FIELDS of VIEW

E-QLT

SIMULATING PATHWAYS TOWARDS HOUSEHOLD RESILIENCE

CLIMATE VULNERABILITY ASSESSMENT FRAMEWORK

THE 22ND EDITION OF INDIA CONFERENCE AT HARVARD
POLICY HACKATHON 2025

FEBRUARY 2025

CLIMATE VULNERABILITY ASSESSMENT USING HOUSEHOLD SIMULATION - E-QLT

India is experiencing increasing damages because of climate change, including extreme weather events like drought, flood, and cyclone[i]. This trend is projected to continue, with developing nations being particularly vulnerable to the effects of climate change[ii,iii] . In India, climate vulnerability has been assessed at the state[iv] and district[v,vi] levels. While these macro-level indexes enable the identification of vulnerable regions, they have limited application in developing strategies for building resilience at the household level. Additionally, current climate vulnerability assessment frameworks require strengthening in the following ways:

- Greater exploration of the interconnections between exposure, sensitivity, and adaptive capacity, which all influence one another[vii]
- Greater consideration of the dynamic nature of vulnerability[viii]

Given that different types of households have varying sensitivities to vulnerabilities[ix], we propose a simulation-based approach, as a complement to existing approaches, that addresses these gaps and assesses climate vulnerability at the household level.

1. PROPOSED FRAMEWORK

We have developed E-QLT, a simulation that models how households manage their monthly expenses, and the effect of their expenditure preferences on various aspects, such as health, education, and living standards, that contribute to the household's vulnerability. The simulation is based on the Sustainable Livelihood Approach (SLA)[x], which considers five kinds of capital and integrates the impact of shocks, household vulnerability, resilience mechanisms, and the trade-offs inherent to the household well-being. For our simulation, we have specifically modelled the physical, financial, and human capital of the households.

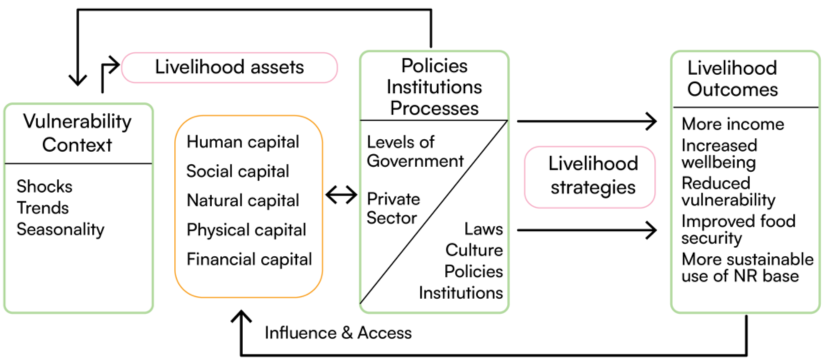

Figure 1. SLA Framework

Our framework has the following components:

a. Household level system dynamics simulation (E-QLT)
b. Calculation of the Social Protection Score (SPS)
c. Utilisation of data and exploratory scenarios that drive the model

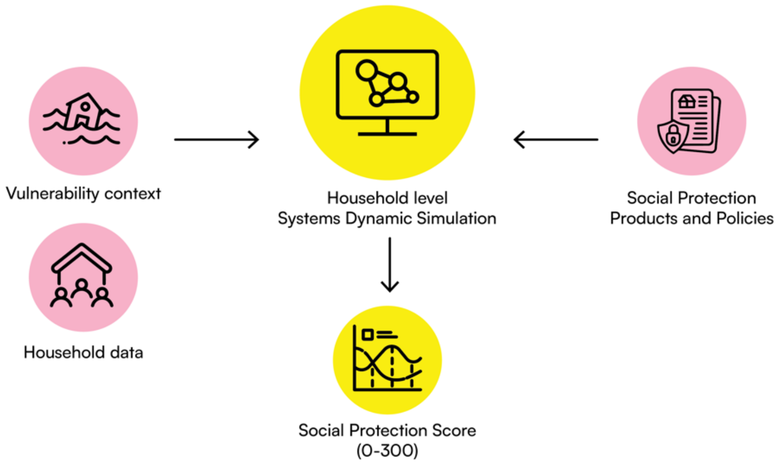

Figure 2. E-QLT methodology

A. HOUSEHOLD LEVEL SYSTEM DYNAMICS SIMULATION

At the core of our method is the system dynamics simulation, E-QLT. In addition to modelling the income and expenditure preferences of households, E-QLT allows for the exploration of different coping mechanisms that the households can adopt in situations where the income is not enough to meet the expenditure. These mechanisms, presented below, have potentially different wellbeing outcomes for the household:

- Utilisation of savings
- Borrowing from formal/informal lenders
- Cutting back on expenditures
- Liquidating physical assets (e.g. house, motor vehicle, etc.)

Utilisation of savings diminishes the household's ability to cope with future expense-related uncertainty and shocks.

Borrowing may incur additional expenditure and debt burden on the household, based on the type of debt (formal/informal), with debt repayment depending on the available income.

Cutting back on expenditures forces the household to allocate resources for different expenditure heads based on the static or dynamic priorities of the household.

Liquidating physical assets decreases the overall financial capital of the household, in turn leading to potential secondary effects. E.g., selling of a house owned by the family would result in an increase in monthly expenditure in the form of rent.

E-QLT models the diverse scenarios that a household may face, e.g., impact on health, income shock, and market fluctuation, and measures the effect of different social protection measures on building resilience - currently, the model considers cash transfers, debt, in-kind support (nutrition), subsidies, and insurance.

This model uses the interconnected sub-models of finance, health, and education to determine a household's vulnerability.

The finance sub-model looks at a household's expenditure priorities in terms of its allocation of income and savings. The health and education sub-models use this understanding of income and savings allocation priorities to compute the impact of scenarios on a household's health and educational outcomes, respectively.

The health sub-model looks at the impact of disease burden[xi] on life expectancy and nutritional deficit with respect to different food groups (cereals, pulses, fat, vegetables, etc.) and calories.

The education sub-model looks at the gap towards educational attainment if the household is not able to allot enough money towards school fees.

B. CALCULATION OF THE SOCIAL PROTECTION SCORE (SPS)

We have developed a metric called the Social Protection Score (SPS) that contextualises the results from the simulation by quantifying vulnerability. The SPS for each household is computed using its simulation run output along 3 dimensions framed in line with the Multi-dimension Poverty Index[xii]: Finance (time taken to repay debt), Health (nutritional deficit and disability-adjusted life years), and Education (age specific years of schooling). The score ranges from 0-300 points, where 0 points denotes a household at critical vulnerability, and 300 points denotes a household at least vulnerability, with each dimension currently having an equal contribution of 100 points.

$$SPS = SPS_{Finance} + SPS_{Education} + SPS_{Health}$$

The contribution of each dimension to the overall SPS is computed as a value between 0 and 1, then multiplied by 100 for ease of comprehension.

Finance

SPS Finance examines whether the household has debt and how long it takes to repay the debt. SPS Finance is calculated for each month using the following formula:

$$SPS_{Finance} = \frac{(Debt\ Duration\ (Standard) - (Debt\ Duration\ (Standard) - Debt\ Duration\ (Current))}{Debt\ duration\ (Current)}$$

We have currently set the Debt Duration (Standard) as 20 years based on the assumption that duration beyond 20 years may indicate intergenerational debt. A value of zero or lower indicates more than 20 years to repay the debt, while a value of 100 implies no debt on the household. The Debt Duration (Current) is calculated as the slope of the debt curve in the model.

Education

SPS education examines the educational attainment of the children in a household and is calculated for each month using the following formula:

$$SPS_{Education} = \frac{Educational\ Attainment(Standard) - (Educational\ Attainment(Expected) - Educational\ Attainment\ (Current))}{Educational\ attainment(Standard)}$$

We have currently set the Educational Attainment (Standard) at 12 years of schooling and considered it to be age-specific, i.e., the child should have completed 12 years of schooling by 18 years of age. A value of zero indicates that the child has attained no education, while a value of 100 indicates that there has been no gap in the child's education. Education Attainment (Expected) is defined as the education level that the child should have attained based on their age. In case the household is not able to spend on education, the Educational Attainment (Current) gets affected, and leads to reduction of SPS Education.

Health

Two aspects of health are covered in the current version of the model: nutritional and physiological.

For the nutritional aspect, we have currently set the BMI of each adult in the household at 20, which is in the normal range, while for children, we have used age-specific height and weight are used to compute expected BMI. We have assumed that a deficit of 500 calories per day for a week would lead to a weight loss of 1 kg. The calorie deficit for each person is then used to calculate SPS Health (Nutritional) for each month using the following formula:

$$SPS_{Health-N} = \frac{BMI(Standard) - (BMI(Standard) - BMI(Current))}{BMI(Standard)}$$

For the physiological aspect, we have currently set the Life Expectancy (LE -Standard) of each member of the household at birth at 82 years. This LE (Standard) is used to compute the LE (Expected) of household members at each age. LE (Current) of a person suffering from sickness is computed by using the disability weights corresponding to the disease to deduct from the life expectancy of the person for the duration of the disease. SPS Health (Physiological) is calculated for each month using the following formula:

$$SPS_{Health-P} = \frac{LE\ (Standard) - (LE(Standard) - LE(Current))}{LE(Standard)}$$

Both components of health are weighed equally in the present version of the model. SPS Health is computed using the following formula:

$$SPS_{Health} = \frac{1}{2}SPS_{Health-P} + \frac{1}{2}SPS_{Health-N}$$

Classification of administrative units

Alongside calculating the SPS for each individual households, we calculated the weighted average of the SPS for all the households in a district. The weighted average is used for classification of administrative units. The SPS for each individual household can be aggregated into the SPS of administrative units at increasingly local levels.

C. UTILISATION OF DATA AND EXPLORATORY SCENARIOS

Data and exploratory scenarios form the starting conditions for the simulation runs. The data we consider at the household level includes demography, income and expenditure patterns, and eligibility for and access to various resilience mechanisms. This data can be primary, secondary, or synthetic based on certain typology, depending on the intended purpose of the analysis. In this study, we demonstrate how E-QLT can analyse household-level vulnerability across regions using household data available at the national and regional levels. Table 1 shows the kinds of datasets that can be used to run the simulation, with the datasets used in this study indicated in bold.

Table 1. Potential Datasets (Highlighted datasets used as part of this study)

Required Variables	Description	National data source	Regional data source (additional datasets)
Household data (Sensitivity)	Human capital-Household individual member age, gender, education attainment Financial capital-Income and expenditure, household priorities for different budget heads, savings, debts Physical capital-Assets	NSS Employment Unemployment Survey NSS Household Consumer Expenditure Survey NSS Debt and Investment Survey **Indian Human Development Survey (IHDS I and II)** Centre for Monitoring Indian economy Pvt Ltd (CMIE) Global socio economic datasets[xiii]	Survey data by CSOs, or creation of typology based on their expertise.
Data on climate change impacts (Exposure)	Data on risks and impact data for particular climate change hazards like cyclone, drought, heatwave, flood etc.	Desinventar – Disaster Information Management System for Sendai Framework **EM-DAT** Sigma GFDRR	**Rapid Damage and Needs Assessment Reports** **Memorandum of losses and damages published by State Disaster Management Authority**
Schemes and policies (Adaptive capacity)	Social protection schemes like pension, PDS, maternity, old age pension, income generation schemes like MGNREGA	Myscheme.gov.in **Indian Human Development Survey (IHDS I and II)**	Interventions by CSOs

Just as with the type of data, the exploratory scenarios to be used are dependent on the intended purpose of the analysis. The scenarios can be determined by involving stakeholders working towards addressing vulnerability and those being impacted by vulnerability[xiv]. In this study, we showcase selected scenarios to demonstrate the potential of this tool to assess climate vulnerabilities in Odisha and Kerala.

Due to climate change, Odisha is likely to face more frequent and intense cyclone[xv,xvi], while Kerala is likely to face frequent and intense floods and landslide[xvii]. We explore the resilience of households to these hazards using historic damage caused by past events as potential future scenarios. We convert the asset losses in historical disaster to income losses at the household level using the methodology proposed by Bangalore et. al, 2016[xviii](Table 2). For the scenarios simulated in this study, we consider 8.42% and 1.44% to be the income losses for selected districts in Odisha and Kerala, respectively. We assume a recovery period of 3 years in case of cyclone and 1 year each in cases of flood and landslide.

Table 2: Computed income losses based on asset losses of historical disasters

State	Disasters Name	Affected Population (millions)	Asset Losses (INR Crore)	Income Losses (computed)
Odisha	Super Cyclone 1999	18	12319.56	8.42%
	Cyclone Phalin 2013	13	4028.42	4.81%
	Cyclone Fai 2019	16.5	24176	5.75%
Kerala	Landslide and Flood 2014	-	25832	1.73%
	Landslide and Flood 2014	5.4	26720	1.44%
	Meppadi Landslide 2024	-	614.62	1.50%

We explore the following scenarios as given in the table 3.

Table 3: Scenarios description and data for the scenarios

Scenarios	Description	Data Source
Scenario 1 (S1)	Baseline	IHDS II (2012) data on Odisha and Kerala household profile
Scenario 2 (S2)	Income shock because of selected climate change disaster	EM-DAT, RDNA and Memorandum
Scenario 3 (S3)	Social protection benefits (old age pension, widows' pension, maternity scheme, disability scheme, Annapurna, income generation programmes except MGNREGA, help from NGOs)	IHDS II (2012) data on social protection benefits of Odisha and Kerala household profiles
Scenario 4 (S4)	MGNREGA benefits	IHDS II (2012) data on MGNREGA incomes of Odisha and Kerala household profiles
Scenario 5 (S5)	Social protection benefits and MGNREGA benefits	IHDS II (2012) data on MGNREGA and cash benefits for Odisha and Kerala
Scenario 6 (S6)	Social protection benefits and MGNREGA benefits during a climate induced income shock	All of the above
Scenario 7 (S7)	Adaptive social protection	Hypothetical

2. VULNERABILITY PROFILES

We have collated the district-level weighted average SPS for baseline and other scenarios for both Odisha and Kerala to show how vulnerability changes across districts. Thereby helping policymakers identify regions of higher vulnerability.

In Kerala, the districts of Alappuzha and Pathanamthitta emerge as the most vulnerable and the district of Thiruvananthapuram as the least vulnerable in Scenario 1 (Figure 3, yellow being the most vulnerable and green the least). Scenario 2 shows that flood and landslide related income shocks have the largest effect on the Pathanamthitta district, followed by the district of Thrissur, which was less vulnerable than Alappuzha in Scenario 1 (Figure 4).

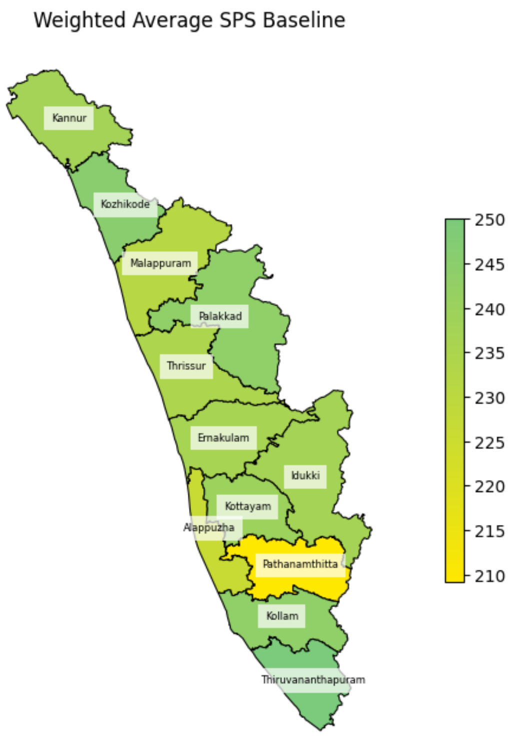

Figure 3. Baseline SPS (Scenario 1) for Kerala Districts

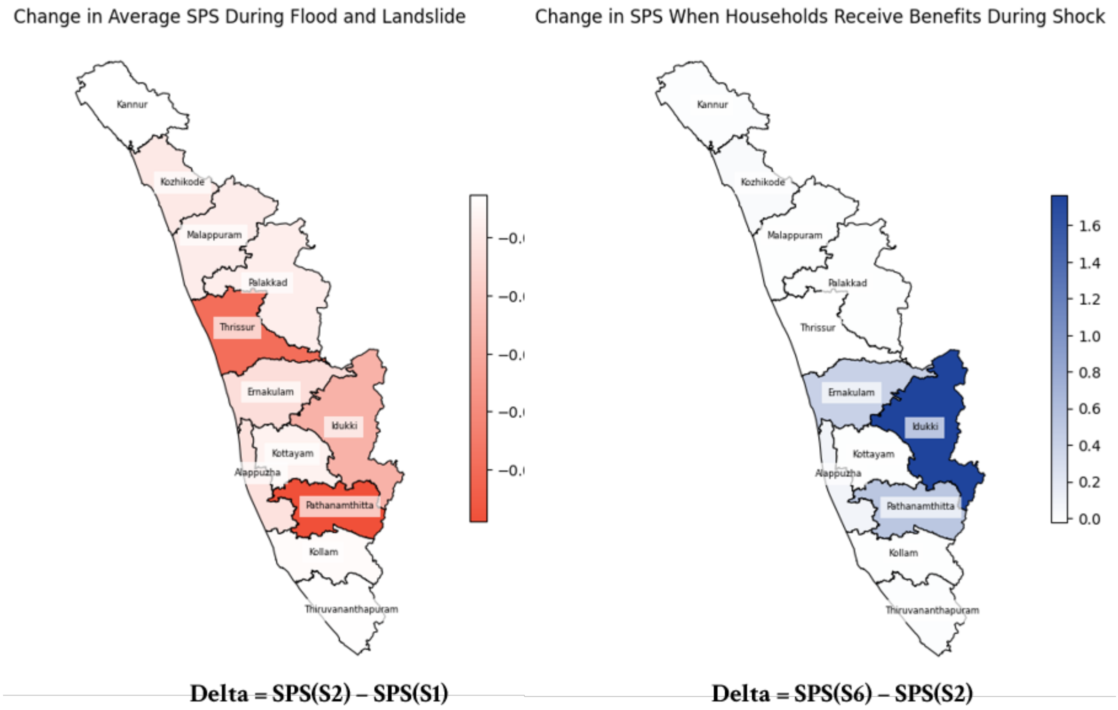

Figure 4. Change in SPS for Scenario 2 and 6

This finding highlights the advantage of E-QLT in assessing district-level vulnerability to shocks, challenging the common assumption that the most vulnerable regions are always the most affected.

Scenario 4 shows that Idukki district gets an average of INR 250 from the MGNREGA scheme per household (Figure 5). A corresponding change is reflected in the SPS for this district, indicating that the SPS increased because of extra income from MGNREGA. Households in Idukki, Alappuzha, Thrissur, and Palakkad have an average monthly surplus of INR 200 to 250 as a result of social protection benefits (Figure 5). This surplus is evident in Scenario 6 (Figure 4), especially when compared to Scenario 2, where the change in SPS was negative due to income shocks from floods and landslides.

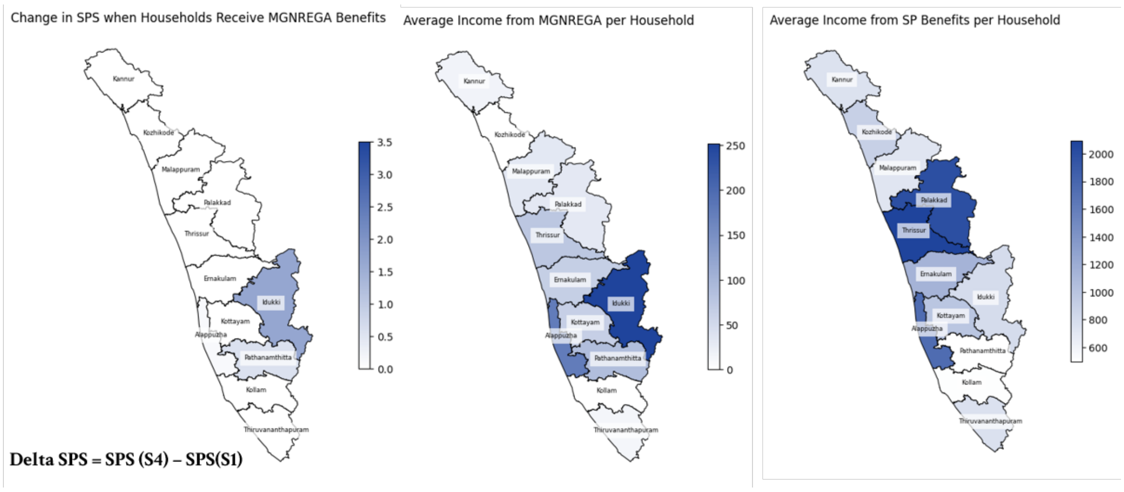

Figure 5. Average income as per IHDS II surveyed data at district-level in Kerala per household for Scenario 4

In Odisha, the district of Nabarangpura is the most vulnerable. All coastal districts except Malkangiri are relatively more vulnerable (SPS ranges from 200 to 220) than other districts (Figure 6, Scenario 1). The districts of Jagatshinghapura, Kendrapara, Jajapur, Angul, and Ganjam experience the most vulnerability when it comes to cyclone-related income shocks, followed by the already most vulnerable district of Nabarangpura.

This scenario reiterates the utility of the E-QLT simulation in showing that these 4 districts, which did not have baseline vulnerability, experience a reduction in their SPS due to cyclone-related impact (Figure 6, Scenario 2).

The combination of social protection benefits and income from the MGNREGA scheme increases the SPS for 7 districts (Scenario 5). This is reflected in the near lack of change in their SPS during cyclone, which otherwise would have resulted in a negative SPS (Scenario 2). Thus, our simulation shows how households are less vulnerable to cyclone-related impacts when they have social protection benefits.

These findings can help further investigate the causal relationship between vulnerability and SPS Finance, Health, and Education, and its effect on SPS is being affected.

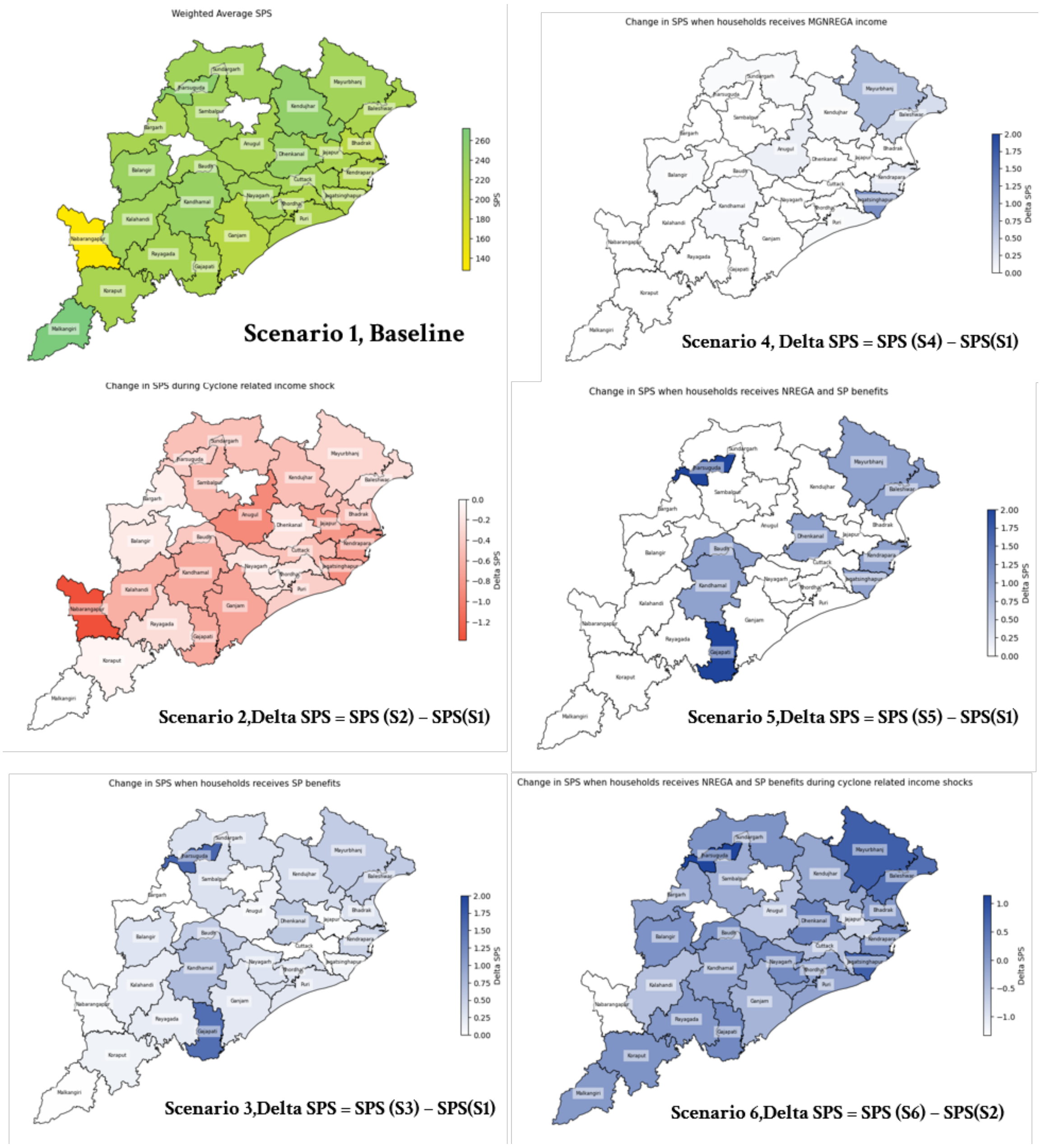

Figure 6. Baseline SPS and delta SPS of Odisha districts for each scenario (empty white districts do not have data in IHDSII)

The granularity of our model enables policymakers to specify down from a macro-level analysis to the household level, allowing them to identify and analyse the profiles of households with low and high SPS. Using the case of four households (HH) from Odisha, we demonstrate how E-QLT allows for the exploration of changing vulnerabilities across the different scenarios established earlier (Table 4). HH1 has access to MGNREGA income and cash transfer benefits; HH2 has access to cash benefits; while HH3 and HH4 no other source of income.

Table 4: Household composition and details

Variables	HH1	HH2	HH3	HH4
Weights as per IHDS	3640	2497	15043	2809
SPS baseline (S1)	182	189	153	141
Main income source	Cultivation	Petty shop	Non-agricultural wage labour	Salaried
Total monthly income	9084	9583	2400	32000
Total monthly expenditure	7852	7168	3035	28076
Total monthly savings (before benefits of SP measures)	1232	2415	-635	3924
Monthly income from MGNREGA	1300	0	0	0
Monthly income from cash benefits	200	400	0	0
Number of adults	4	4	2	2
Number of children	2	3	2	1
Number of teens	0	0	0	1
Number of elderly	1	1	0	0
Number of persons	6	8	4	4
Number of household Assets	10	17	11	27
Debt	0	Yes	Yes	Yes

Figure 7, 8, 9 and 10 shows how the SPSs of these 4 households changes in different scenarios.

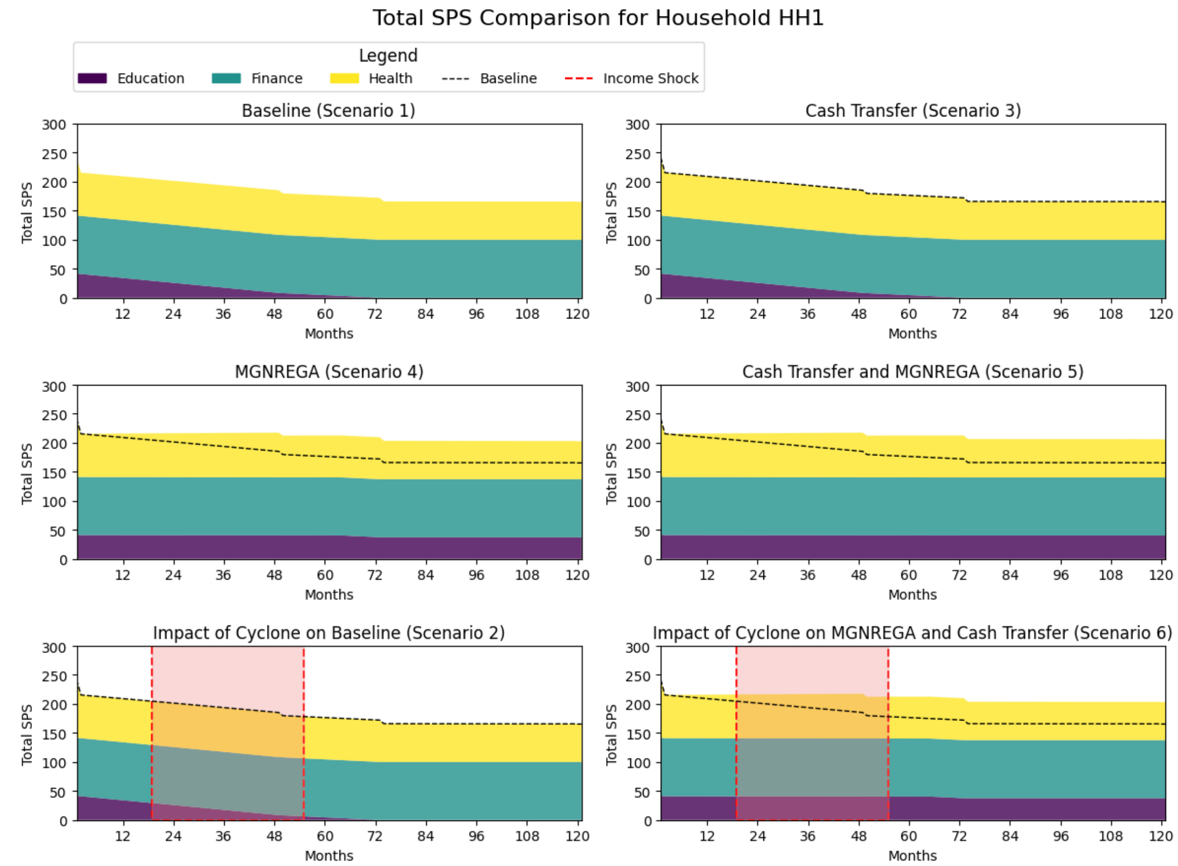

Figure 7. Temporal comparison of SPS for HH1

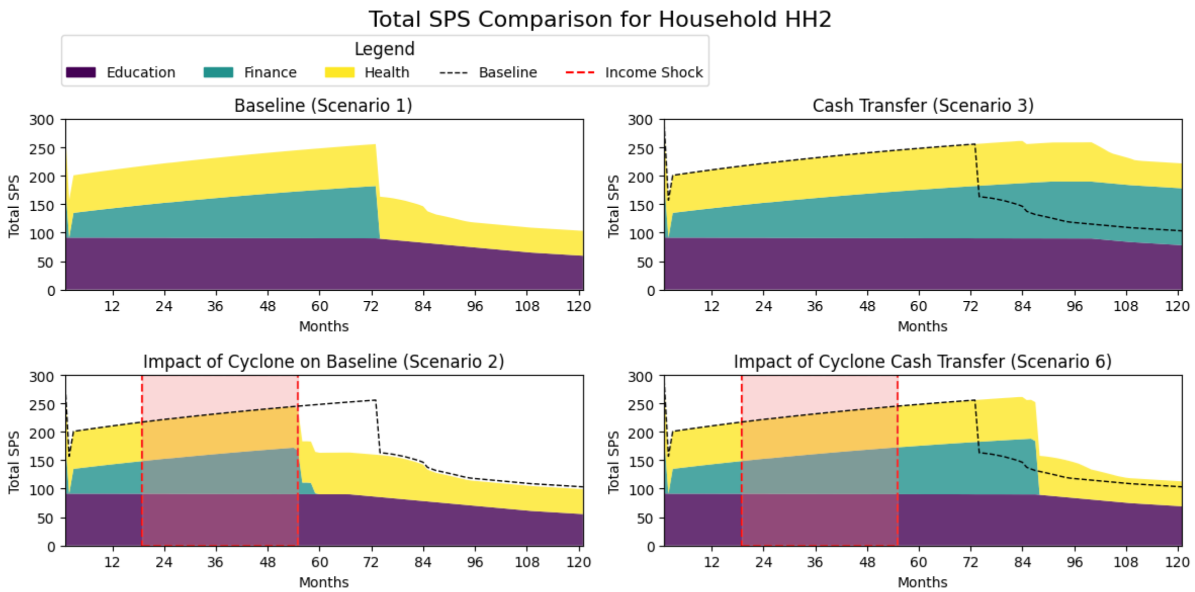

Figure 8. Temporal comparison of SPS for HH2

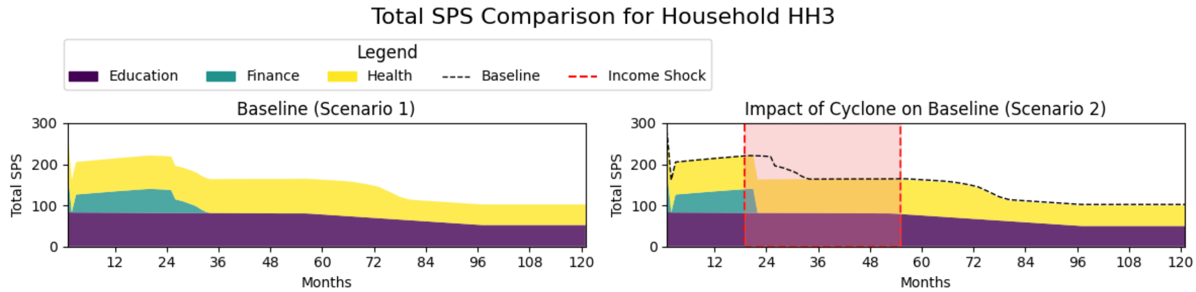

Figure 9. Temporal comparison of SPS for HH3

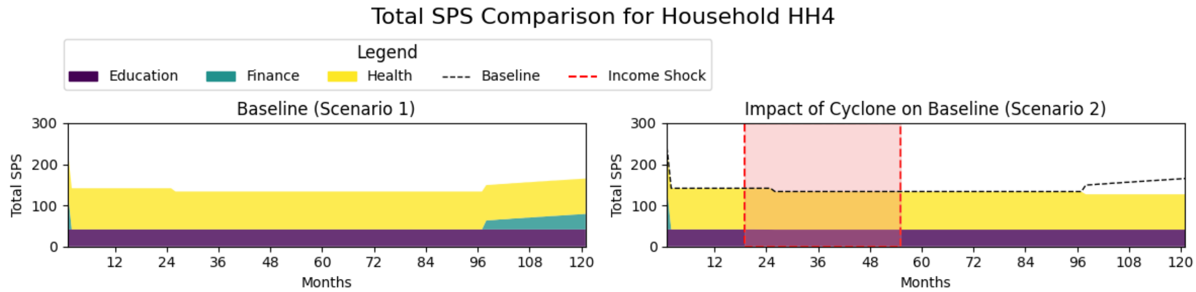

Figure 10. Temporal comparison of SPS for HH4

HH1 and HH2 both have access to cash transfer schemes (INR 200 and INR 400, respectively), but the impact on both households is different: cash transfer has a negligible effect on the SPS of HH1, but causes a substantial increase in the SPS of HH2.

HH1 sees an increase in SPS due to monthly MGNREGA transfers of INR 1200. Further, HH1 experiences limited impact of cyclone shock, while HH2 is significantly impacted. The shock leads to erosion of savings during the shock period, leading to a reduced SPS with respect to the baseline.

HH3 and HH4 currently have no SP measures, and both see a reduction in their SPSs due to the cyclone shock. The results of these analyses and impacts can be used by policymakers for more nuanced engagement with vulnerability and better tailoring of protection measures.

3. POLICY RECOMMENDATION

So far, we have looked at how households are vulnerable due to their socio-economic conditions, how their vulnerability increases due to a climatic shock, and how different social protection measures can help reduce vulnerability in both situations.

In this section, we explore Scenario 7 to test how Adaptive Social Protection (ASP) can help address climate shocks[xix]. ASP aims to increase both horizontal (cover more vulnerable people) and vertical (increase existing benefits) coverage of social protection measures.

In this study, we test a hypothetical ASP which is activated during shock. While the actual amount of benefit provided through ASP should be decided at the administrative level, for exploratory purpose, we have considered a cash transfer under ASP of INR 500 to each household in Odisha, in addition to the support provided by existing social protection measures. To test the ASP, we have chosen households with a baseline SPS of less than 200. 711 households from Odisha fall into this category (IHDS II). The ASP benefit is applied both to households that don't have any existing benefits and those that do. At the district level, ASP leads to average SPS increase of 0.05 for Odisha (Figure 11). ASP helps in the reduction the vulnerability as seen during the shocks of -0.047 for the Odisha.

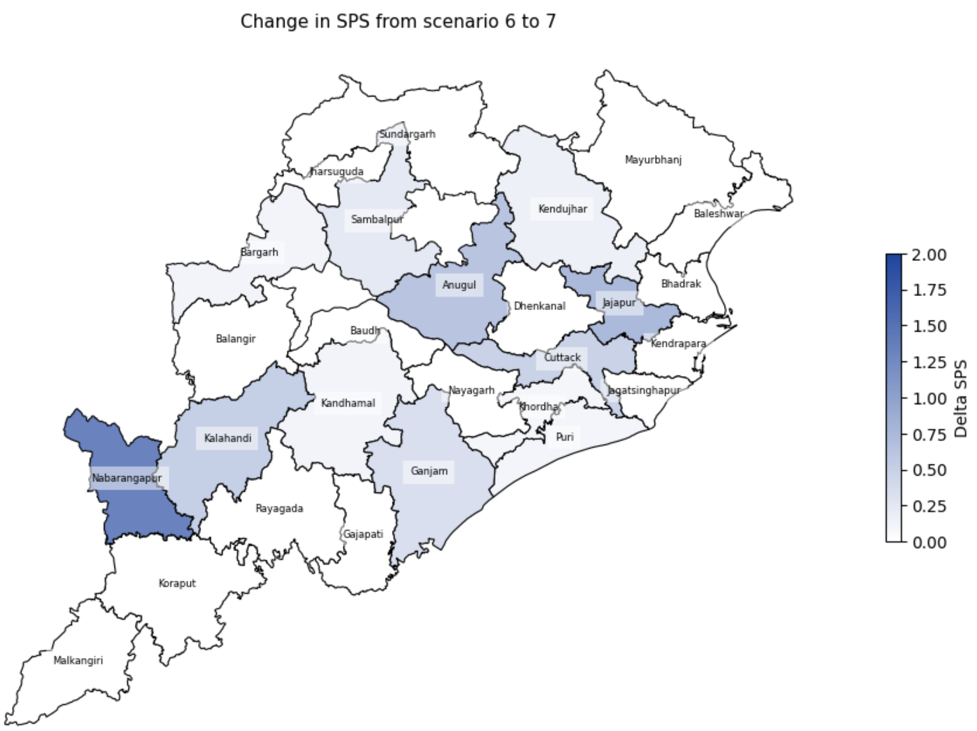

Figure 11. Odisha district level change in average SPS due to adaptive social protection

We next explore the role of ASP at the household level using data from the four households presented earlier (Figure 12 to 15). HH2 and HH3 see a significant increase in their SPS because of ASP; HH4 sees a marginal increase; and HH1 shows no changes. The increase in SPS can be understood as the additional income from ASP helping households repay debt, contributing towards education, and preventing further reduction of health status.

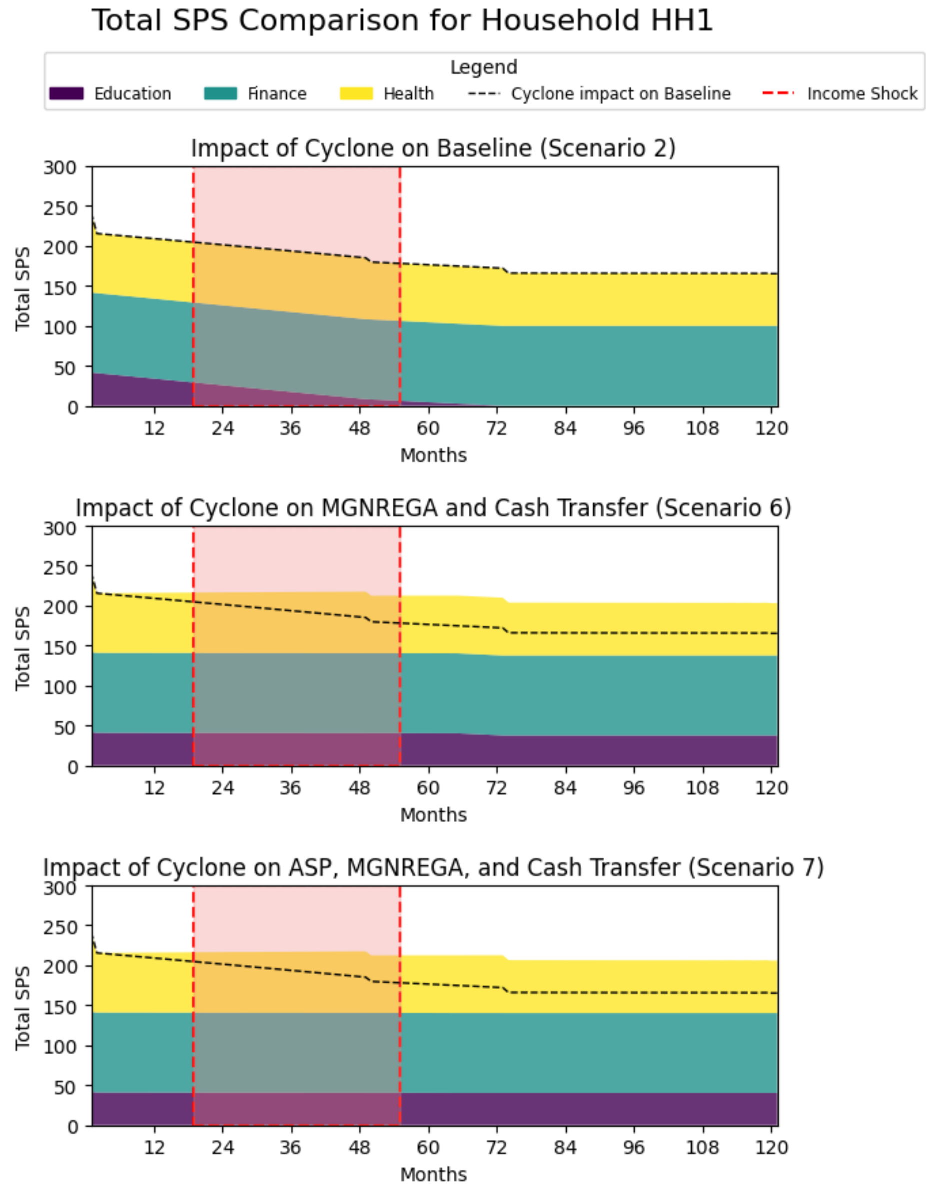

Figure 12. Change in SPS for HH1 due to Adaptive social protection

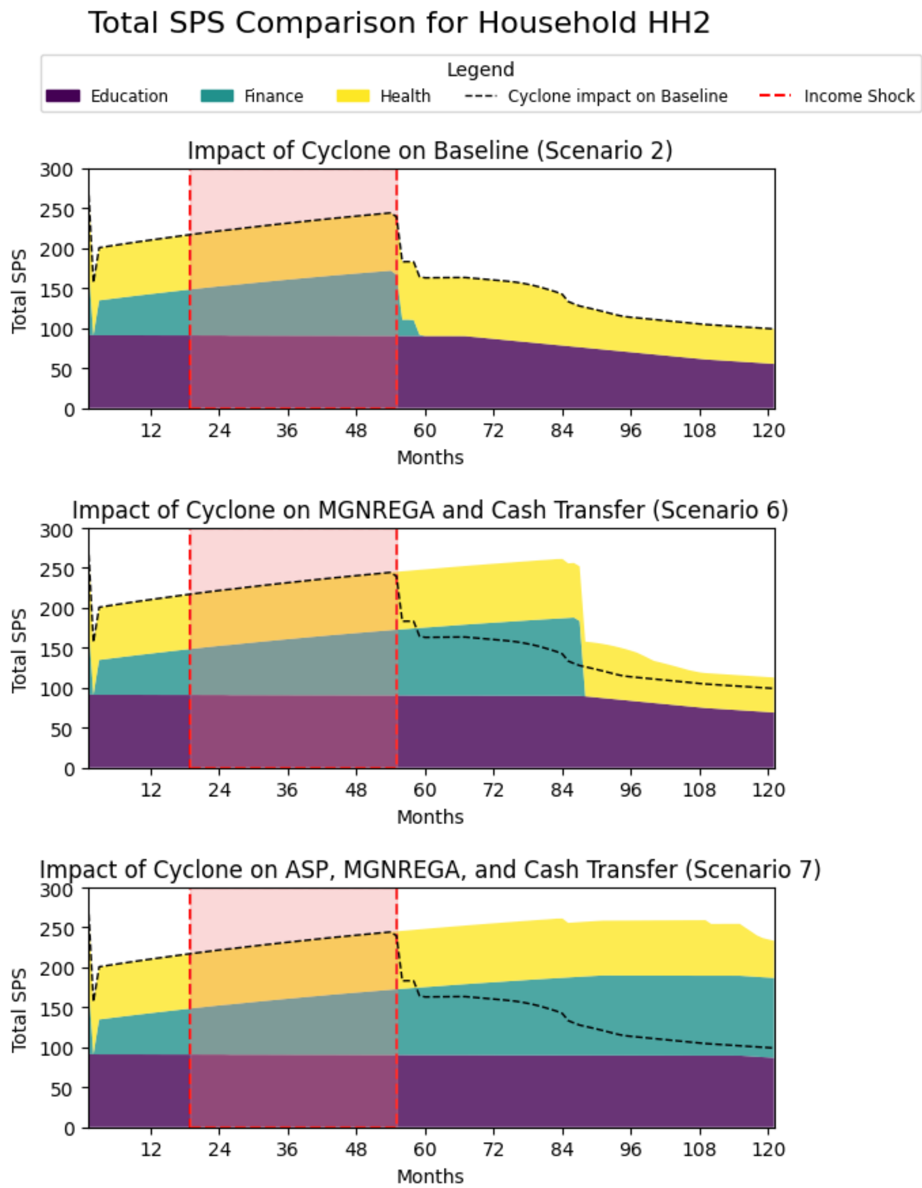

Figure 13. Change in SPS for HH2 due to Adaptive social protection

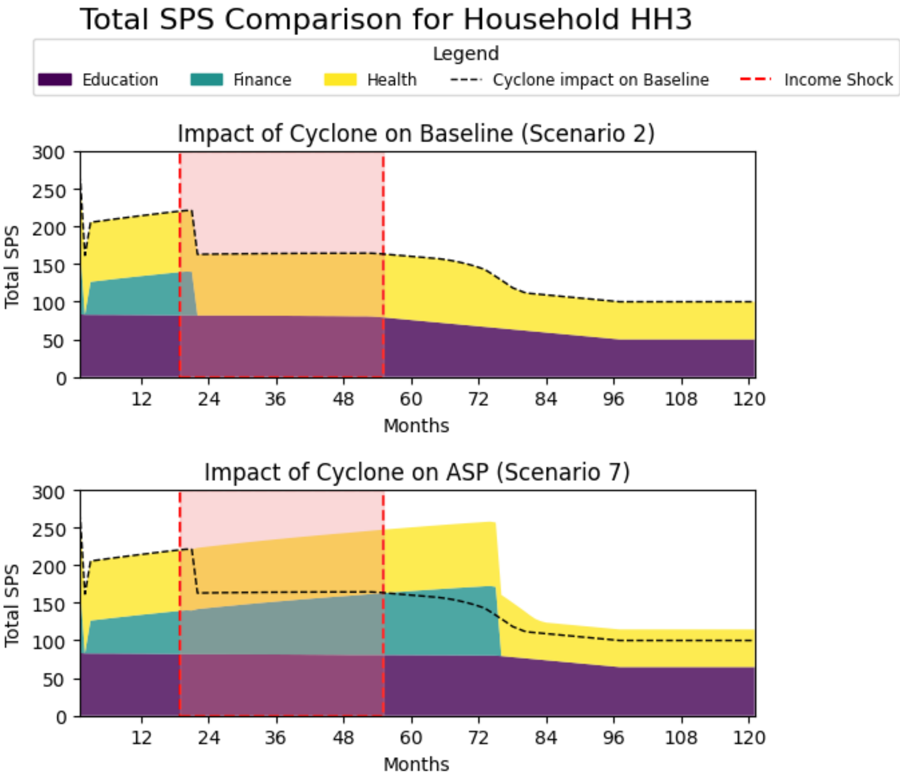

Figure 14. Change in SPS for HH3 due to Adaptive social protection

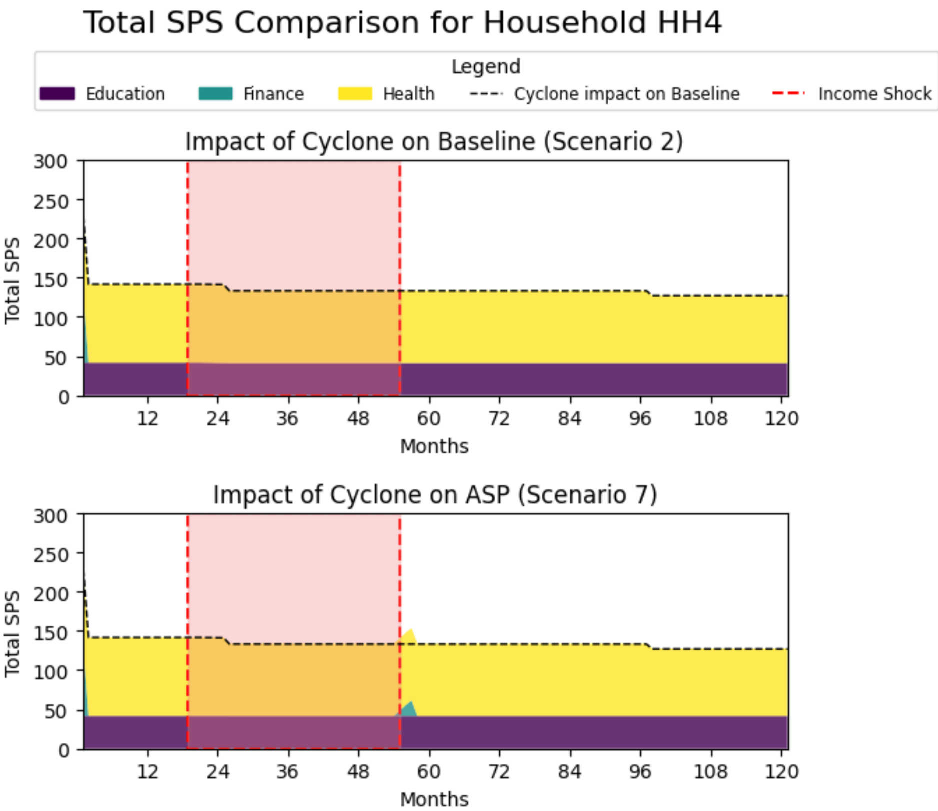

Figure 15. Change in SPS for HH4 due to Adaptive social protection

4. WAY FORWARD

In this study, we demonstrate how the E-QLT simulation can be used to assess climate vulnerability through exploratory scenarios. The framework we propose can inform both the understanding of vulnerability and measure the impact of hypothetical policy options at different spatial and temporal scales. With India set to face increasing climate-related vulnerabilities, we propose that this framework be used in following ways:

- District level administrative decision makers use this model to reduce vulnerability and target vulnerable populations to build more resilience
- Government departments, both at the state and central levels, use the model to evaluate current schemes and test hypothetical intervention, thereby informing the design of new schemes
- CSOs use the model for more robust, data-informed advocacy around the social protection measures needed by communities they represent

In May 2025, we will launch an open platform that enable CSOs, researchers, and policymakers to use the model with their own datasets and explore different scenarios.

References

i Krishnan, R. et al. (2020). Introduction to Climate Change Over the Indian Region. In: Krishnan, R., Sanjay, J., Gnanaseelan, C., Mujumdar, M., Kulkarni, A., Chakraborty, S. (eds) Assessment of Climate Change over the Indian Region. Springer, Singapore. https://doi.org/10.1007/978-981-15-4327-2_1

ii Field, C. B., Barros, V., Stocker, T. F., & Dahe, Q. (Eds.). (2012). Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation: Special Report of the Intergovernmental Panel on Climate Change (1st ed.). Cambridge University Press. https://doi.org/10.1017/CBO9781139177245

iii Mirza, M. M. Q. (2003). Climate change and extreme weather events: Can developing countries adapt? Climate Policy, 3(3), 233–248. https://doi.org/10.3763/cpol.2003.0330

iv IIT Guwahati, I. B. (2020). Climate Vulnerability Assessment for Adaptation Planning in India Using a Common Framework. Department of Science and Technology. https://dst.gov.in/sites/default/files/Full%20Report%20%281%29.pdf

v Mohanty, A., & Wadhawan, S. (n.d.). Mapping India's Climate Vulnerability.

vi Ramesh, A., Jain, G., & Shanmugam, K. (n.d.). WRI climate vulnerability index.

vii Jurgilevich, A., Räsänen, A., Groundstroem, F., & Juhola, S. (2017). A systematic review of dynamics in climate risk and vulnerability assessments. Environmental Research Letters, 12(1), 013002. https://doi.org/10.1088/1748-9326/aa5508

viii Ramieri, E.; Hartley, A.; Barbanti, A.; Santos, F.D.; Gomes, A.; Hilden, M.; Laihonen, P.; Marinova, N.; Santini, M. Methods for Assessing Coastal Vulnerability to Climate Change; Technical Paper 1; European Topic Centre on Climate Change Impacts, Vulnerability and Adaptation: Bologna, Italy, 2011

ix Koerth, J.; Vafeidis, A.; Hinkel, J. Household-Level Coastal Adaptation and Its Drivers: A Systematic Case Study Review. Risk Anal. 2016, 37, 629–646.

x The Sustainable Livelihoods Approach | SpringerLink. (n.d.). Retrieved February 14, 2022, from https://link.springer.com/chapter/10.1007/978-981-10-0983-9_5

xi Global Burden of Disease Collaborative Network. Global Burden of Disease Study 2021 (GBD 2021). Seattle, United States: Institute for Health Metrics and Evaluation (IHME), 2024

xii Alkire, S., Conconi, A., & Seth, S. (2014). Multidimensional Poverty Index 2014: Brief Methodological Note and Results. University of Oxford. https://doi.org/10.35648/20.500.12413/11781/ii028 xiii Ton, M. J., Ingels, M. W., De Bruijn, J. A., De Moel, H., Reimann, L., Botzen, W. J. W., & Aerts, J. C. J. H. (2024). A global dataset of 7 billion individuals with socio-economic characteristics. Scientific Data, 11(1), 1096. https://doi.org/10.1038/s41597-024-03864-2

xiv Jurgilevich, A., Räsänen, A., Groundstroem, F., & Juhola, S. (2017). A systematic review of dynamics in climate risk and vulnerability assessments. Environmental Research Letters, 12(1), 013002. https://doi.org/10.1088/1748-9326/aa5508

xv Walsh, K. J. E., McBride, J. L., Klotzbach, P. J., Balachandran, S., Camargo, S. J., Holland, G., Knutson, T. R., Kossin, J. P., Lee, T., Sobel, A., & Sugi, M. (2016). Tropical cyclones and climate change. WIREs Climate Change, 7(1), 65–89. https://doi.org/10.1002/wcc.371

xvi Walsh, K. J. E., McBride, J. L., Klotzbach, P. J., Balachandran, S., Camargo, S. J., Holland, G., Knutson, T. R., Kossin, J. P., Lee, T., Sobel, A., & Sugi, M. (2016). Tropical cyclones and climate change. WIREs Climate Change, 7(1), 65–89. https://doi.org/10.1002/wcc.371

xvii Pal, S. C., Chowdhuri, I., Das, B., Chakrabortty, R., Roy, P., Saha, A., & Shit, M. (2022). Threats of climate change and land use patterns enhance the susceptibility of future floods in India. Journal of Environmental Management, 305, 114317. https://doi.org/10.1016/j.jenvman.2021.114317

xviii Bangalore, M., Hallegatte, S., & Vogt-Schilb, A. (2016). Assessing Socioeconomic Resilience to Floods in 90 Countries. World Bank, Washington, DC. https://doi.org/10.1596/1813-9450-7663

xix Bagolle, A., Costella, C., & Goyeneche, L. (2023). Social Protection and Climate Change: How Can We Protect the Most Vulnerable Households Against New Climate Threats? [Policy Brief]. Inter American Development Bank.