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AMALGAMATING FUZZY COGNITIVE MAPPING (FCM) AND MACHINE LEARNING TO ANALYZE CLIMATIC VARIABILITY

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Abstract: *Predictive Mechanisms This hybrid approach may be central to vulnerability and resilience systems, as well as climate change analysis. Almost every scientific discipline deal with prediction modeling, yet at the same time the subject is often viewed as highly complex consisting of numerous factors that have contrasting nature. Therefore, the resultant outcome varies from model to model and prediction may appear to be highly uncertain at times. This novel approach to integrate prediction models through machine learning and Fuzzy Cognitive Mapping (FCM) may bring nearly accurate results with a hybrid approach in climate change analysis. In prediction mechanism, this hybrid approach could be pivotal not only for analyzing climate change but also for the vulnerability and resilience systems.*

Key words: Fuzzy Cognitive Mapping, Predication, Climate Variability, Spatial Simulation.

Introduction

Despite the advancement in the field of science and technology and the enhanced ability of mankind to achieve ecological dominance step by step, the integrated use of technology is still on the way. Therefore, all the stakeholders including academicians, policymakers, scientists, researchers, and politicians are required to work in public-private partnerships in creating a way out of predisposition to the negative effect of climate change. This paper aims to provide a platform for analyzing the heterogeneous concoction of qualitative, semi-quantitative, and quantitative measures aiming to produce an understanding of climate change and sustainability goals. It would probably ease to decrypt responses and perceptions of individuals on climate vulnerability and its induced threats in achieving sustainability solutions. Fuzzy Cognitive Mapping (FCM) is steadily developing as an alternate practice in hybrid modeling. The significant changes in the statistical distribution of long-term weather conditions are known as climate change. These climatic processes take over periods ranging from few decades to millions of years to unveil some pattern. It is caused by factorial variations in its processes such as; altering wind, precipitation, insolation, temperature, Outgoing Longwave Radiation (OLR) or albedo, air pressure, radiative forcing, etc., these dynamic factors are hybrid in nature meaning thereby it incorporates both natural as well as anthropogenic elements that significantly causes variation in recent pattern. Climate change and induced risk in its dependent sectors have been widely studied. There is an urgent need to study the humanistic aspect of climate-induced vulnerability besides the natural aspect of it. The multifaceted climate-human-environment space vulnerability assessments in the current generation are optimistically intruding at a micro level rather than just focused on an umbrella-cut approach. The first-generation modeling that was limited to the Risk hazard (RH) model started including both biophysical jeopardy aspects and its resultant potential for loss of lives and property to the exposed population (Singh and Singh 2021; O' Brien et al. 2004; Boddiger 2007; Giabbanelli et.al 2019; Singh 1998; Singh and Singh 2014) then after second-generation Pressure and Release (PAR) model brought political ecology and economy for highlighting a vulnerability in prevailing social inequities. But these two generations of models were little incapable to address issues relating to the system's aptitude to recover from distress. It was only recently realized the need for the amalgam of dynamic resilience, economy, society, and policy concerns in assessing vulnerability stimulated by global environmental change. This integration of dynamic machine learning and FCM analysis is based on active indicators and metrics that has been tested to link global system from macro (national) to micro (household) levels to assess vulnerability indices (VI) (Singh and Singh 2020; Eakin and Bojorquez 2008; Hahn et al. 2009; Gray et al., 2019).

Climate Variability in Western Himalayan District: Hamirpur a Case Study

The agrarian economy of Hamirpur district located in the South-West part of Himachal Pradesh is highly dependent on the topography and climatic conditions. It constitutes the central micro-region having a moderately hilly tract where elevation varies from 400 meters to 1100 meters, enclosed by the Shivalik range located between 76º 18′ to 76º 44' E longitudes and 31º 25′ to 31º 52′ N Latitude. Climatic change is already threatening the present and future existence and the significant impacts of these changes have already been observed through erratic weather phenomena, extinction of species, and unfavorable effects on human health and quality of life. With the consequential changes in the future biosphere, biodiversity, and natural resources the district will confront further more serious issues related to climate change. Many believe agriculture is the most susceptible sector to climate change and the changing climate directly affects the main inputs of agricultural production i.e., precipitation and temperature. The diverse aspects and altitudes demonstrate considerable variation in the distribution of temperature and rainfall in Hamirpur, whereas finding out the precise magnitude of climatic trends has become a daunting task due to inadequate long-term in-situ observations and complex topographic conditions of the district. The aggregated data from seven meteorological stations (on annual maximum, minimum, and average temperature and precipitation have been taken for five decades (1970–2020) to produce hybrid results through this geospatial machine learning approach.

DATABASE AND METHODOLOGY

Baseline Data Requirement

The mean monthly maximum and minimum temperature and precipitation together with annual minima and maxima from networks of metrological stations, for the period 1970–2020 have been compiled because these are fundamental instrumental statistics for the analysis of climate dynamics in the micro study area. Though it can be noticed that the meteorological systems recording network are noticeably less in number, therefore, for the current ten years/ decade Atmospheric Infrared Sounder (AIRS) satellite, TRMM, and PRECIS data have been considered to analyze the gap. Consequently, several checks have been made for missing values in the previous data set to distinguish the regular pattern of regional precipitation and temperature variation in the district. The annual and seasonal temperatures and precipitation progression for the winter-months (December-January-February), pre-monsoon (March-April-May), monsoon (June-July-August-September) and post-monsoon (October-November) months have been calibrated. These variations have been recorded for the entire district from all the three regions; the *Shivalik*-hill, the mid-hill and the high-hill region. To calibrate the past and current climatic trends two different data sources have been taken into consideration in machine learning.

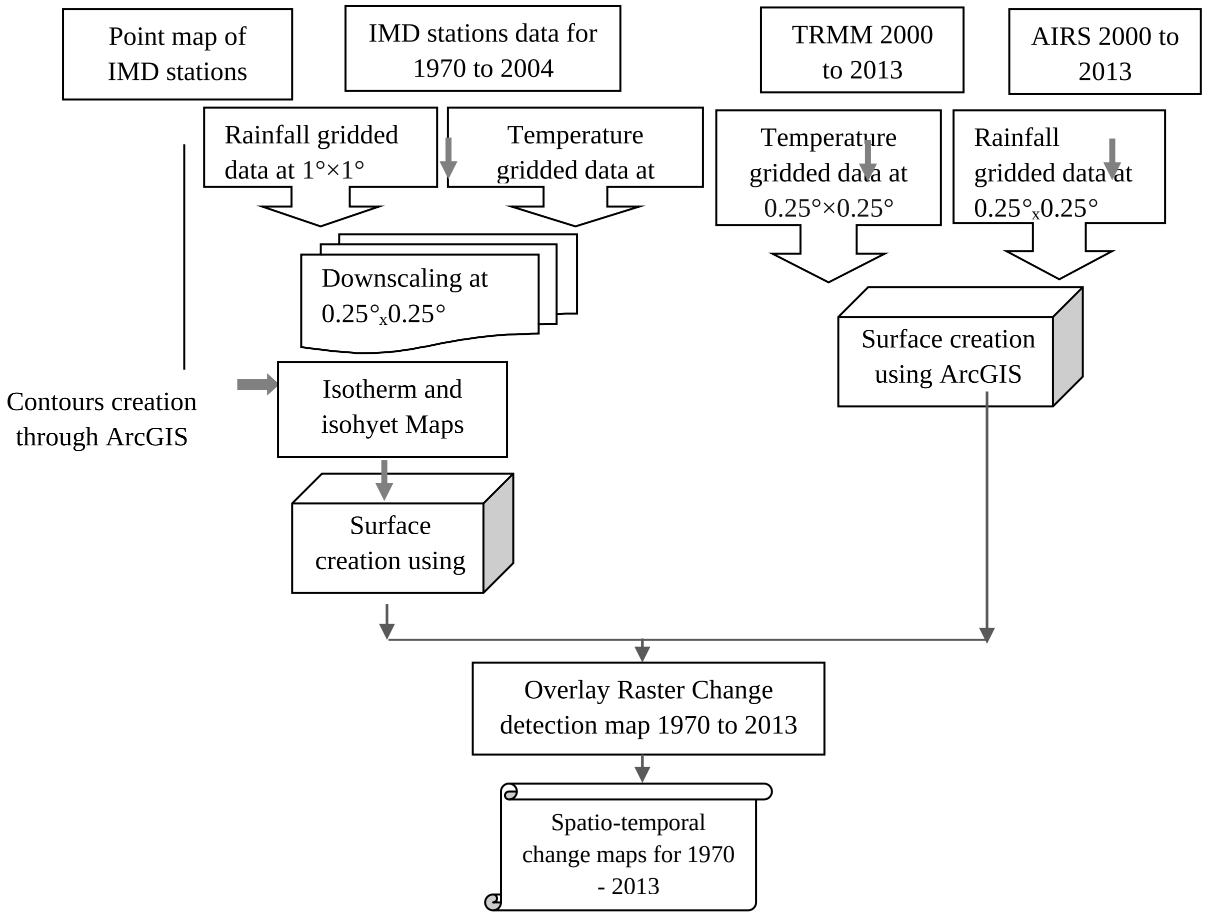
Machine Learning Integration of Satellite Data Mechanism

The AIRS data is having high spectral resolution spectrometer on board Aqua satellite with 2,378 bands in the thermal infrared (3.7 to 15.3 μm) and four bands in the visible (0.4 to 7.8 μm). These ranges have been precisely elected to allow atmospheric temperature and humidity in the troposphere with a precision of 0.5°C in 1-kilometer-thick layer and 80 per cent accuracy in the case of humidity in 2 km thick layers. The nadir is scanned in every two seconds afterward a prompt scan in ⅔rd of the second by appropriating standardization related data of four independent Cold Space Views (CSVs). These CSVs are Onboard namely; the blackbody calibrator, the spectral reference source, two views combining a photometric calibrator for the Visible Spectrum (VS) and Near Infra-Red (NIR) photometer where each scan line includes 90 IR paths for detailed information. The VS / NIR spatial resolution is around 2.31 km at nadir, provides 15 channel microwave temperature sounder at two independent operated modules of Advanced Microwave Sounding Units (AMSU). Although it requires a numerical model for its authentication and development over the time. In this study, a new gridded daily temperature and rainfall dataset at 1°×1° latitude and longitude resolution covering 40 monsoon seasons (1970–2020) has been downscaled on the PRECIS norm and amalgamated with Merged Satellite Gauge rainfall dataset (MSG) through machine learning has been explained in methodological flowchart (Fig. 1). The MSG data combines Tropical Rainfall Measuring Mission (TRMM) rainfall estimates of multi-satellite precipitation and gauge information from IMD through its product 2A-53and 3B-42 and AIRS. It has become suitable to use downscaled data for monthly average rain and temperature parameter respectively at $0.25_{x}0.25$ latitude and longitude with the help of Ground Radar (GR). This dataset may provide valuable intra-seasonal studies output for the model development and micro climate baseline research further.

Need for Fuzzy Cognitive Model (FCM)

Climate change studies are increasingly authenticating the local and indigenous impacts of climate variability and locally developed tools for knowledge generation, adaptation, rational management and exploitation of resources are being reviewed at global to local level's governments, inter-government and non-government organizations (Fields 2005; Fowler 2002; Fussel et al., 2006). Therefore, perceptions-based vulnerability index is required to entangle the vulnerability with evidence-based decision-making where each stakeholder of society can effectively participate to reduce the climatic stress. The construction of FCM is based on semi-quantification of people's perceptions where the perception regarding knowledge, information, values, and relationships are mapped to demonstrate cause-effect relations.

Figure 01: Methodological Framework for Spatio-temporal Climate Change



Fuzzy Cognitive Mapping Algorithms (FCMA)

In fuzzy cognitive mapping the set is used as a map, where μ: A → [varies between 0 and1] where A belong to any set called the domain (like climate change) and [0, 1] is the impacted or vulnerability range. That is to every element a ϵ A, μ allocates relationship value in the interval [0, 1]. In fuzzy algorithms it is often showed as relational function in two-dimensional graphs. While analysing fuzzy cognitive mapping both the climate variability (agent) A= (a_1, a_2…..a_n) and the vulnerable element μ: A → [0 and1], domains consider plotting in spider diagram or triangle, where it is a resultant of close inputs to close outputs. It can be assumed that there are n characteristics of changing climate like; c_1, c_2….. c_n, where n is predetermined, and let L_1, L_2, …,L_n be the descriptions related with the livelihood. The connection matrix is created and named as "A" of command c_n X L_n is acquired. Where c_1 will be the initial input element or condition vector of changing climate is kept in ON (1) condition and all other components in OFF (0) condition (Table 1a and 1b). The condition vector c_1 then been passed through the connection matrix A, then for the conversion of the resultant vector in connection matrix A with signal function the first two highest values have been put at ON (1) and other values to OFF (0) or 1 and 0 respectively to symbolize this progression. With this forward and backward progression, the resulted vector is multiplied with A^T and the maxima yields a new vector B_1. The resultant vector which is product of 1^{st} is been related with the connection matrix and that vector which gives the highest number of attributes to ON state is chosen as C_2 (Table 1a and 1b). Therefore, in this way the same procedure has been repeated till a fixed point/ a till the limit cycle is achieved. This progression is prepared to provide separate but appropriate significance to each vector. For each run of ON and OFF case several hidden patterns of various vectors have been observed that provided the guidelines to draw inferences through these hidden patterns that expose the causes of vulnerability. The following characteristics have been outlined in the table 1a and 1b are associated with the outcomes of changing climate as connections/points in the local space domain:

Table 1a: Changing Climate Attributes

c_1 - Heat waves	c_{12} - Land use/land cover change
c_2 - Cold spells	c_{13} - Fresh water availability
c_3 - Rainfall/precipitation variability	c_{14} - Shifts in farming system
c_4 - Warm nights	c_{15} - Displacement/ shift or Migration of species
c_5 - Warm days	c_{16} - Ecological disturbance
c_6 - Cool nights	c_{17} - Increment in infectious disease
c_7 - Cool days	c_{18} - Local pollutants Species extinction
c_8 - Diurnal temperature range	c_{19}- Local level disasters; landslides, floods, droughts
c_9 - Length of Growing Period	c_{20} - Loss of Biodiversity
c_{10} –Summer days	c_{21} - Threatened food supply
c_{11} - Frost days	

Table 1b: Changing Means of support Attributes

	Minor Variables (in Percent)	Abbreviation Minor Variables	Major Component
L_1-	Households having agricultural land	HAL	Natural Capital Category (NCC)
L_2-	Households having cultivated area under irrigation	HCAI	
L_3-	Households that utilize a natural water source	HNW	
L_4-	Households grow multiple crops in a season	HMCS	
L_5-	Household having surplus production at present	HSP_Present	
L_6-	Households sell the product out of total production	HSoPro_Tpro	
L_7-	Households dependent on family farm for food	DH_FF	
L_8-	Households dependent on livestock for milk and other	DHL_M	
L_9-	Average agricultural livelihood diversification index	AAgri_LD	
L_{10}-	Households where head of household has not attended school	H_Edu	Social Capital Category (SCC)
L_{11}-	Households not having basic education facility	NB_Edu	
L_{12}-	Average time spend in having medical facility	NB_Med	
L_{13}-	Households having pucca house types	Puuca_H	
L_{14}-	Households who are dependent on well/ponds for drinking water	Pwell	Physical Capital Category (PCC)
L_{15}-	Households dependent on forests for NTFPs (honey, medicine etc.)	H_NTFPs	
L_{16}-	Household facing plantation impact on agricultural land availability	Plan_LA	
L_{17}-	Percent of households dependent solely on the family farm for food	D_FF	
L_{18}-	Average number of months households struggle to find food	Av_Sfood	
L_{19}-	Working population to the total population	%WP_TP	Financial Capital Category (FCC)
L_{20}-	Households dependent solely on agriculture as a source of income	D_AI	

Based on the above 41 attributes of climate change and livelihood vulnerability the relational matrix ‘A’ is computed and shown in the form of the table to display the fuzzy value ranging between 0 and 1, where the input vector c_1 = (1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0). That is the attribute Heat wave is kept in ON condition and the rest of the nodes in OFF condition.

c_1 = (1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0)

c_1A = (0.5 0.6 0.8 0.5 0.9 0.3 0.4 0.1 0.30.5 0.6 0.7 0.9 0.1 0.8 0.7 0.2 0.6 0.8 0.5) and so on till A^T times.

A=

	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12	L13	L14	L15	L16	L17	L18	L19	L20
c1	0.5	0.6	0.8	0.5	0.9	0.3	0.4	0.1	0.3	0.5	0.6	0.7	0.9	0.1	0.8	0.7	0.2	0.6	0.8	0.5
c2	0.7	0.2	0.4	0.5	0.7	0.5	0.3	0.2	0.1	0	0.6	0.3	0.4	0.2	0.3	0.9	0.6	0.4	0.1	0.7
c3	0	0.8	0.4	0.6	1	0.3	0.5	0.5	0	0.8	0.1	1	0.6	0.8	0.5	0.6	0.	1	0.9	0.9
c4	0.6	0.7	0.9	0.6	0.8	0.7	0.2	0.6	0.5	0.5	0.9	0.5	0.9	0.4	0.1	0.8	0.7	0.2	0.6	0.8
c5	0.6	0.3	0.4	0.6	0.3	0.9	0.6	0.4	0.5	0.9	0.3	0.4	0.1	0.5	0.5	0.3	0.9	0.6	0.4	0.3
c6	0.1	1	0.6	0.1	0.5	0.6	0.	1	0.5	0.7	0.5	0.3	0.2	0.5	0.5	0.5	0.6	0.	1	0.5
c7	0.5	0.5	0.5	0.5	0.8	0.7	0.2	0.6	0.6	1	0.3	0.5	0.5	0.5	0.5	0.8	0.7	0.2	0.6	0.8

These computed integrated climate change induced paths can be combined and display through spider graph (will be discussed in results).

Climate Change Induced Vulnerability Categories (CCVC)

To calculate composite index of Climate Change Induced Vulnerability Category (CCVC) the FCM set have been used where the value ranges between -1 to +1, where -1 denotes least vulnerable, 0 signifies vulnerable and 1 designates highly vulnerable, the calculation has been done through the following steps as;

Step 1: (reiterate for all variables) $VPr_t = \frac{TPr_{ob} - TPr_{min}}{TPr_{max} - TPr_{min}}$

Where, VPr_t is productivity of a particular crop has increased with temperature variable, that has been computed based on 30 years data, TPr_{ob} is observed productivity in that temperature range, TPr_{min} and TPr_{max} are minimum and maximum productivity at that temperature range. In other words, it is (observed - minimum) / (maximum - minimum)

Step 2: (reiterate for all components) if for the temperature component;

$$T_I = \Sigma\left(\frac{V_{Ob} + V_{LU} + V_{OLR} + V_{Albedo} + \dots\dots V_n +}{N*}\right)$$

where, T_I is temperature Index component, the variable; V_{ob} is observed changes, V_{LU} is Land use changes, V_{Albedo} is albedo changes with spatio-temporal temperature trend. Where, the temperature component is having 6 variables and the respective values of $V_{ob\dots}$ …..…V_n.

Step 3: would follow Climate Change Vulnerability Indices (CCVI) with summation of its all components, the variable values are multiplied by the assign weightages (where, V_t=temperature, V_r= rainfall, V_{LU} = Land use) that are divided by their respective total weights as: CCVC = $\Sigma\left(\frac{W_1 Vt + W_2 V_{LU} + W_3 V_r}{W_1 + W_2 + W_3}\right)$ Where *CCVC* = $\Sigma\left(\frac{4\times0.511 + 3\times0.532 + 4\times0.614}{4+3+4}\right)$ = 0.932

Finally the $CCVC_s$ of the district is calculated for initially three primary sectors dependent community i.e. farmers, fisherman, and agricultural laborers in the district where all the information have been clubbed together with their respective Vulnerability Categories

($VC_{s)}$ to show negative climate impact for all the respective Natural Capital Categories (NCCs), Physical Capital Categories (PCCs), Human Capital Categories (HCCs), Social Capital Indices (SCCs) and Financial Capital Indices (FCCs) across region (based on computation from Table 1b).

Results and Discussion

The variation in mean maximum and minimum temperatures over the period of 1970 to 2020 has observed over Hamirpur where a net escalation in temperature ranges from 0.86˚C ± 0.04˚C (Table 2). The five color categories of seasonal temperature change ranging from less than 0.0˚C to more than 0.75˚C of Hamirpur district with a general rise in mean seasonal temperature in its blocks from 1970 to 2020 explains that the temperature variability has increased over time.

Table 02: List of 12 Core Climate Indices and the Rate of Change Over 1970 to 2020

ID	Indicator	Explanation	Measured Unit	Change
FD0	Frost days	Annual count when daily minimum temperature is <0 ˚C	days	-12.3(-10....5.6)
SD25	Summer days	Annual count when Txmax (daily maximum)>25˚C	Days	6.78 (2.3…27.6)
LGP	Length of Growing Period	Annual (1st Jan to 31 st Dec in Northern Hemisphere) count between first span of at least 6 days with > 5˚C	Days	9.84 (0.4….21.6)
TXmax	Maximum Temperature of Tmax	Monthly maximum value of daily maximum temp	˚C	1.2 (-1.0…1.5)
TXmin	Maximum Temperature Tmin	Monthly maximum value of daily minimum temp	˚C	0.86 (-1.3…3.1)
TYmax	Minimum Temperature Tmax	Monthly minimum value of daily maximum temp	˚C	1.57(-0.25…3.9)
TYmin	Minimum Temperature Tmin	Monthly minimum value of daily minimum temp	˚C	0.7(-0.4…2.1)
DTR	Diurnal temperature range	Monthly mean difference between TX and TN	˚C	-0.65(-6.5…0.9)
TX10p	Cool nights	Percentage of days when TXmax<10th percentile	Days	6.3(2.5…9.5)
TX10p	Cool days	Percentage of days when Txmin <10th percentile	Days	-5.2(-4…-12.2)
TY90p	Warm nights	Percentage of days when TYmax>90th percentile	Days	4.8(3.7…13.6)
TY90p	Warm days	Percentage of days when TYmin>90th percentile	Days	-0.8(-2.0…0.9)

Source: Machine learning results from PRECIS and TRMM

The overall spatio-temporal study of temperature and precipitation has been done to compute and analyse the past, present and future simulated scenario (i.e., 2020s). Most of the meteorological stations indicated warming and erratic trend in temporal mean surface temperature and precipitation respectively (Collins and Cooper, 2001; Kumar et al., 2006). The Regional Climate Model (RCM) prediction shows that the temperature of the study area has already rose from 0.5 to 1.5°C in eastern and western region respectively between 1970 to 2020 and the monsoon rainfall has decreased by 5 to 12 per cent of the annual rainfall, whereas the total annual rainfall will increase by 7 per cent by 2020. The maximum and minimum temperature represents inconsistent signal of climatic change, and more precisely the maximum temperature exhibits higher magnitude for warming whereas the minimum temperature displays much larger variability such as no change, positive or negative change. The sudden increment in maximum temperature and variable average precipitation has been observed during the last and current decade.

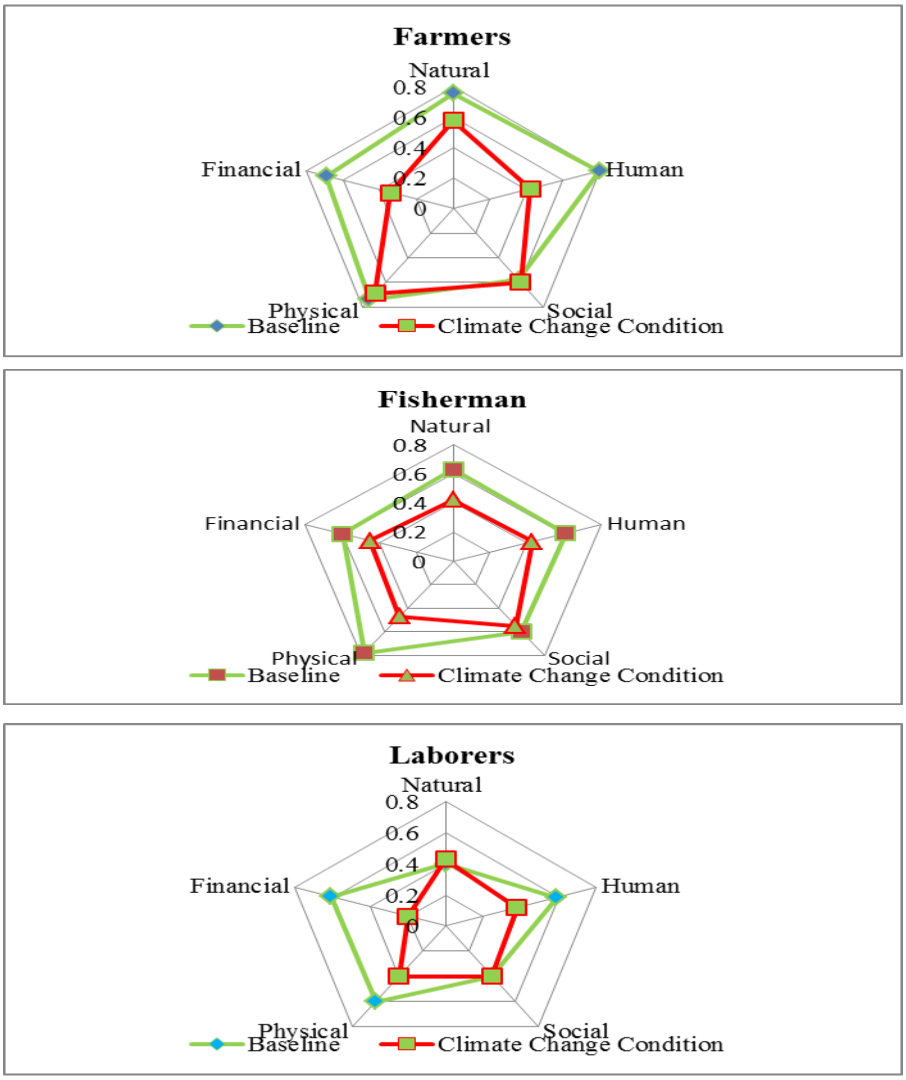
The Scenario Analysis

As soon as the FCMs are done the possible climate change/variability scenario has been developed to analyse the strength and the relationships of various primary sector focus groups where the variables/attributes of changing climate and livelihood vulnerability and their relationships have already been entered into the relational matrix 'A.' The two scenarios have been drawn; one is the baseline or business as usual and other is the climate change scenario based on existing anticipations from changing climate. This are probable increase of minimum summer temperature, changing degree days, shifting or intrusion of new species etc., due to above climatic perturbations.

Baseline Scenario

It is all dependent on normal precipitation along with the district standard where there are few events of damage of crop, livestock, and livelihood. It would have been a potential and accessible system that permits the local population including farmers, fisherman and Agricultural laborer to access resources without any intricacy. In appendage to it there are very sporadic chances of livestock death, crop failure and non-remittance of recognizable contribution to household in the form of cash and food (Fig. 2).

Figure 02: Asset Pentagon for Livelihood Groups in Baseline (Present) and under Climate Change Scenario (1970-2020)

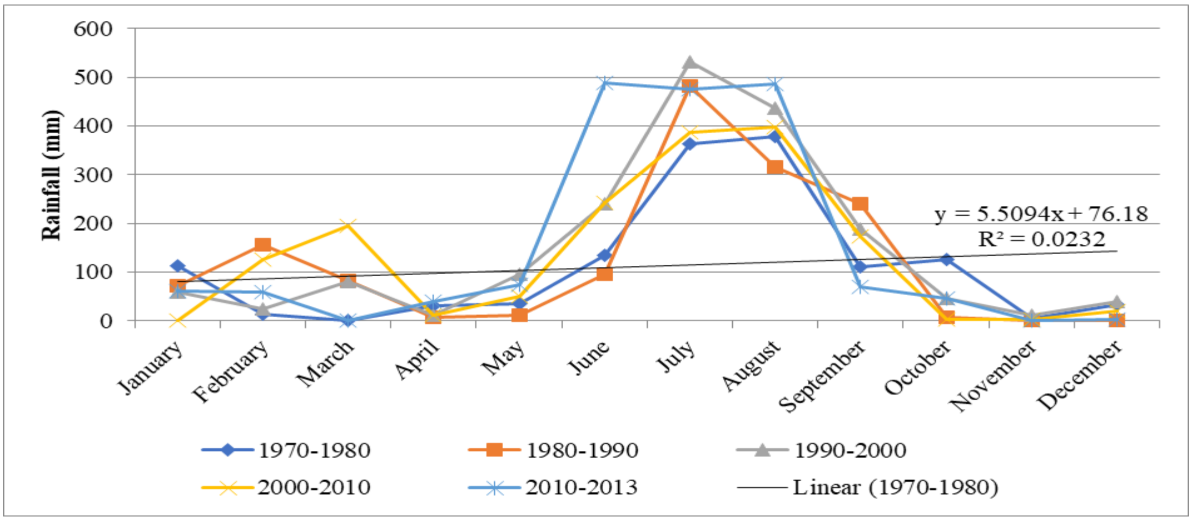


Source: Calculated from Primary Survey, 2014-20.

Climate Change Scenario

There are 21 selected indicators on which the observed change has been analysed for the entire region. The total number of frost days, summer days, Length of Growing Period (LGP), maximum and minimum temperature, diurnal temperature range, cool and warm nights and days trend results exhibit the patterned geographical distribution is reflecting significant decreases in cold nights and increase in warm night meaning thereby the general warming trend is predominant in the entire region. The Daily Temperature Range (DTR) is reflecting consistent decreasing trend of -0.65°C. The annual count of summer days trends when maximum temperature is no less than 25˚C (standard deviation 25) have increased by 6.78 days and frost days have decreased by 12.3 days over period through big data and machine learning. The Length of Growing Period (LGP is extended by 9.84 days. This smaller warming of day time versus night time extremes is due to the amount of annual precipitation that decreases drastically as compared to mean 1458.7 for 2000-2020 showing significant change with latitudinal distribution of temperatures and rainfall. Rainfall is insufficient for cropping, and there is a high degree of uncertainty as to when it will rain next. There is no harvest from upland fields, many more livestock will die, less inflow of remittances are universal and becoming more common climate change scenario.

Figure 03: Changing Rainfall Trend over 43 Years for Prediction Modeling



Conclusion and Suggestions

The basic aim of this paper was to propose a new hybrid model integration to improve the precision of a real-time estimation. The method of integrating geospatial data and machine learning is an upcoming field that would overpower the difficulties faced in such multifaceted and multi-conflicting environments. The analyzed approach has been constructed so that it can divulge inter-relationships between the climatic inputs of a given dataset and deliver a concealed variable through this conjunction approach for precise prediction modeling.

By using the FCM model one can say that the priority should be given to interconnectedness of climate vulnerability. This study has been done to show impartial results through hybrid geospatial system analysis, where the blame is not put on climate change without logical investigation. The findings of the study are based on local people's response to climate change, where the researcher has tried to establish a micro-level sustainable framework for varied. The impact was also observed for the loss of productive agricultural land that has forced many youths and active labor force to go to other districts in search of employment. This has created labor crisis in their communities and have subjected to influence women labor force in order to rescue and rehabilitate their families and livelihood assets. Thus, the climatic and non-climatic stressors will continue to increase the degradation and pressurize natural resource base that will further exacerbate the society's vulnerability. It can only be minimized by integration of public, private and government initiatives.

References

1. Boddiger, D., 2007. Boosting biofuel crops could threaten food security. *Lancet*, vol. 370: 923–924.
2. Collins, M., Tett, S.F.B. and Cooper, C., (2001). The internal climate variability of HadCM3, a version of the Hadley Centre coupled model without flux adjustments. *Climate Dynamics*, vol. 17: 61–81.
3. Eakin, H., Bojorquez-Tapia, L.A., (2008). Insights into the composition of household vulnerability from multicriteria decision analysis. *Global Environmental Change,* vol. 18: 112–127.
4. Fields, S., (2005). Why Africa's climate change burden is greater. *Environmental Health Perspectives* vol. 113: A534–A537.
5. Fowler, F.J., (2002). Survey Research Methods, 3rd ed. Sage Publications, Inc., Thousand Oaks, CA.
6. Fussel, H.M., Klein, R.J.T., (2006). Climate change vulnerability assessments: an evolution of conceptual thinking. *Climatic Change*, vol. 75: 301–329.
7. Giabbanelli, P., Fattoruso, M., Norman, M.L., (2019). Cofluences: Simulating the spread of social influences via a hybrid agent-based/fuzzy cognitive maps architecture, Proceedings of the 2019 ACM SIGSIM Conference on Principles of Advanced Discrete Simulation, pp. 71-82.
8. Gray, S., Sterling, E.J., et al., (2019). Assessing (Social-Ecological) Systems Thinking by Evaluating Cognitive Maps. Sustainability 11(20) 5753. https://www.mdpi.com/2071-1050/11/20/5753
9. Hahn, M.B., Riederer, A.M. and Stanley, O. F., (2009). The livelihood vulnerability index: A pragmatic approach to assessing risks from climate variability and change—A case study in Mozambique. *Global Environmental Change*, vol. 19: 74–88.
10. India Meteorological Department (2014). Climatological Tables for (1931 - 2013), Indian Meteorological Department, Pune, India
11. Kumar R. K., et al., (2006). High-resolution climate change scenarios for India for the 21st century, *Current Science,* vol. 90(3):334-344
12. O'Brien, K., Leichenko, R., Kelkar, U., Venema, H., Aandahl, G., Tompkins, H., Javed, A.,Bhadwal, S., Barg, S., Nygaard, L., West, J., 2004. Mapping vulnerability to multiple stressors: climate change and globalization in India. Global Environ-mental Change 14, 303–313.
13. Singh, R. B. and Singh, S., (2014). Human induced biome and livelihood security, in Livelihood security of Northwestern Himalaya: Case studies from changing socio-economic environments in Himachal Pradesh, Singh RB, Hietala R (eds.) Springer publication. pp. 53-66.
14. Singh, R. B., (1998). Land use/ cover changes, extreme events and eco-hydrological responses in the Himalayan region, *Hydrological Processes*, vol.12, pp. 2043-2055.
15. Singh, S. and Singh, R. B. (2021). Simulating Climate Change and Livelihood Security. Springer Singapore.