in mean temperature can bring serious implications to economic stability of developing countries like Pakistan. Likewise, unawareness of vulnerability in regions of a country can direct mitigation efforts towards unwanted areas instead of towards ones that are genuinely deprived of. To address these two issues for Pakistan, we adopted a compendium of five metrics by using climate model data of near surface mean monthly temperature from output of a general circulation model MRI-ESM2-0 of Meteorological Research Institute (MRI), simulated under historical (1850-2014) and projected (2015-2100) periods for five shared socioeconomic pathways (SSPs) described in the sixth assessment report (AR6) of the Intergovernmental Panel on Climate Change (IPCC) originally published in the year 2021. To identify potential hotspot regions, we used four out of the five metrics i.e., change in mean (DM–vulnerability metric), standard Euclidean distance (SED–vulnerability metric), change in standard deviation (DSD–stability metric), and standard score (Z-Score–stability metric) statistics for regional bounds of Pakistan. To investigate emergence of climate change signal, we computed the fifth metric viz. signal to noise ratio (SNR–agility metric) from time series of the near surface mean monthly temperature and checked how rapidly the subject signal emerged out of variability in the studied data under different scenarios. On the estimation of vulnerability and stability, our results revealed that the Himalayan region of Pakistan (the northeast corner) repeatedly appeared to be the most qualified region to be acclaimed as a hotspot due to its reach to optimal echelons in the associated metrics of the DM (more than four degrees), the SED (up to one), the DSD (close to null) and the Z-Score (close to null) under all the studied SSP scenarios. On the estimation of agility, our results revealed that owing to allegedly sustainable scenarios (with low to medium challenges to mitigation), the SSP1, the SSP2, and the SSP4 delayed the evolution of climate change signal (between 2070 to 2100) by at least two decades as compared to allegedly perplexing (high challenges to mitigation) SSP3 and SSP5 scenarios that accelerated the appearance of the signal by crossing the SNR threshold fairly earlier (between 2040 to 2060) in the 21^{st} century. With such knowledge at hand, this scientific contribution can advise policymakers and stakeholder agencies to exercise conversant decisions and to equip themselves with evidence to prioritize and target their resources in an informed way over Pakistan region.

Keywords: hotspot, time of emergence, standard Euclidean distance, SNR, shared socioeconomic pathways

INTRODUCTION

A crucial objective of the 2015 Paris Climate Agreement was to retain global mean temperature change at 2°C and if plausible, under 1.5°C by mid of the 21^{st} century. Wherein mean temperature is commonly cited to project increase, subsequent attributions are likewise quoted to present severe implications of incessant climatic changes around the globe (Ghimire & Singh, 2021). While financial improvement in recent years have made mitigation and adaptation efforts more feasible, unremitting anthropogenic changes, however, have perpetually attempted to recede human control over associated societal impacts around the globe. Hence, quantifying liability to climate change and hazards remains crucial for various agencies and state actors in order to make competent decisions–capable to enact sensible guidelines and approaches for handling climate risks–to sanction practices for optimal climate change scenarios that can thereafter aim for building resilience and consequently achieve sustainable development goals (SDGs) (Feldmeyer et al., 2021). Therefore, a nations' adequacy in harnessing strength to combat environmental challenges rely upon rapidity of advancement under various socioeconomic and emission pathways (Schleussner et al., 2021).

As per a recent study of Ma et al. (2022), timing of significant surge in a climatic feature compared to its natural variability is defined as "time of emergence" of that feature. Earlier, Ignjacevic et al. (2021) defined the concept of time of emergence of impacts as the first instance of occurrence when a climate change impact signal exceeded a defined threshold over their studied geographic regions. Ma et al. (2022) elaborated it further and established that investigations on timing of significant surge in a climatic attribute–to determine any potential delay in impacts of emergence of compound hot extremes–could refer to the concept of the time of emergence, in another context. The concept was also defined by Swaminathan et al. (2022) who proposed prospects of reaching the 2015 Paris Climate Agreement targets by computing year of exceedance of a warming temperature threshold, as attribution to their model for the time of emergence, under their frame of study.

Region whose climate is particularly receptive to global warming is typically referred to as a climate change hotspot (Giorgi, 2006). To innovate this concept, Rao et al. (2019) assumed that locations with concentrated high climatic variability, societal vulnerability, and negative impacts on livelihood systems, could be termed as potential climate change hotspots. On declaration of regions whose temperature distribution warmed at a faster rate than rest of a temperature distribution in response to mean global warming increase, Lewis et al. (2019) proclaimed such expanses as hotspots, in their study. Also, in an earlier study, areas found to remain particularly exposed to risks and compounded challenges were termed as hotspots whose future populations could remain vulnerable to a range of climate change-related hazards of varying intensities (Byers et al., 2018).

A multinational team of economists, climate scientists, and energy system modellers have attempted to develop a number of new "pathways" that investigate factors on how society, economy, and demographics might change over the course of the 21st century. The pathways are referred to as "shared socioeconomic pathways" (SSPs) and range from 1 to 5–depending upon their respective level of challenges to integrate mitigation and adaptation strategies (Riahi et al., 2017). With significant investments in education, health, economic growth, and well-functioning institutions, SSP1 and SSP5 predicts reasonably hopeful trends for human progress. They vary such that the SSP5 anticipates a fossil fuel and energy-intensive driven economy, whereas the SSP1 foresees a growing transition of the world toward sustainable practices. On the other hand, with insufficient investment in health and education in poorer nations, a rapidly expanding population, and rising inequality, SSP3 and SSP4 remain depressed about their future economic and social progress. Nonetheless, SSP2 is termed as a "middle of the road" scenario in which historical development patterns are integrated to sustain into the 21st century. There are several instances of the SSP integration in coupled model intercomparison project phase 6 (CMIP6) models to determine climate change hotspots and time of emergence of the climate change signal over a variety of regions. For instance, in a recent study, Ma et al. (2022) inspected the time of emergence of summertime compound hot extremes using the CMIP6 climate model projections under the SSP scenarios to measure cumulative fraction of inhabitants exposed at global and continental scales. In another study, Swaminathan et al. (2022) engaged CMIP6 models under the SSP scenarios to determine the time of emergence of an exceeded warming threshold that projected a 2°C of global warming by the end of the 21st century. Another such instance was presented by Fan et al. (2021) who engaged the CMIP6 climate model data simulated under the SSP scenarios to find global hotspots by the end of the 21st century.

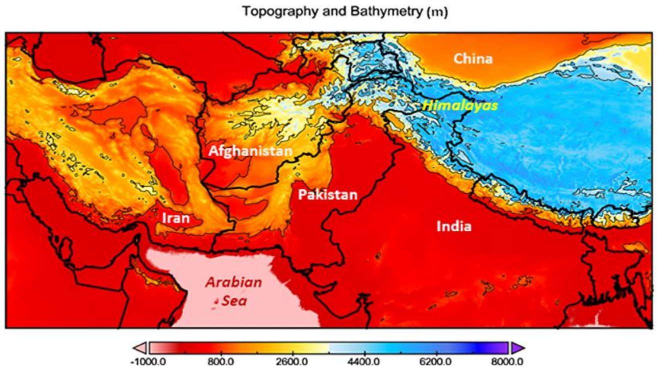

Figure 1. Geographical location, topography, and bathymetry data of Pakistan (Data Source: OW Smith and Sandwell v8.2-1/30 degree bathymetry & topography)

With a purpose to facilitate climate resilience and sustainable development, and subsequently to reach terms of the Paris Climate Agreement, it is perceived that *timely* action regulated under *socioeconomic pathways* could extraordinarily censor the likelihood of enormous *population exposure* to *climatic hazards* and related impacts. Hence in this paper we deploy the *hotspot identification* and the *time of emergence* methodologies whose results can be engaged by concerned policymakers for timely execution of suitable climate policies to avoid theoretically large socioeconomic shocks due to effects of regional warming attributed to climate change. We believe that if applied resolutely, knowledge on such attributes (the *hotspot identification* and the *time of emergence*) can halt impacts on such socioeconomic factors by several years in the times to come.

Area of Interest

Our target region is Pakistan, which lies in the west of south Asia between 23°39/N-37°01/N latitude and 60°49/E-77°40/E longitude comprising of Indus agricultural plains and northern high lands. The aggregate geographical area of Pakistan is 79.6 million hectares. Pakistan borders with the India and the Arabian Sea in the east, Afghanistan and Iran in the west, and China in the north (**Figure 1**). The climate of Pakistan is very diverse in terms of temperature (Burhan et al., 2021). One side of it is mostly arid to semiarid, followed by warm summers and icy winters with extreme temperature variations. In the north, the area is mountainous which is quite snowy and frigid on peaks of Himalayas. In mountainous areas of North and West, the climate is continental, with a wide temperature range between winter and summer, and often between day and night. Temperature over the region naturally decreases with increasing altitude (Burhan et al., 2019).

MATERIALS AND METHODS

Climate Model Data

Historical (1850-2014) and projected (2015-2100, SSPs 1-5, depicted by Riahi et al., 2017) states of the atmosphere simulated under the CMIP6 experiments (https://esgf-node.llnl.gov/projects/cmip6/) were used in this study. Latest version of Meteorological Research Institute earth system model version 2.0 (MRI-ESM2.0)–an advancement of its predecessor models–was engaged. The model is stated to have undertaken several improvements intended for exceedingly precise climate reproducibility over the globe (Kawai et al., 2019). The model bears a horizontal resolution of 100 km for atmospheric and oceanic modules.

A highly convincing imitation of both mean climate and interannual variability to observations made this model a perfect choice for targeted applicability (Yukimoto et al., 2019). Attributed to the stated enriched features in the MRI-ESM2.0 over its former versions–MRI-CGCM3/MRI-ESM1–the model was anticipated to reveal greater performance in research intended under the CMIP6. A recent utilization and validation of the MRI-ESM2.0 over Pakistan may be seen in Burhan et al. (2022).

Socioeconomic Data

To provide associations and attributions to results of this study, we acquired socioeconomic data from two sources:

1. Socioeconomic Data and Applications Center (SEDAC): A data center in NASA's earth observing system data and information system (EOSDIS)–hosted by CIESIN at Columbia University (Center for International Earth Science Information Network - CIESIN - Columbia University, 2018).
2. The International Institute for Applied Systems Analysis (IIASA) energy program's SSP database (Cuaresma, 2017; Delink et al., 2017; Jiang & O'Neill, 2017; Leimbach et al., 2017; Samir & Lutz, 2017).

Urban land extent projection and base year grids data

We engaged global one-eighth degree urban land extent projection and base year grids that consisted of global SSP-consistent spatial urban land fraction data for the base year 2000 and projections at ten-year intervals for 2010-2100 at a resolution of one-eighth degree (7.5 arc-minutes). The spatial urban land projections were our key inputs for attribution of climate change vulnerability, impacts and adaptation. The data set is advocated to present a set of global, spatially explicit urban land scenarios–consistent with the SSPs–to produce an empirically-grounded set of urban land spatial distributions over the 21st century (Gao & O'Neill, 2021).

Population, GDP, and urbanization data

For each SSP, population and urbanization projections over Pakistan, developed by the IIASA and the National Center for Atmospheric Research (NCAR), were used. For gross domestic product (GDP) data over Pakistan, instances from three alternative interpretations of the SSPs by the teams from the Organization for Economic Co-operation and Development (OECD), the IIASA, and the Potsdam Institute for Climate Impact Research (PIK) were used. As per O'Neill et al. (2017), the GDP projections are based on harmonized assumptions for interpretation of the SSP storylines that terms them as main drivers of economic growth in a country.

METHODOLOGY

Methods to identify climate change hotspots have shown diversity in approaches adopted under contemporary research. For example, Pacifici et al. (2018) presented a framework for identification of climate change hotspots risk by engaging vulnerability, eexposure, and hazard metrics over their targeted region of study. Adopting a muti-sectoral technique, Byers et al. (2018) identified the climate change hotspots by calculating a set of impact indicators at different levels of global mean temperature change and socioeconomic development covering water, energy, and land sectors from an ensemble of integrated assessment and impact models. In another attempt, Liu et al. (2018) proclaimed change patterns in annual transitions of climatically triggered land cover change as an identifier of a climate change hotspot.

Shrestha and Shrestha (2019) identified climate change triggered hotspots by calculating changes in both diversity and extent of potentially suitable regions under current and future climate. By engaging temperature and precipitation data, Ali et al. (2021) identified climate change hotspots in terms of extremes by executing a comparative analysis of local cities with sub-regional rate of change in future at annual and seasonal scales. Das et al. (2021) engaged five properties namely frequency, severity, duration, peak, and areal spread of drought indices to analyze climate change hotspots in future projections. Also very recently, researchers identified thermal hotspots through heat index determination and urban heat island mitigation using a numerical microclimate model for their area of study (Perera et al., 2022).

Climate change impacts can be evaluated not only by intensity and frequency of diverse climatic threats but also by the susceptibility of system, society or population exposed (Feldmeyer et al., 2021). Therefore, approaches to quantify vulnerability differ in terms of the indicators used. To let decision makers and stakeholders make timely and robust interventions in their current mitigation and adaptation actions for Pakistan, we specified our analysis to identification of climate change hotspot expanses and their time of emergence - a critical approach deemed by Fan et al. (2021).

As may be assessed from our cited approaches, previous studies–that identified hotspots predicted by climate models–have engaged such metrics that limited their scope to address of the vulnerability factor only. Here, we broaden our scope and augment a stability factor that is capable of determining sustenance of a proclaimed hotspot by analyzing changes in standard deviation and Z-Score of monthly temperature along the stretch of the hotspot region. Via this approach, we were able to identify area where highest ranking mean changes calculated via vulnerability approaches, tend to recur with smallest of variability in the studied temporal expanse of the data, thereby declaring them as potentially stable hotspot over the region.

To identify potential hotspot regions, we engaged model simulated and projected, near surface mean monthly temperature and used four metrics i.e., mean change (DM–vulnerability metric), standard Euclidean distance (SED–vulnerability metric), change in standard deviation (DSD–stability metric), and standard score (Z-Score–stability metric) statistics for regional bounds of Pakistan. To investigate emergence of climate change signal, we computed a metric viz. signal to noise ratio (SNR–agility metric) from time series of the near surface mean monthly temperature and determined its year (or years) of transitioning period as it crosses a particular threshold described later in detail.

Although both temperature and precipitation are routinely used for hotspot identification, yet, since we particularly seek to examine warming hotspots, we defined and identified hotspots by employing only temperature attributes, as was previously engaged by Lewis et al. (2019). Exclusive engagement of temperature attribute to detect climate impact hotspots was also exercised by Piontek et al. (2014) who analyzed different levels of global mean temperature at different levels of global warming, in their study. In another instance, Bathiany et al. (2018) identified regional hotspots based on sole inclusion of monthly temperature attributes at a local scale. Hence, use of mere temperature attributes for identification of climate change hotspots is well cited in literature and is therefore applied for further engagement in this study.

Delta Mean Analysis for Warming Potentials

Monthly mean near-surface (two meters) air temperature from the engaged climate model were annually averaged over each grid to analyze mean differences for warming potentials. One definition of local warming, proposed by Varela et al. (2022), was used in this study. As per their study, the arithmetic average (μ) of near-surface (two meters) mean air temperature difference between baseline (B; 1850-2014) and projected (P; 2015-2100) periods, symbolized by delta mean (DM) can be determined by Eq. 1., as follows:

$$\text{DM}=(\mu_{near\ surface\ mean\ air\ temperature})_P-(\mu_{near\ surface\ mean\ air\ temperature})_B \tag{1}$$

It should be noted that the more positive DM, the stronger the warming signal.

Standard Euclidean Distance for Hotspot Identification

Our hotspot identification equation was created on the method engaged by Fan et al. (2021). They deployed an SED to measure change in space between projected and baseline periods in the climate model outputs. In our current approach, we selected similar method and engaged the temperature based climate indicator to compute regional (Pakistan) level climate change hotspots, including mean values. The SED was calculated by determining changes in the climate indicator between projection period (2015-2100) and the baseline period (1850-2014) within the climate model simulations. At each land grid point, the total SED was calculated as described in Eq 2, as follows:

$$\text{SED}=(x_P-x_B)^2/[max(abs[x_P-x_B])]^2 \tag{2}$$

where x_P represents value of the climate indicator in the projection period, x_B represents value of the climate indicator in the baseline period, and $max(abs[x_P-x_B])$ represents the maximum absolute value of grid-point change in the climate indicator over all grid points in longitude degrees between [60, 80] and latitude degrees between [20, 40] for the period 2015-2100 under the five SSPs.

Delta Standard Deviation for Projected Climate Stability

Prognosticated climate stability was calculated with arithmetic difference in standard deviation (σ) of near-surface (two meters) mean air temperature between baseline (B; 1850-2014) and projected (P; 2015-2100) periods, as in Eq. 3:

$$\text{DSD}=(\sigma_{near\ surface\ mean\ air\ temperature})_P-(\sigma_{near\ surface\ mean\ air\ temperature})_B \tag{3}$$

Climate change hotspots that experienced low variability across temporal scales were likely to be particularly vulnerable to changes in mean climate (Trew & Maclean, 2021).

Z-Score for Hotspot Analysis

A Z-Score is an anomaly detection tool that is able to determine features where outliers do and do not exist in a time series (see e.g., Fatima et al., 2021; Rousseeuw & Hubert, 2018). In our analysis, zero-approaching Z-Score values were used to determine intense clustering of values that remained convergent over high values of the DM and the SED over the domain of Pakistan. By engaging this metric, we intended to elucidate spots where recurrence of mean converging near surface mean temperature values persisted over the expanse of the analyzed domain. That way, we were able to filter out areas with extreme values of the departure and declare only those areas as potential hotspots whose anomalies remained steady over the associated Gaussian distribution.

Calculation of the Z-Score was made by subtracting the arithmetic average (μ) of near-surface (two meters) mean air temperature of the baseline (B; 1850-2014) from the arithmetic average(μ) of near-surface (two meters) mean air temperature of the projection (P; 2015-2100) periods and dividing the result with the standard deviation (σ) of the baseline period (B; 1850-2014), as in Eq. 4:

$$\text{Z-Score}=[(\mu_{near\ surface\ mean\ air\ temperature})_P-(\mu_{near\ surface\ mean\ air\ temperature})_B]/(\sigma_{near\ surface\ mean\ air\ temperature})_B \tag{4}$$

Signal to Noise Ratio for Time of Emergence

We were also particularly curious about when the climate change signal emerged out from the underlying variability noise in areas classified as future climate change hotspots. The concept, known as “time of emergence,” assisted us in determining periods (or years) of transitioning phases of a pulse to a climate change signal computed under the engaged socioeconomic pathways scenarios over Pakistan. We calculated it by determining the “ratio” between the “signal” of near-surface (two meters) mean air temperature change and the estimated “noise” in hotspots projected for the 21st century (Eqs. 5-7).

We defined the signal as the near-surface (two meters) mean air temperature change of the projection period (P; 2015-2100) using a 1032-month running window (*nRM*) of the difference with respect to the base period (B; 1850-2014). The noise was estimated by determining square root of variance (*sqVar*) of the near-surface (two meters) mean air temperature of the projection period (P; 2015-2100) to the near-surface (two meters) mean air temperature of the baseline period (B;

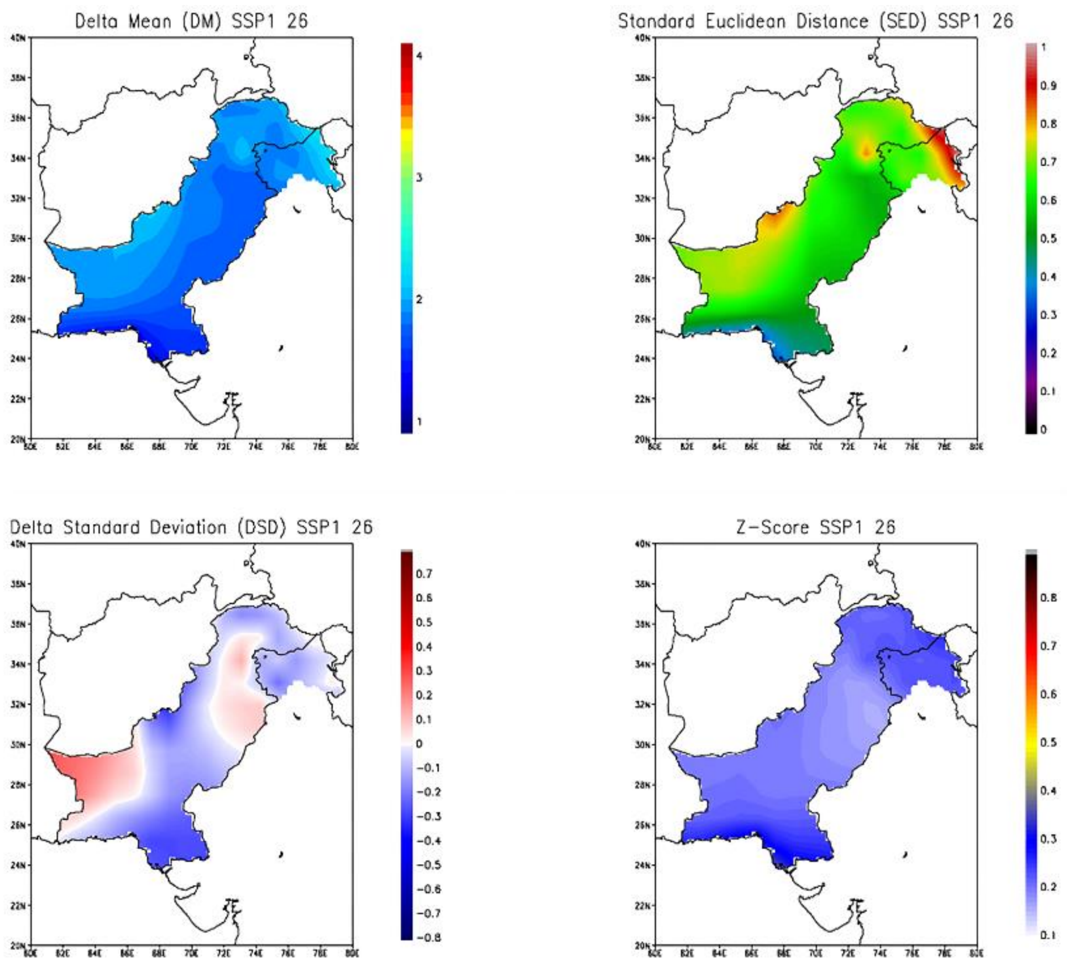

Figure 2. Spatial distribution of metrics for identification of hotspots in projected climate (2015-2100) under SSP1 scenario over Pakistan (Data Source: https://www.wdc-climate.de/ui/cmip6?input=CMIP6.CMIP.MRI.MRI-ESM2-0)

1850-2014). If this metric–the SNR–exceeded a threshold of one and remained above that threshold value for the rest of the analyzed period, we declared that a climate change signal had emerged from the noise of the variability (Fan et al., 2021).

$$\mathrm{SNR}(i)=nRM/sqVar \tag{5}$$

where i={0, 1, 2, ..., 1032}, and

$$nRM=\frac{1}{n}\sum_{j=i}^{i+n-1}(a_{iP}-\overline{a_B})_j\ \forall a_i\in\{a_i\}_{i=1}^{N}, n=N=1032 \tag{6}$$

$$sqVar=\sqrt{\sum_{i=1}^{n}\frac{(a_{iP}-\overline{a_B})^2}{n-1}}\ \forall a_i\in\{a_i\}_{i=1}^{N}, n=1032 \tag{7}$$

and $\{a_i\}_{i=1}^{N}$ is the sequence of monthly near surface mean air temperature over Pakistan.

Concurrence of the SNR to Socioeconomic Factors

In our final step of analyses, we checked sensitivities of the breaching SNRs to our engaged population data in order to provide rational attributions to the proclaimed emergence of the climate change signal under the five SSPs over the studied region. We further attributed variation in evolution of the SNRs to growth or decay in the engaged GDP projections under the five SSP scenarios. By following that line of action, we were able to identify trade-offs in climate forcing and socioeconomic balances represented under each of the studied scenarios over the region.

RESULTS

Distribution of Hotspots, Time of Emergence, and Its Attributions Under the SSP1 Scenario

Distribution of the DM, focused over Pakistan region exhibits fairly visible hotspots whose magnitude are seen to vary from less than one degree over coastal south to fairly above two degrees over south-western and north-eastern (thereafter Himalayan) extents under the SSP1 scenario (**Figure 2**).

By only restricting the analysis to the DM, the coastal regime, followed by considerable fraction of the eastern regime of the country, are seen to bear minimum impact of mean change in their climate. The associated SED based identifier also replicates similar patterns of the mean temperature change and puts the aforementioned south-western and Himalayan regimes at high values of the indicator which virtually approaches to one under the SSP1 scenario. The DSD under the SSP1 scenario depicts a combination of changes with southern half of the domain exhibiting strong positive values towards west and strong negative values towards east indicating higher and lower variability respectively, in the projection period.

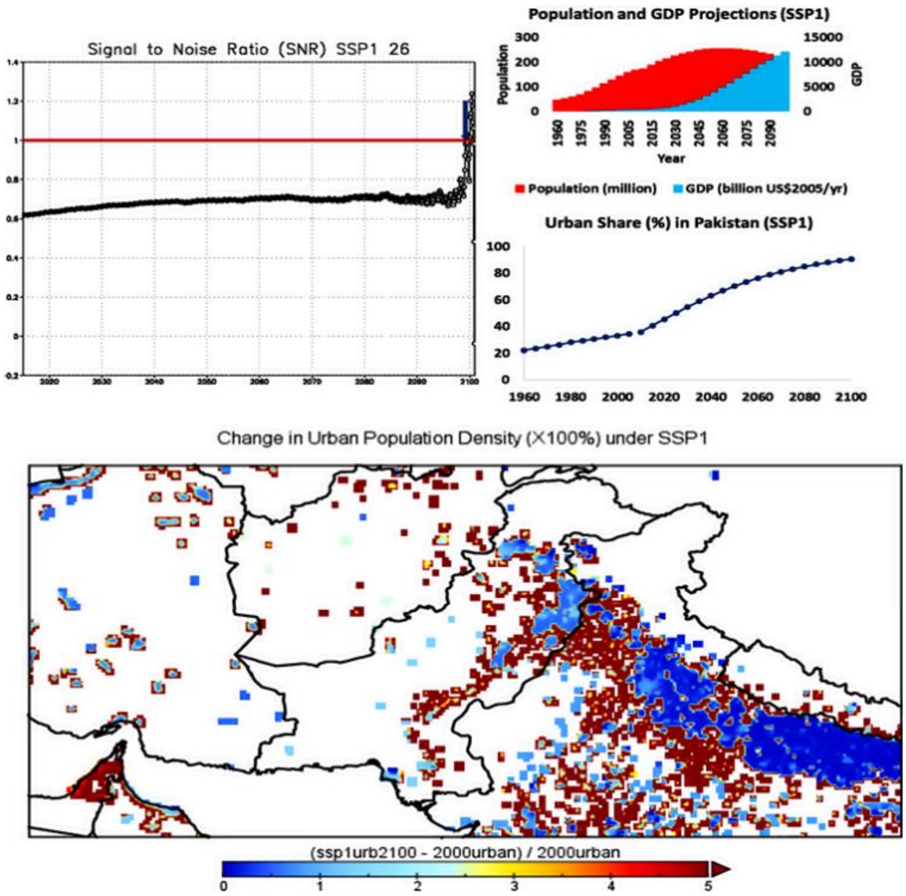

Figure 3. Representation of time of emergence (top-left panel) of climate change signal where red line (threshold one) intersects the SNR (blue pointer), assisted with socioeconomic factors (bottom and right panels) under SSP1 scenario over Pakistan (Data sources: https://www.wdc-climate.de/ui/cmip6?input=CMIP6.CMIP.MRI.MRI-ESM2-0; https://sedac.ciesin.columbia.edu/data/set/ssp-1-8th-urban-land-extent-projection-base-year-ssp-2000-2100; https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=10)

Moreover, the country (inclusive of the Himalayas) is seen to experience small magnitude of the Z-Score index, which means that nearly all grid points of the analyzed domain are void of mean-divergent values of the DM, and hence, the DM can be expected to remain persistent under the SSP1 scenario. It is pertinent to mention here that, even under the SSP1 scenario (labelled with low emissions and sustainable practices), there are strong indications of appearance of hotspots over the Himalayas, which, due to their smaller variability (determined via the DSD and the Z-Score) are also considerably consistent in their time series. However, the associated magnitude of change inferred via the DM restricts overshooting of mean temperature to fairly close to two degrees by the end of the 21st century. The matter is of significance since the region declared as hotspot under this scenario, hosts significantly large volumes of snow and ice reserves, which are lifelines for water and food security, especially in dry months of the country (Burhan et al., 2015).

Despite the evident indication of potential changes and appearance of associated hotspots, it is seen that the SNR fails to cross the one standard deviation threshold till the last pentad of the 21st century (**Figure 3**). Such delay in the appearance of the change signal can be attributed to projection of the urban share magnitude–which is not linear or exponential–but tends to suppress its growth rate under a receding arc under the SSP1 scenario, by the end of the 21st century. Attributions to such tolerant conduct of the SSP1 scenario under the changing climate can also be related to its integrated controlled expansion in urban spaces over Pakistan–especially when compared to their expansion in immediate east–by the end of 21st century. Hence, control on effects of urban heat island and on associated anthropogenic warming can be expected to delay the change signal by a significant time under the SSP1 scenario.

Although population number peaks to 255 million by the end of mid-21st century, it rises only to fall back to a modest, 217 million by the end of the century, under the SSP1 scenario. This is a trade-off; the country is shown to experience in order to appreciate fruits of sustainability in the future. However, the GDP projection under this scenario is seen at an optimistic pace of improvement with a sturdy progression that stretches to US$(2005)/yr 12,060 billion by the end of the century.

Distribution of Hotspots, Time of Emergence, and Its Attributions Under the SSP2 Scenario

Major expanse of the country under the SSP2 scenario experiences two to three degrees of departure from the mean historical temperature, by the end of the 21st century (**Figure 4**). However, some relief at particular regions is seen–like at those, associated with monsoonal tracks over the East and the South–under the SSP2, which collapses the departure by up to 1 degree by the end of the century. Nevertheless, over to the

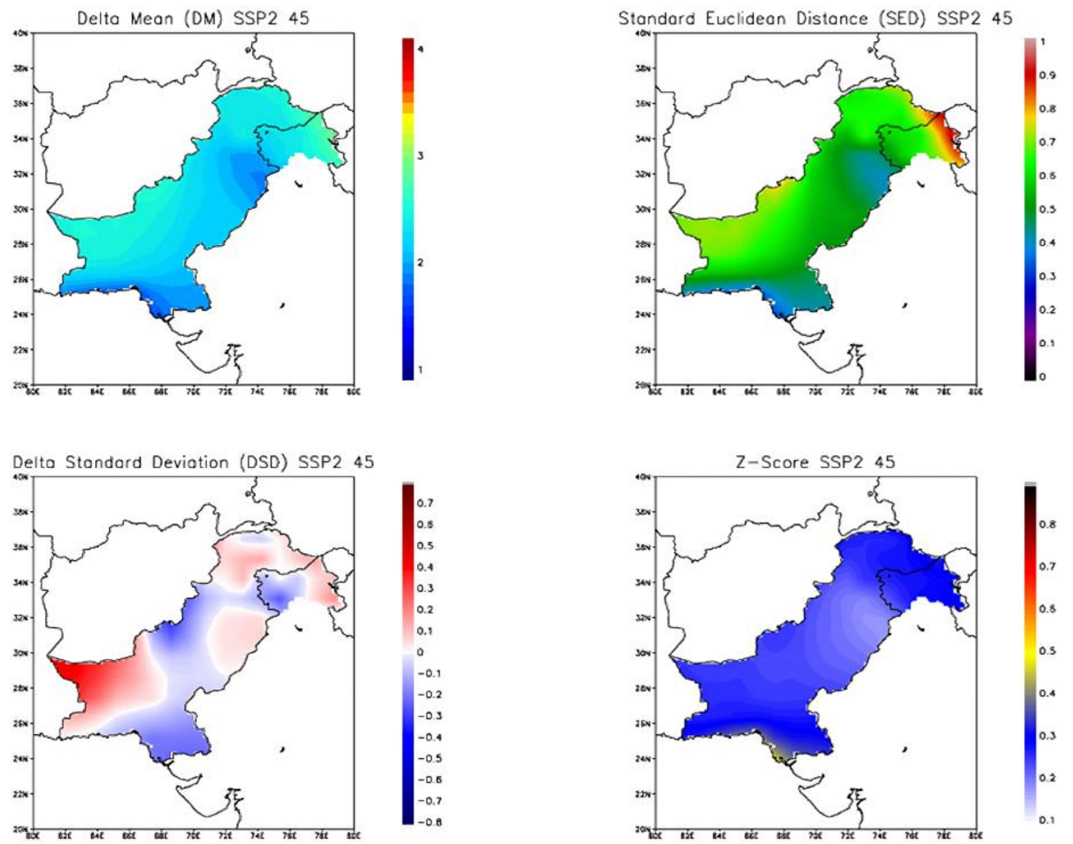

Figure 4. Spatial distribution of metrics for identification of hotspots in projected climate (2015-2100) under SSP2 scenario over Pakistan (Data Source: https://www.wdc-climate.de/ui/cmip6?input=CMIP6.CMIP.MRI.MRI-ESM2-0)

north, the Himalayan region experiences highest of the changes with precisely three degrees of temperature departure from the mean of the historical, under the SSP2 scenario. The SED also declares the Himalayan region as the potential hotspot by converging its magnitude considerably close to one under the SSP2 scenario. Some indication of potentially vulnerable region is also seen towards the south-western regime of the country whose extent of the SED theoretically approaches to one under the SSP2 scenario. However, as seen via the DSD, the south-western regime of the country bears highest magnitude of positive departure which depicts that inter-monthly variability of the temperature magnitude can remain high over the locality in the projections under the SSP2 scenario. On the other hand, the DSD values associated with the Himalayan region are seen to remain fairly close to zero which means that amplitude of the temporal variation remains contracted over the alleged hotspot region under the SSP2 scenario. Also, signals from the Z-Score essentially labels the whole country with zero-approaching values (with the exception of over to the southern monsoonal tracks whose values are seen to go as high as 0.5) under the SSP2 scenario. Hence, attributed to the computed three degrees departure in the DM, to the overshooting value of the SED, to the small inter-monthly variability in the DSD, and to the zero-approaching values of the Z-Score, the Himalayan region is declared as a potential hotspot vulnerable to a recurrent change in mean temperature under the studied SSP2 scenario.

As seen through the SNR analysis, there is a steep climb in its pulse till the mid of the 21st century, where it detracts just by a modest magnitude of 0.1 to reach the one unit threshold under the SSP2 scenario (**Figure 5**).

Pace of the increasing slope of the SNR is less steep after the mid-century, though it continues to ascend till the 9th decade of the 21st century under the SSP2 scenario. However, sharp variability is seen in the last decade of the century, where it eventually crosses the one unit threshold of the SNR scale and hence indicates a delayed evolution of the climate change signal under the SSP2 scenario. Near to similar pattern of the SNR is seen in population increase under the SSP2 scenario where it forces an expansion in number of masses, initially–till the mid-century–only to execute a stability thereafter till the end of the century. This pattern advocates effects of rising carbon footprints associated with initially increasing and eventually stabilizing population number on evolution of the change signal under the SSP2 scenario. The associated GDP rises slowly by limiting its growth for the period of increasing SNR and population number (nearly 20 years before the end of the 21st century). However, the GDP holds a staggering place on its scale when the SNR dampens, and the population number stabilizes for the next 10 years of projection (2081-2090) under the SSP2 scenario.

Interestingly, even with a delayed progression, the GDP under the SSP2 scenario presents a confounding figure of US$(2005)/yr 13,333 billion, which remains US$(2005)/yr 1,273 billion surplus as compared to the sustainable SSP1 scenario, by the end of the 21st century. This shows heavy sensitivity of the rising GDP projection to the dampening of the SNR and to the stability of the population number under the SSP2 scenario, near to end of the 21st century. Modulation of the SNR pulse along the period of upturn in the GDP may also be attributed to stabilizing urban share of population which conforms to nearly 74% of the total population under the SSP2

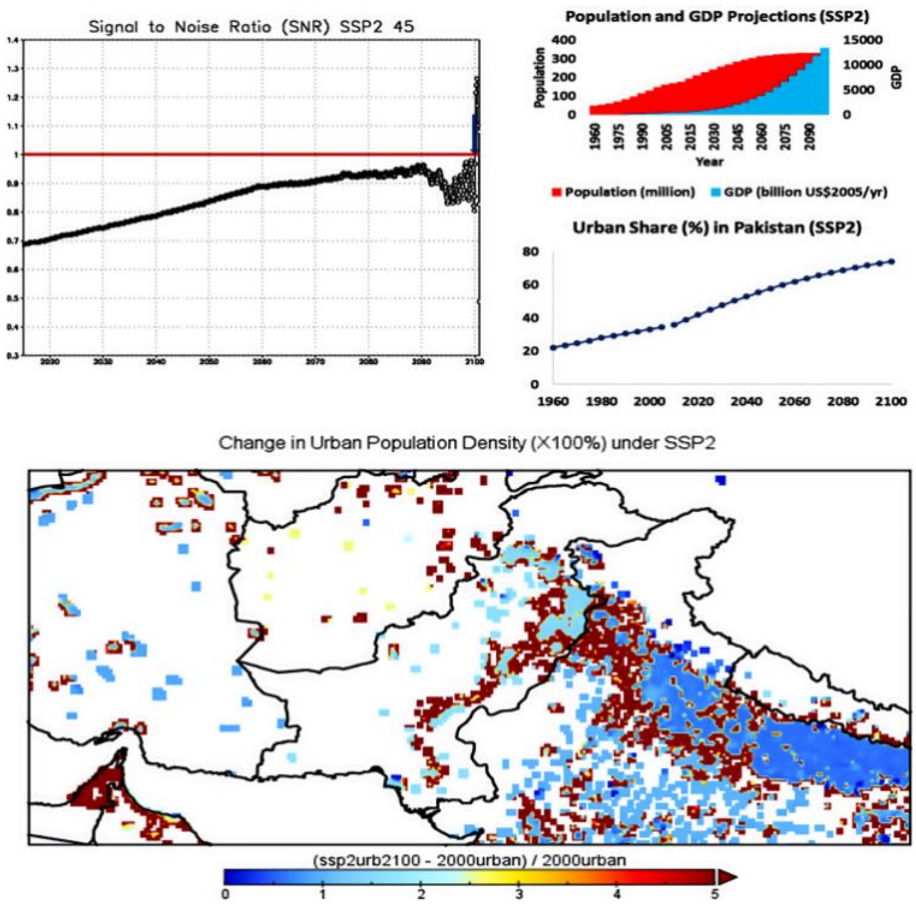

Figure 5. Representation of time of emergence (top-left panel) of climate change signal where red line (threshold one) intersects the SNR (blue pointer), assisted with socioeconomic factors (bottom and right panels) under SSP2 scenario over Pakistan (Data sources: https://www.wdc-climate.de/ui/cmip6?input=CMIP6.CMIP.MRI.MRI-ESM2-0; https://sedac.ciesin.columbia.edu/data/set/ssp-1-8th-urban-land-extent-projection-base-year-ssp-2000-2100; https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=10)

scenario, by the end of the 21st century. Moreover, significant urban population density changes–that are not less than 150% in major expanses–can induce increased pressure on future urban management and development errands run under the SSP2 scenario, by the end of the 21st century. It therefore galvanizes GDP growth on one hand and triggers the SNR pulse to cross the threshold on other, under the SSP2 scenario, by the end of the 21st century.

Distribution of Hotspots, Time of Emergence, and Its Attributions Under the SSP3 Scenario

As seen in **Figure 6**, the SSP3 pulls out serious concerns by pushing the DM to values significantly beyond three degrees in the 21st century. Similar to those of the SSP1 and the SSP2, patterns of the SED under the SSP3 indicates potential vulnerability to hazards associated with change in mean temperature over both the south-western and the Himalayan regions. Impact represented by the SED is high over the Himalayas as compared to that over the South-Western regime, which may be associated with smaller changes in variability of mean projected temperature over the Himalayas as compared to those over the South-Western regime, as represented by the DSD under the SSP3 scenario. This indicates a compliance of future variability pattern to its historical magnitude of variability due to small deviation departure in the mean temperature over the Himalayas. Nonetheless, high (low) volatility in persistence of representative mean temperature over the southern (Himalayan) extents, represented by the Z-Score does not (does) render the respective areas to qualify for being a hotspot under the SSP3 scenario. Although high variability in manifestation of temperature magnitude is itself hazardous–since it renders hesitant decisions by stakeholders to direct mitigation and adaptation resources to areas of calling–yet to address such risks are beyond our current scope and hence are left as such at this stage of the study.

With a 7.0 Watts/m^2 of solar radiation forcing (near to business as usual scenario, without engagement of mitigation efforts), Pakistan faces instigation of climate change signal right after transition to the second half of the 21st century, under the SSP3 scenario (**Figure 7**).

The evolution of the SNR in the post-trigger period is symmetrical to its slope pattern in the pre-trigger period till the 9th decade of the 21st century, however it experiences considerably large variability in the last decade where it attempts to stretch significantly close to two units of threshold by the end of the century, under the SSP3 scenario. Population growth (with a staggering 551 million number by the end of the century), under the SSP3 scenario, accelerates initially at the transitioning period from the historical period to the projection, and thereafter maintains its surge to imitate growing pattern of the SNR in the 21st century.

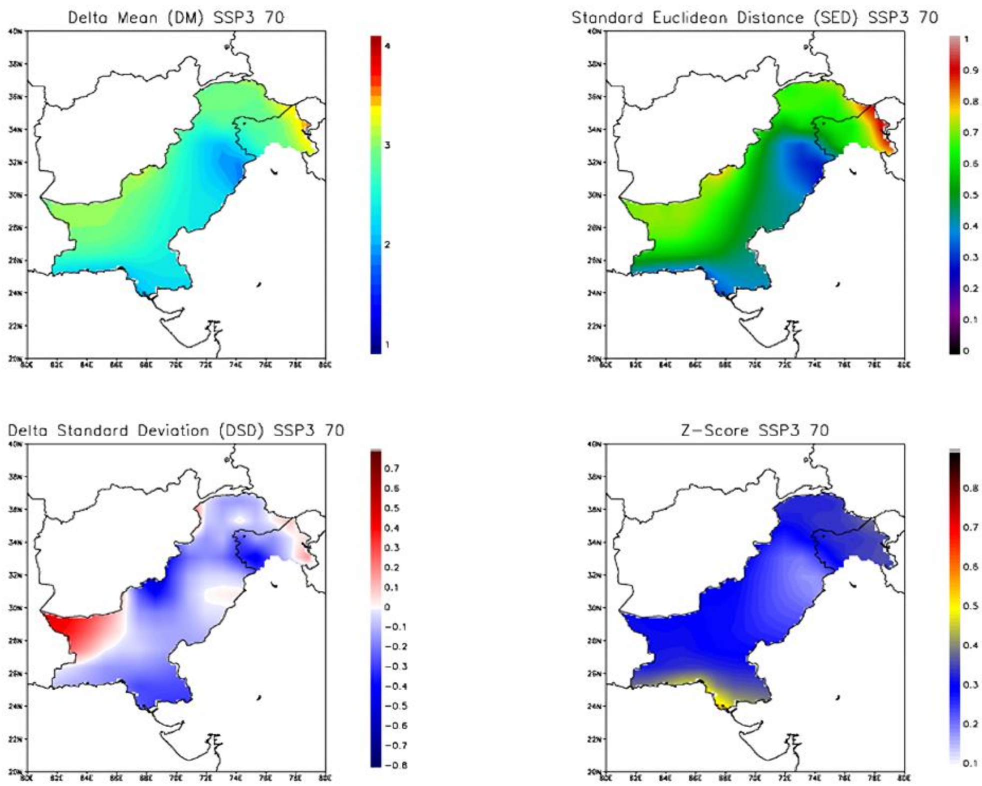

Figure 6. Spatial distribution of metrics for identification of hotspots in projected climate (2015-2100) under SSP3 scenario over Pakistan (Data Source: https://www.wdc-climate.de/ui/cmip6?input=CMIP6.CMIP.MRI.MRI-ESM2-0)

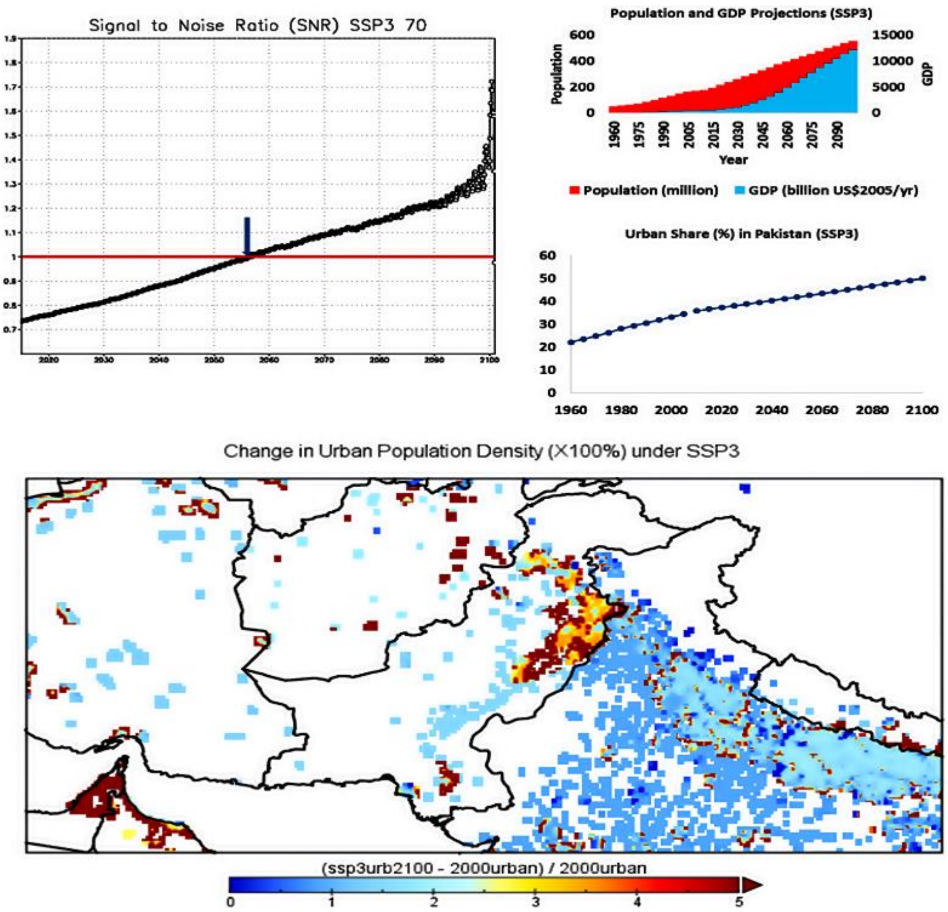

Figure 7. Representation of time of emergence (top-left panel) of climate change signal where red line (threshold one) intersects the SNR (blue pointer), assisted with socioeconomic factors (bottom and right panels) under SSP3 scenario over Pakistan (Data sources: https://www.wdc-climate.de/ui/cmip6?input=CMIP6.CMIP.MRI.MRI-ESM2-0; https://sedac.ciesin.columbia.edu/data/set/ssp-1-8th-urban-land-extent-projection-base-year-ssp-2000-2100; https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=10)

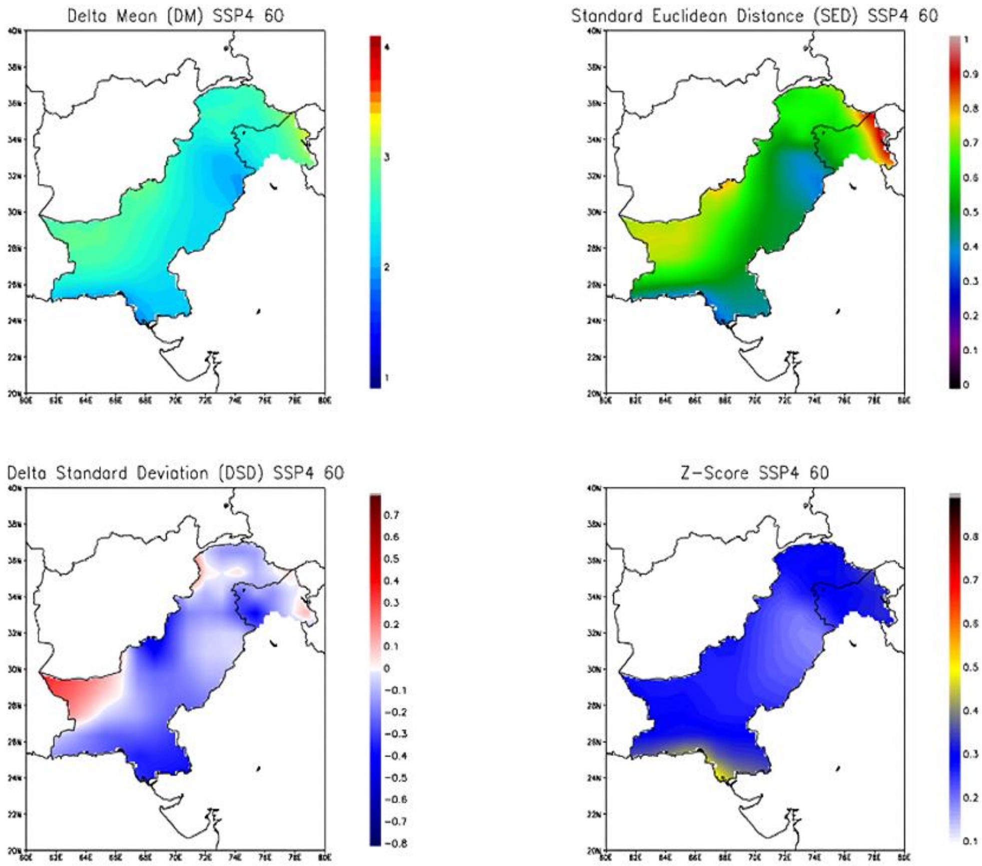

Figure 8. Spatial distribution of metrics for identification of hotspots in projected climate (2015-2100) under SSP4 scenario over Pakistan (Data Source: https://www.wdc-climate.de/ui/cmip6?input=CMIP6.CMIP.MRI.MRI-ESM2-0)

This means that the steep population surge over the transitioning period can force the magnitude of the SNR pulse to cross the vulnerability threshold, merely within 50 years of its inception, under the SSP3 scenario. GDP growth (that hits US$(2005)/yr 12,060 billion by the end of the century) is nearly collinear to the population growth which indicates that the increasing GDP can augment the effect of population number on the early emergence of the change signal over the country, under the SSP3 scenario.

Moreover, under the SSP3 scenario, it is seen that urban share to the total population composite is merely 50% (that too with a modest rate of change of nearly 1.8% per decade only) by the end of the century. It means that major contribution to the early onset of the climate change signal are likely to come from practicing traditional norms in agricultural and livestock amenities that are capable of inducing significant amount of greenhouse gases (especially methane) into the atmosphere of the rural areas of the country. Also, change in population density of the existing urban spaces over the country is relatively weak which further strengthens our claim on rural share of the population as potential contributor to the emergence of the signal, under the SSP3 scenario.

Distribution of Hotspots, Time of Emergence, and Its Attributions Under the SSP4 Scenario

Mean temperature change in the future maximizes at three degrees under the SSP4 scenario (**Figure 8**). The DM, under the SSP4 scenario concentrates its potential hotspot grids over the same extents as those under the SSP2 and the SSP3 scenarios, over the South-Western and the Himalayan regions of the country. However, magnitude of the DM under the SSP4 scenario remains intermediary to those represented under the SSP2 and the SSP3 scenarios. The difference is essentially attributed to a restrained solar radiation forcing of 6.0 Watts/m^2 under the engaged SSP4 scenario as compared to the modest 4.5 Watts/m^2 of forcing under the engaged SSP2 scenario and to the assertive 7.0 Watts/m^2 of forcing under the engaged SSP3 scenario, by the end of the 21st century. The magnitudes associated with the SED, the DSD, and the Z-Score under the SSP4 scenario, similar to their magnitudes in the preceding SSPs, nominates the Himalayan region as the most vulnerable hotspot that can potentially undergo the effects of climate change in the future.

Emergence of the change signal is seen as delayed under the SSP4 scenario (**Figure 9**). The SNR, under the SSP4 scenario crosses the one unit threshold not before the commencement of the 2070's, however it attempts to control the signal to limit its modulation to 1.5 units of scale, by the end of the 21st century. Population number–that remains synchronous to the climb of the SNR pulse–sees a steady rise throughout, and attempts to reach an enormous 530 million, by the end of the 21st century, under the SSP4 scenario. However, compared to the relatively closer SSP3 scenario, population number regresses by 21 million, which explains the predicted delay in the emergence of the signal by up to 17 years under the SSP4 scenario.

The associated GDP projection, under the SSP4 scenario, however, indicates merely a US$(2005)/yr 4,307 billion growth, by the end of the 21st century. This stands as an example of low

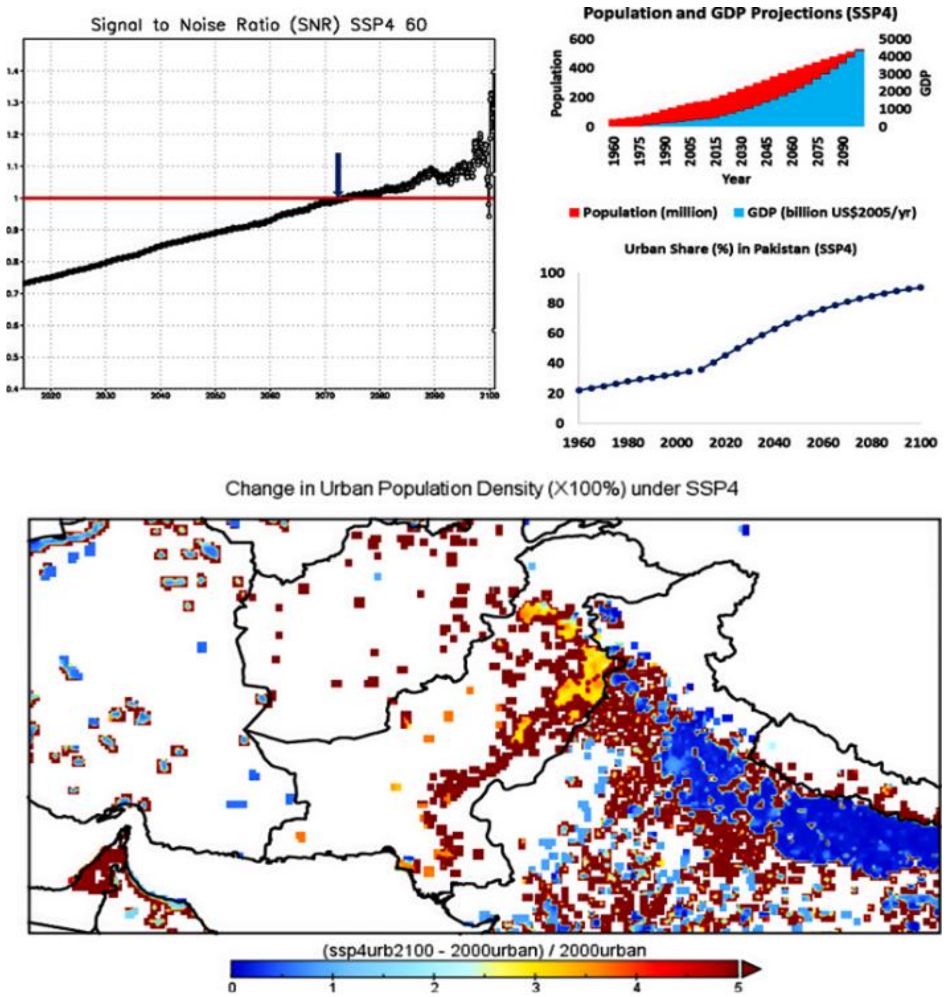

Figure 9. Representation of time of emergence (top-left panel) of climate change signal where red line (threshold one) intersects the SNR (blue pointer), assisted with socioeconomic factors (bottom and right panels) under SSP4 scenario over Pakistan (Data sources: https://www.wdc-climate.de/ui/cmip6?input=CMIP6.CMIP.MRI.MRI-ESM2-0; https://sedac.ciesin.columbia.edu/data/set/ssp-1-8th-urban-land-extent-projection-base-year-ssp-2000-2100; https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=10)

budget tradeoff where compromises on census and economy are seen to render significant delays in the emergence of the change signal over the country. Interestingly, share of the urban masses to total population, under the SSP4 scenario, reaches a massive 90% by the end of the 21st century. This means that, although urban development remains considerably large under the SSP4 scenario, yet it can contribute neither to the economy nor to the arrival of the change signal over the country, significantly, before commencement of the seventh decade of the 21st century. This further establishes significant role of agricultural and livestock practices (from the rural areas of the country) in boosting economic numbers of the country, as discussed previously, under the results on the SSP3 scenario. Moreover, urban density of existing urban extents also see significant increases, under the SSP4 scenario, where the departures are not less than 200% throughout the expanse of the country.

This further establishes that both the urban population census and the urban population density–even with significant increases–does not cater to boost local economy with optimal figures, under the SSP4 scenario. However, a simultaneous decrease in rural extents–if not coupled with traditional farming and livestock practices–can hamper implications to environmental sustainability by restricting release of significant amount of greenhouse gases to its immediate atmosphere. Also, since urban communities tend to remain more sustainable, environmental degradation takes its time to develop and force its impacts there, and hence attempts to resist emergence of the signal for a duration of a particular period of time.

Distribution of Hotspots, Time of Emergence, and Its Attributions Under the SSP5 Scenario

Projection of mean temperature under the SSP5 scenario crosses four degrees of departure from the mean of the historical period, in the 21st century (**Figure 10**). Echelons of the DM crossing the four degrees departure are essentially located over the Himalayan region and traverse major extents of the adjacent regions, under the SSP5 scenario. The SED also designates the same region as potential hotspot with fairly large values converging to one unit of threshold under the SSP5 scenario. The DSD represents the same with small variability associated with the DM in the projection period, under the SSP5 scenario. It therefore establishes that under the SSP5 scenario, the Himalayan region is most sensitive to recurrence of associated +4 degrees departure of temperature

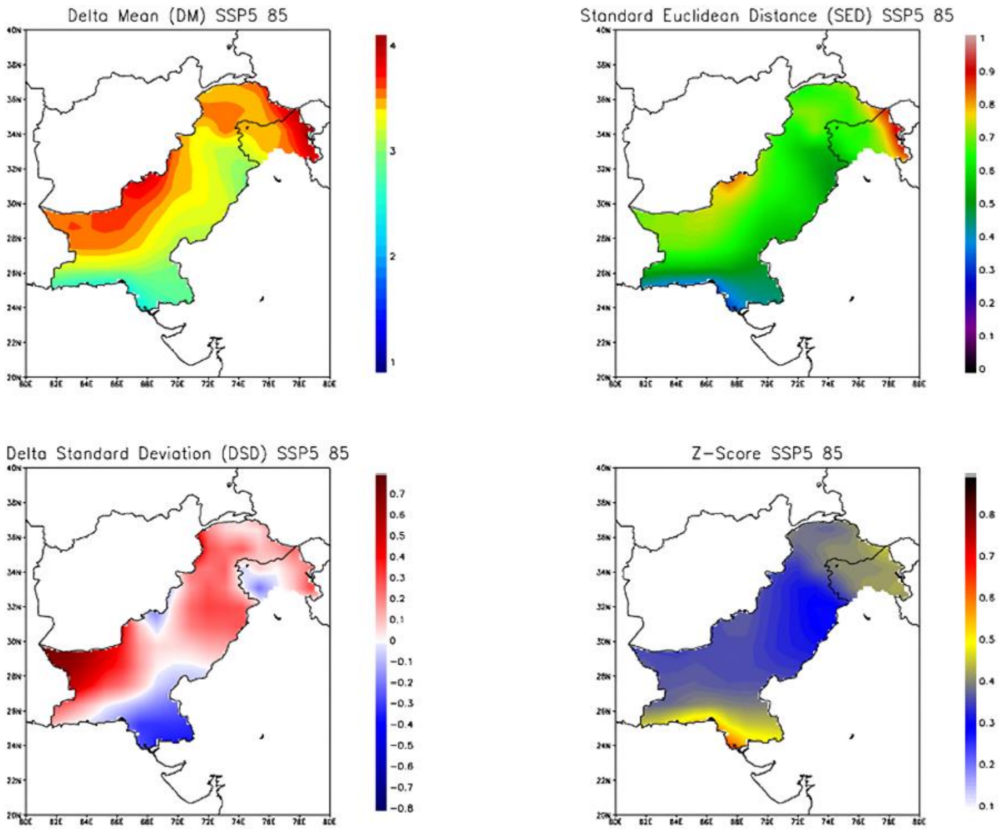

Figure 10. Spatial distribution of metrics for identification of hotspots in projected climate (2015-2100) under SSP5 scenario over Pakistan (Data Source: https://www.wdc-climate.de/ui/cmip6?input=CMIP6.CMIP.MRI.MRI-ESM2-0)

in the 21st century. Also, since the Z-Score index expresses low to medium range magnitudes over the Himalayas, the associated volatility in recurrence of deviated temperatures dampens and hence clear signals are projected under the SSP5 scenario.

Time to mitigate impacts of climate change is seen very short, since emergence of the climate change signal is seen well before the commencement of the mid-21st century under the SSP5 scenario (**Figure 11**). In fact, Pakistan sees transition of the SNR to threshold greater than one, right after it ages to complete forty six years of the 21st century, under the SSP5 scenario. Population number of the country increases till mid of the century, however it decays significantly thereafter under the SSP5 scenario. Although, the echelon reached for the population number under the SSP5 scenario matches that under the SSP1 scenario (nearly 200 million) by the end of the century, yet, emergence of the change signal is seen significantly faster under the SSP5 scenario, than that under the SSP1 scenario in the 21st century.

Attribution to such anomalous behaviour of the scenarios can be taken from their GDP projections according to which the SSP5 outnumbers the SSP1 by a staggering US$(2005)/yr 7,260 billion of departure by the end of the 21st century. Attributed to narrated fossil fuel development course of the SSP5, the extravagant economic boost in the said scenario is deemed as the main driver of early inception of the change signal in the 21st century, over the country. Also, the urban share of population is seen to accelerate rapidly till it catches 90% of the share, by the end of the century.

This further clarifies association of the fossil fuel-based thrust in the economy, to the rapid urban development and subsequently to the early onset of the signal, under the SSP5 scenario, in the 21st century. Moreover, it is seen that the existing urban extents, show only modest changes in their density (nearly 50 % of departure), while the existing suburban areas show considerably large departures (more than 500%) under the SSP5 scenario. This shows expansion in territorial bounds of urban areas by up-gradation of existing spaces from suburban to the urban, under the SSP5 scenario. Although such projections of modest increases in the central, and significant increases in the peripheral regions of the urban spaces can subside pressures from a potentially congested development in the future, yet they can equally contribute to trigger significant migration practices from rural to urban, along with a potential to shift occupational preferences for several–from farming to fossil fuel-based industry–over the country, along the course of the 21st century.

DISCUSSION

One of the factors deemed crucial–in time dependent analytics–is assessment of volatility of hazard along a course of a particular period of time, over any acclaimed hotspot region. Although previous studies have detected hotspots with well integrated series of approaches that involved identification of expanses exposed to climatic hazards (the vulnerability factor), yet these somehow overlooked the significance to assess magnitude of change in temporal variability of the associated hazard (the stability factor) in their risk assessment methodologies. For instance, Diffenbaugh et al. (2008) remained silent on the engagement

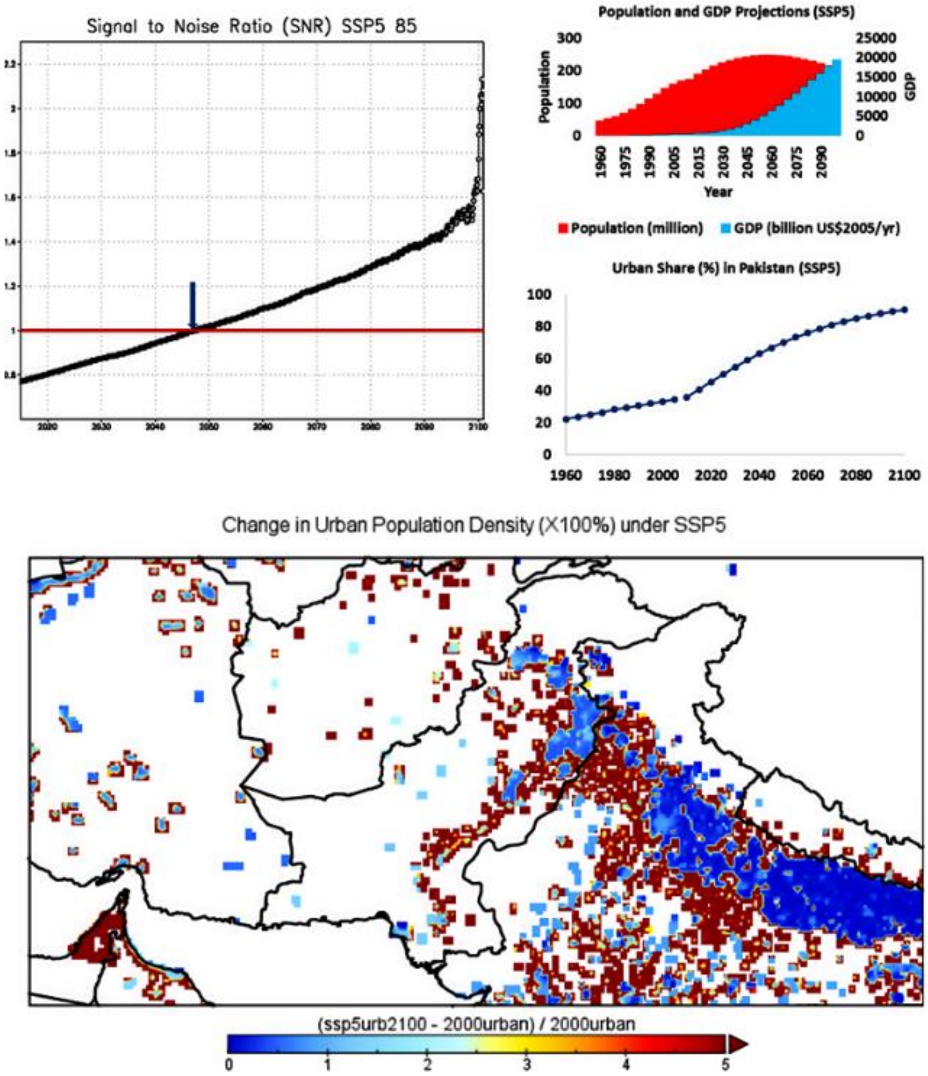

Figure 11. Representation of time of emergence (top-left panel) of climate change signal where red line (threshold one) intersects the SNR (blue pointer), assisted with socioeconomic factors (bottom and right panels) under SSP5 scenario over Pakistan (Data sources: https://www.wdc-climate.de/ui/cmip6?input=CMIP6.CMIP.MRI.MRI-ESM2-0; https://sedac.ciesin.columbia.edu/data/set/ssp-1-8th-urban-land-extent-projection-base-year-ssp-2000-2100; https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=10)

of stability factor and engaged the vulnerability factor only, when they attempted to identify hotspots from certain climatic variables, in their study. Byers et al. (2018) also remained silent on the engagement of the stability factor and addressed the vulnerability factor only, in order to identify climate change hotspots at different levels of global mean temperature change and socioeconomic pathways, in their study. Still, in another recent paper, the stability factor was missed out, and only the vulnerability factor–the SED–was engaged by Fan et al. (2021) for hotspot identification at global scale under different future warming levels in the 21st century. Consequently, to bridge this persistently appearing gap in the literature, we additionally analysed the DSD and changes in the Z-score of monthly temperature on a local scale, with the aim to pinpoint only those regional hotspots whose temporal variation in the mean monthly values converge on largest magnitude changes in the DM and the SED of the respective SSPs under study. Via this approach, we were able to identify areas with recursive appearance of mean approaching values, thereby declaring them as being stable over a potential hotspot region.

Our engagement of the SNR was targeted to measure magnitude of the temperature stability relative to its standard deviation over the course of the engaged time period. In our experience, small SNRs developed from effect of uncertainties derived from large standard deviations observed in our engaged data (results not shown for brevity). For our cases of the large SNRs, the magnitude of the signals were acclaimed large, relative to their noise (measured with the standard deviation) and hence the signals were found significant–that did not come merely out of a random variation (Holmes & Mergen, 2007). In context of the time of emergence of the climate change detection signal, we soughed to remain sure that the average value of the mean near surface air temperature was fairly away from zero standard deviation that one might not assume that that would have simply resulted from a random variation (i.e., noise) in the engaged data.

One of the most interesting take from this study is that the regions identified as hotspots through the engaged metrics rarely showed any progression in population expansion and density under all the studied SSP scenarios. This means that change in mean climate over those regions may not directly affect major population expanses and densities of those particular regions over the country. However, based on recursive appearance of the Himalayas as a potential hotspot over the region, indirect effects over downstream environments are evident due to their snow and ice composition over the associated high altitude regimes. This can further be considered as an emerging avenue for future research in current field of study.

The Himalayas are the ranges connected with a network of rivers commonly termed as upper Indus basin which have widely been claimed as under significant climate change threat especially when studied using the carbon dioxide emission scenarios, along the course of the 21st century (see e.g., Burhan et al., 2015). Not only the generic extents of Himalayas, but the Himalayas specific to Pakistan too, have been noted to remain increasingly exposed to climate change, evidence of which could be retrieved from statements of indigenous residing communities that perceive climate change as a looming threat to their assets in forms of water, crops, and rearing livestock over the region (Saeed et al., 2022). Rahman et al. (2022) endorsed existence of the threat by noticing that a continuous rise in temperature could lead to eradication of biodiversity, cconservation, and sustainability over the Pakistani extents of the Himalayas. A study by Khalid et al. (2022) further concluded that predicted future temperature increase might alter and devastate the delicate ecosystem of the Himalayas hosted by Pakistan. Another revelation by Gujree et al. (2022) attributed early onset of snow melting period to a noted increase in temperature trends and hence supported previously cited claims of vulnerability of the Himalayas towards drier climatic extremes in the future. Mushtaq et al. (2022) also confirmed temperature triggered melting and emphasized that outbursts in glacial lakes might significantly damage livelihood and infrastructure of existing and projected population expanses located downstream of the upper Indus basin. Hence, it is deemed that changes in the region's temperature attributes can have severe implications on delicate ecological balance and fragile environment of the Himalayas over Pakistan.

Although, as seen through our attributions to the results, the SSP5 predicted reasonably hopeful trends for human progress, yet the associated fossil-fuel driven development can significantly hamper progressions in resilience to mitigate climate change challenges, as is stated by Schleussner et al. (2021). Although Das et al. (2022) mentioned that increase in population exposure to impacts of natural hazards can contribute from climate change, population growth and their interaction, Ma et al. (2022) reasoned that mitigation could defer the time of emergence of the impact by more than a decade and, more essentially, lessen population exposures by up to 50% globally. It is hence established that only a comprehensive and sustainably rigorous mitigation pathway permits effective climate resilient development over the course of the 21st century.

A reasonable proclamation of population projection in Pakistan is provided in United Nations Department of Economic and Social Affairs' document on world population prospects 2019 (United Nations, Department of Economic and Social Affairs, Population Division, 2019) that ranks the country (with 338 million inhabitants in 2050) among the five most populous nations of the world by the end of the 21st century. Also, as projected by the modelled approach of Goldman Sachs global economics paper No.99 (https://www.pwc.com/gx/en/world-2050/assets/pwc-the-world-in-2050-full-report-feb-2017.pdf), fast population growth could boost the GDP in Pakistan by up to US$3.5 trillion in 2050. Thus, it is seen that even without limiting the allegedly perplexing population growth in the country, socioeconomic impacts associated with a projected emergence of a climate change signal can be avoided–at least–till the mid of the 21st century. Also, by virtue of this, not only severe economic shocks can be prevented but reversibly, a better economic condition can be expected in the future for the country.

CONCLUSION

Via this paper, we aimed to inform policymakers about possible spectrum of locality and time of emergence of a warming signal as an early warning and a decision support guidance for targeted and timely interventions to mitigate and to adapt to the emergent threat of climate change over Pakistan. We adopted a five tier approach by computing and analysing DM, SED, DSD, Z-Score, SNR, and associated them with socioeconomic factors under the SSP scenarios to address our objective.

Our results showed that the Himalayan region of Pakistan, was frequently seen to appear as a climate change hotspot with highest magnitude of the DM and the SED, and with highest stability in the DSD and the Z-Score metrics under all of the analysed scenarios. On the contrary, high volatility in recurrence of mean state of the DM (high variability) was repeatedly seen over the southern extents, which rendered those areas excluded as potential hotspots over the country. Our results further established that the quickest of the climate change signals was approached under the SSP5 scenario with time of emergence significantly before the year 2050, over the country.

Our analysis showed that under the influence of socioeconomic factors, climate change signal could reach its impact thresholds significantly earlier than expected, over the Pakistan region. If effects of urban expansion were to be controlled within the country, one could expect a delay in the emergence of a warming signal by a significant time under the SSP1 scenario. High sensitivity of the rising GDP projection to dampening of the warming signal and to stability of the population number was found under the SSP2 scenario, near to end of the 21st century. Under the SSP3 scenario, major contribution to early onset of the warming signal was believed to come from practicing traditional norms in agricultural and livestock amenities that could induce significant amount of greenhouse gases (especially methane) into the atmosphere of the rural areas of the country. Although urban development remained considerably large under the SSP4 scenario, yet it was found to have contributed neither to the economy nor to the arrival of the warming signal, significantly, any time before the seventh decade of the 21st century. While the SSP5 predicted reasonably hopeful trends for human progress, the associated fossil-fuel driven development was found to significantly hamper progressions in resilience to mitigate climate change challenges over the country. It is thus concluded that resolute control over socioeconomic factors and over associated greenhouse gas emissions can trigger economic growth, subside challenges related to population growth, and encourage widespread development in the future.

Limitations

Generally, for the impacts assessment associated with climate models, most studies use ensembles for as many members as possible. As a result, robustness in the results can be imparted via use of underlying ensembles in the model outputs. However, some instances of single model data engagement for impacts assessment in literature encouraged us to follow suit in the current study. For example, Haider and Ullah (2020, 2021) engaged single model output for use in evaluation of regional impacts assessment in their studies. Nevertheless, based on potential uncertainties that could arise from single model use, they advised to exercise caution in attempting to use such outputs and conditioned the use of such with pre-assessment of the engaged model output for use in impacts assessment studies. We therefore engaged that particular model out of the CMIP6 data repository whose output had been already evaluated over our region of interest (Burhan et al., 2022). In this regard, it is therefore advised to treat the results as projections only, especially when they are derived from single climate model data outputs.

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Ethics approval and consent to participate: Ethics committee approval and participant consent are not required since data used in the study is already in public domain and openly accessible.

Data sharing statement: Data supporting the findings and conclusions are available upon request from corresponding author.

REFERENCES

Ali, S., Kiani, R. S., Reboita, M. S., Dan, L., Eum, H. I., Cho, J., Dairaku, K., Khan, F., & Shreshta, M. L. (2021). Identifying hotspots cities vulnerable to climate change in Pakistan under CMIP5 climate projections. *International Journal of Climatology, 41*(1), 559-581. https://doi.org/10.1002/joc.6638

Bathiany, S., Dakos, V., Scheffer, M., & Lenton, T. M. (2018). Climate models predict increasing temperature variability in poor countries. *Science Advances, 4*(5), eaar5809. https://doi.org/10.1126/sciadv.aar5809

Burhan, A. K., Khan, A. H., Bukhari, S. A. A., & Riaz, K. (2021). Univariate statistics of the RCPs forced ET-SCI based extreme climate indices over Pakistan. *European Journal of Sustainable Development Research, 5*(3), em0166. https://doi.org/10.21601/ejosdr/11091

Burhan, A., Ali Bukhari, S. A., & Babar Cheema, S. (2019). Generation of cressman interpolated high-resolution gauge-based gridded observations (CIHGGO) for climatic variables using in-situ data over Pakistan. *European Journal of Scientific Exploration, 2*(4), 1-7.

Burhan, A., Waheed, I., Syed, A. A. B., Rasul, G., Shreshtha, A. B., & Shea, J. M. (2015). Generation of high-resolution gridded climate fields for the upper Indus River basin by downscaling CMIP5 outputs. *Journal of Earth Science & Climatic Change, 6*(2), 1. https://doi.org/10.4172/2157-7617.1000254

Burhan, A., Wazir, A., Riaz, K., Syed Ahsan, A., & Sajjad, H. (2022). Identification of climate change impacts and tradeoffs established under shared socioeconomic pathways of IPCC AR6 using a moderate resolution GCM viz. MRI-ESM2-0 of CMIP6 over Pakistan. *Shanlax International Journal of Economics, 10*(2), 25-46. https://doi.org/10.34293/economics.v10i2.4615

Byers, E., Gidden, M., Leclère, D., Balkovic, J., Burek, P., Ebi, K., Greve, P., Grey, D., Havlik, P., Hillers, A., Johnson, N., Kahil, T., Krey, V., Langan, S., Nakicenovic, N., Novak, R., Obersteiner, M., Pachauri, S., Palazzo, A., ..., & Riahi, K. (2018). Global exposure and vulnerability to multi-sector development and climate change hotspots. *Environmental Research Letters, 13*(5), 055012. https://doi.org/10.1088/1748-9326/aabf45

Center for International Earth Science Information Network - CIESIN - Columbia University. (2018). *Gridded Population of the World, Version 4.11 (GPWv4): Population Count, Revision 11*. NASA Socioeconomic Data and Applications Center (SEDAC). https://doi.org/10.7927/H4JW8BX5

Cuaresma, J. C. (2017). Income projections for climate change research: A framework based on human capital dynamics. *Global Environmental Change, 42*, 226-236. https://doi.org/10.1016/j.gloenvcha.2015.02.012

Das, J., Manikanta, V., & Umamahesh, N. V. (2022). Population exposure to compound extreme events in India under different emission and population scenarios. *Science of the Total Environment, 806*, 150424. https://doi.org/10.1016/j.scitotenv.2021.150424

Das, S., Das, J., & Umamahesh, N. V. (2021). Identification of future meteorological drought hotspots over Indian region: A study based on NEX-GDDP data. *International Journal of Climatology, 41*(12), 5644-5662. https://doi.org/10.1002/joc.7145

Dellink, R., Chateau, J., Lanzi, E., & Magné, B. (2017). Long-term economic growth projections in the Shared Socioeconomic Pathways. *Global Environmental Change, 42*, 200-214. https://doi.org/10.1016/j.gloenvcha.2015.06.004

Diffenbaugh, N. S., Giorgi, F., & Pal, J. S. (2008). Climate change hotspots in the United States. *Geophysical Research Letters, 35*(16), L16709. https://doi.org/10.1029/2008GL035075

Fan, X., Miao, C., Duan, Q., Shen, C., & Wu, Y. (2021). Future climate change hotspots under different 21st century warming scenarios. *Earth's Future, 9*(6), e2021EF002027. https://doi.org/10.1029/2021EF002027

Fatima, M., Arshad, S., Butt, I., & Arshad, S. (2021). Geospatial clustering and hotspot detection of COVID-19 incidence in 2020: A global analysis. *International Journal of Geospatial and Environmental Research, 8*(1), 4. https://doi.org/10.1007/s10708-021-10535-x

Feldmeyer, D., Birkmann, J., McMillan, J. M., Stringer, L., Leal Filho, W., Djalante, R., Pinho, P. F., & Liwenga, E. (2021). Global vulnerability hotspots: Differences and agreement between international indicator-based assessments. *Climatic Change, 169*(1), 1-22. https://doi.org/10.1007/s10584-021-03203-z

Gao, J., & B. C. O'Neill. (2021). Global one-eighth degree urban land extent projection and base year grids by SSP scenarios, 2000-2100. *NASA Socioeconomic Data and Applications Center*. https://doi.org/10.7927/nj0x-8y67

Ghimire, U., & Singh, G. (2021). Identification of climate change induced heat stress sensitive environments and prediction for diverse representative concentration pathways–A novel approach for tracking hotspots. *EuropePMC*. https://doi.org/10.21203/rs.3.rs-308962/v1

Giorgi, F. (2006). Climate change hot-spots. *Geophysical Research Letters, 33*(8), L08707. https://doi.org/10.1029/2006gl025734

Gujree, I., Ahmad, I., Zhang, F., & Arshad, A. (2022). Innovative trend analysis of high-altitude climatology of Kashmir valley, North-West Himalayas. *Atmosphere, 13*(5), 764. https://doi.org/10.3390/atmos13050764

Haider, S., & Ullah, K. (2020). Projected crop water requirement over agro-climatically diversified region of Pakistan. *Agricultural and Forest Meteorology, 281*, 107824. https://doi.org/10.1016/j.agrformet.2019.107824

Haider, S., & Ullah, K. (2021). Historical and projected shift in agro-climatic zones and associated variations of daily temperature and precipitation extremes using CORDEX-SA over Pakistan. *Asia-Pacific Journal of Atmospheric Sciences, 57*(4), 757-771. https://doi.org/10.1007/s13143-021-00231-8

Ignjacevic, P., Porrua, F. E., & Botzen, W. J. W. (2021). Time of emergence of economic impacts of climate change. *Environmental Research Letters, 16*, 074039. https://doi.org/10.1088/1748-9326/ac0d7a

Jiang, L., & O'Neill, B. C. (2017). Global urbanization projections for the shared socioeconomic pathways. *Global Environmental Change, 42*, 193-199. https://doi.org/10.1016/j.gloenvcha.2015.03.008

Kawai, H., Yukimoto, S., Koshiro, T., Oshima, N., Tanaka, T., Yoshimura, H., & Nagasawa, R. (2019). Significant improvement of cloud representation in the global climate model MRI-ESM2. *Geoscientific Model Development, 12*(7), 2875-2897. https://doi.org/10.5194/gmd-12-2875-2019

Khalid, N., Khan, A. M., Qureshi, R., Saqib, Z., Zahid, N., & Bussmann, R. W. (2022). Exploration of important environmental determinants of flowering phenology in the western Himalayan forests of Dhirkot, Azad Jammu and Kashmir, Pakistan. *Applied Ecology and Environmental Research, 20*(1), 301-337. https://doi.org/10.15666/aeer/2001_301337

Leimbach, M., Kriegler, E., Roming, N., & Schwanitz, J. (2017). Future growth patterns of world regions–A GDP scenario approach. *Global Environmental Change, 42*, 215-225. https://doi.org/10.1016/j.gloenvcha.2015.02.005

Lewis, S. C., King, A. D., Perkins-Kirkpatrick, S. E., & Mitchell, D. M. (2019). Regional hotspots of temperature extremes under 1.5°C and 2°C of global mean warming. *Weather and Climate Extremes, 26*, 100233. https://doi.org/10.1016/j.wace.2019.100233

Liu, X., Yu, L., Si, Y., Zhang, C., Lu, H., Yu, C., & Gong, P. (2018). Identifying patterns and hotspots of global land cover transitions using the ESA CCI land cover dataset. *Remote Sensing Letters, 9*(10), 972-981. https://doi.org/10.1080/2150704X.2018.1500070

Ma, F., Yuan, X., Wu, P., & Zeng, Z. (2022). A moderate mitigation can significantly delay the emergence of compound hot extremes. *Journal of Geophysical Research: Atmospheres, 127*(2), e2021JD035427. https://doi.org/10.1029/2021JD035427

Mushtaq, F., Mantoo, A. G., Tirkey, A. S., & Ahmad, S. Z. (2022). Hazards in the perspective of Himalayan terrain: A review. In S. Kanga, G. Meraj, M. Farooq, S. K. Singh, &M. S. Nathawat (Eds.), *Disaster management in the complex Himalayan terrains* (pp. 11-30). Springer. https://doi.org/10.1007/978-3-030-89308-8_2

O'Neill, B. C., Kriegler, E., Ebi, K. L., Kemp-Benedict, E., Riahi, K., Rothman, D. S., van Ruijven, B. J., van Vuuren, D. P., Birkmann, J., Kok, K., levy, M., & Solecki, W. (2017). The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Global Environmental Change, 42*, 169-180. https://doi.org/10.1016/j.gloenvcha.2015.01.004

Pacifici, M., Visconti, P., & Rondinini, C. (2018). A framework for the identification of hotspots of climate change risk for mammals. *Global Change Biology, 24*(4), 1626-1636. https://doi.org/10.1111/gcb.13942

Perera, T. A. N. T., Nayanajith, T. M. D., Jayasinghe, G. Y., & Premasiri, H. D. S. (2022). Identification of thermal hotspots through heat index determination and urban heat island mitigation using ENVImet numerical microclimate model. *Modeling Earth Systems and Environment, 8*(1), 209-226. https://doi.org/10.1007/s40808-021-01091-x

Piontek, F., Müller, C., Pugh, T. A., Clark, D. B., Deryng, D., Elliott, J., de Jesus Colon Gonzalez, F., Flörke, M., Folberth, C., Franssen, W., Frieler, K., Friend, A. D., Gosling, S. N., Hemming, D., Khabarov, N., Kim, H., Lomas, M. R., Masaki, Y., Mengel, M., & Schellnhuber, H. J. (2014). Multisectoral climate impact hotspots in a warming world. *PNAS, 111*(9), 3233-3238. https://doi.org/10.1073/pnas.1222471110

Rahman, A., Gurbuz, E., Chen, J., & Ekercin, S. (2022). Spatial diversity, patterns of forest vegetation, and sustainability analysis of the Murree Mountains of Western Himalayas. In M. Ozturk, V. Altay, & R. Efe (Eds.), *Biodiversity, conservation and sustainability in Asia* (pp. 267-286). Springer. https://doi.org/10.1007/978-3-030-73943-0_15

Rao, N., Mishra, A., Prakash, A., Singh, C., Qaisrani, A., Poonacha, P., Vincent, K., & Bedelian, C. (2019). A qualitative comparative analysis of women's agency and adaptive capacity in climate change hotspots in Asia and Africa. *Nature Climate Change, 9*(12), 964-971. https://doi.org/10.1038/s41558-019-0638-y

Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J. C., KC, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., & Tavoni, M. (2017). The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change, 42*, 153-168. https://doi.org/10.1016/j.gloenvcha.2016.05.009

Rousseeuw, P. J., & Hubert, M. (2018). Anomaly detection by robust statistics. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 8*(2), e1236. https://doi.org/10.1002/widm.1236

Saeed, U., Arshad, M., Hayat, S., Morelli, T. L., & Nawaz, M. A. (2022). Analysis of provisioning ecosystem services and perceptions of climate change for indigenous communities in the Western Himalayan Gurez Valley, Pakistan. *Ecosystem Services, 56*, 101453. https://doi.org/10.1016/j.ecoser.2022.101453

Samir, K. C., & Lutz, W. (2017). The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100. *Global Environmental Change, 42*, 181-192. https://doi.org/10.1016/j.gloenvcha.2014.06.004

Schleussner, C. F., Pfleiderer, P., Andrijevic, M., Vogel, M. M., Otto, F. E., & Seneviratne, S. I. (2021). Pathways of climate resilience over the 21st century. *Environmental Research Letters, 16*(5), 054058. https://doi.org/10.1088/1748-9326/abed79

Shrestha, U. B., & Shrestha, B. B. (2019). Climate change amplifies plant invasion hotspots in Nepal. *Diversity and Distributions, 25*(10), 1599-1612. https://doi.org/10.1111/ddi.12963

Swaminathan, R., Parker, R. J., Jones, C. G., Allan, R. P., Quaife, T., Kelley, D. I., de Mora, L., & Walton, J. (2022). The physical climate at global warming thresholds as seen in the UK earth system model. *Journal of Climate, 35*(1), 29-48. https://doi.org/10.1175/JCLI-D-21-0234.1

Trew, B. T., & Maclean, I. M. D. (2021). Vulnerability of global biodiversity hotspots to climate change. *Global Ecology and Biogeography, 30*(4), 768-783. https://doi.org/10.1111/geb.13272

United Nations, Department of Economic and Social Affairs, Population Division (2019). *World population prospects 2019*.

Varela, R., Rodríguez-Díaz, L., de Castro, M., & Gómez-Gesteira, M. (2022). Influence of canary upwelling system on coastal SST warming along the 21st century using CMIP6 GCMs. *Global and Planetary Change, 208*, 103692. https://doi.org/10.1016/j.gloplacha.2021.103692

Yukimoto, S., Kawai, H., Koshiro, T., Oshima, N., Yoshida, K., Urakawa, S., Tsujino, H., Deushi, M., Tanaka, T., Hosaka, M., Yabu, S., Yoshimura, H., Shindo, E., Mızuta, R., Obata, A., Adachi, Y., & Ishii, M. (2019). The Meteorological Research Institute earth system model version 2.0, MRI-ESM2. 0: Description and basic evaluation of the physical component. *Journal of the Meteorological Society of Japan. Ser. II, 97*(5), 931-965. https://doi.org/10.2151/jmsj.2019-051