Online Appendix (Supplement)

Appendix A: Variable Definitions and Data Processing

This appendix provides variable definitions, sources, and data processing details, including transformations, imputation, and scaling.

Table A1: Data descriptions and transformations

Source	Variable	Description and Transforms
CDC ACS 5-Year	hou_units_occupied	Occupied housing units
	hou_units_unoccupied	Unoccupied Housing units
	hou_units_1_attached	Housing, one-unit attached
	hou_units_mobile	Mobile homes
	hou_units_van	Dwelling units that are boat, RV, van, etc.
	hou_units_1	Housing with 1 units
	hou_units_2	Housing with 2 units
	hou_units_3	Housing with 3 units
	hou_units_4	Housing with 4 units
	hou_units_5	Housing with 5 units
	hou_units_6	Housing with 6 units
	hou_units_7	Housing with 7 units
	hou_units_8	Housing with 8 units
	hou_units_9_plus	Housing with 9+ units
	hou_age_since_2010	Housing built since 2010
	hou_age_2000	Housing built 2000 to 2009
	hou_age_1990	Housing built 1990 to 1999
	hou_age_1980	Housing built 1980 to 1989
	hou_age_1970	Housing built 1970 to 1979
	hou_age_1960	Housing built 1960 to 1969
	hou_age_1950	Housing built 1950 to 1959

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Table A1: Data descriptions and transformations (Continued)

Source	Variable	Description and Transforms
	hou_age_1940	Housing built 1940 to 1949
	hou_age_1939_plus	Housing older than 1939
	hou_units_no_mortgage	
	hou_units_value_median_2022	
	hou_units_mortgage_pymt_median	If mortgaged, median mortgage amount in 2022 USD, CPI adjusted
	hou_units_gross_rent_median	Housing units median gross rent in 2022 USD, CPI adjusted
	hou_occupants_1_1.5	Housing crowding - Occupied housing units rate, people to room, 1.01 to 1.5
	hou_occupants_1.5_plus	Housing crowding - Occupied housing units rate, people to room, 1.51+
	hou_units_no_vehicle	Housing units with no vehicle
	eco_employment_in_labor_force	Population older than 16 in the labor force
	eco_employment_in_civilian_labor_force	Population older than 16 in the civilian labor force
	eco_employment_in_armed_force	Population older than 16 in the armed forces
	eco_employment_not_in_labor_force	Population not in the labor force
	eco_commute_single	Population older than 16 that drove alone to work
	eco_commute_carpool	Population older than 16 that commuted to work.
	eco_commute_public_transport	Population older than 16 that used public transport to travel to work.
	eco_commute_walked	Population older than 16 that walked to work
	eco_commute_wfh	Population older than 16 that worked from home.
	eco_commute_other	Population older than 16 that took an alternative form of transport to work.

Continued on next page

Table A1: Data descriptions and transformations (Continued)

Source	Variable	Description and Transforms
	eco_occ_mgmt	Proportion of reported occupations in management, business, science, and arts
	eco_occ_svsc	Proportion of reported occupations in services
	eco_occ_sales	Proportion of reported occupations in sales
	eco_occ_mine	Proportion of reported occupations in natural resources, construction, and maintenance
	eco_occ_trans	Proportion of reported occupations in production, transportation, and material moving
	eco_ind_ag	Proportion of reported occupations in agriculture, forestry, fishing and hunting, and mining
	eco_ind_construction	Proportion of reported occupations in construction
	eco_ind_manufacturing	Proportion of reported occupations in manufacturing
	eco_ind_wholesale	Proportion of reported occupations in wholesale
	eco_ind_retail	Proportion of reported occupations in retail
	eco_ind_warehouse	Proportion of reported occupations in transportation and warehousing, and utilities
	eco_ind_information	Proportion of reported occupations in information
	eco_ind_finance	Proportion of reported occupations in finance
	eco_ind_prof	Proportion of reported occupations in professional, scientific, and management, and administrative and waste management services
	eco_ind_edu	Proportion of reported occupations in educational services, and health care and social assistance
	eco_ind_arts	Proportion of reported occupations in arts, entertainment, and recreation, and accommodation and food services
	eco_ind_other	Proportion of reported occupations in other services, except public administration
	eco_ind_public_admin	Proportion of reported occupations in public administration

Continued on next page

Table A1: Data descriptions and transformations (Continued)

Source	Variable	Description and Transforms
	eco_income_hhld_ssi_2022	Households with Supplemental Security Income
	eco_income_hhld_public_assist_2022	Households with cash public assistance income. While 2022 is listed in the name, the variable is household count.
	eco_income_hhld_snap	Households with Food Stamp/SNAP benefits in the past 12 month
	eco_income_mean_wages_2022	Mean wages (2022 adjusted), log transformed
	eco_poverty_below	Households below the federal poverty limit
	eco_poverty_below_150_lvl	Households below 150% the federal poverty limit, inclusive of the population below the federal poverty limit
	eco_health_ins_has_ins	Population with insurance
	eco_health_ins_public_ins	Population with public health coverage
	soc_minority_race_ethnicity	Population in a minority race or ethnicity (as defined in SVI, total population not white & non-hispanic.
	soc_elderly_pop	Population 65+
	soc_youth_pop	Population below 18
	soc_birthrate	Proportion of population who are women in prime birth years, 20-34 years old
	soc_veteran	Veteran population
	soc_family_comp_single_parent	Households composed of single parents with minor-aged children
	soc_family_comp_single_elderly	Households composed of single, elderly individuals
	soc_multigeneration	Households with both grandparents and children
	soc_group_qtr_pop	Persons who are in institutional and non- institutional group homes
	soc_education_lt_9th	Population with lower than high school population
	soc_education_9_12	Population with only partial high school education
	soc_education_hs_grad	Population with a high school degree.

Continued on next page

Table A1: Data descriptions and transformations (Continued)

Source	Variable	Description and Transforms
	soc_education_bs_grad	Population with a college degree.
	soc_disability_pop	Population with a disability.
	soc_elderly_disability_non_inst_elderly	Elderly population with a disability and not in a shared facility.
	soc_recent_move	Population that moved recently.
	soc_migrant_foreign_born	Population that are foreign born.
	soc_migrant_foreign_born_not_citizen	Population that are foreign born and not US citizens.
	soc_language_limited_english	Population self-identifying as limited English proficiency.
	soc_computer_available	Households with a computer available.
	soc_computer_broadband	Households with broadband available.
CDC Places	ho_arthritis_prevalence	Arthritis among adults
	ho_child_asthma_prevalence	Asthma among children
	ho_bp_high_prevalence	High blood pressure among adults
	ho_cancer_prevalence	Cancer (non-skin) or melanoma among adults
	ho_high_cholesterol_prevalence	High cholesterol among adults who have ever been screened
	ho_kidney_prevalence	Chronic kidney disease among adults
	ho_copd_prevalence	Chronic obstructive pulmonary disease among adults
	ho_chd_prevalence	Coronary heart disease among adults
	ho_diabetes_prevalence	Diagnosed diabetes among adults
	ho_obesity_prevalence	Obesity among adults
	ho_teeth_lost_prevalence	All teeth lost among adults aged 65+ years
	ho_stroke_prevalence	Stroke among adults
	pr_lack_of_insurance_prevalence	Lack of health insurance among adults aged 18–64 years
	pr_annual_checkup_prevalence	Routine checkup within the past year among adults

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Table A1: Data descriptions and transformations (Continued)

Source	Variable	Description and Transforms
	pr_dental_visits_prevalence	Visited dentist or dental clinic in the past year among adults
	pr_bp_medicine_adhere_prevalence	Taking medicine to control high blood pressure among adults with high blood pressure
	pr_cholesterol_screening_prevalence	Cholesterol screening among adults
	pr_mammography_use_prevalence	Mammography use among women aged 50–74 years
	pr_cervical_cancer_screening_prevalence	Cervical cancer screening among women aged 21–65 years
	pr_colorectal_cancer_screening_prevalence	Colorectal cancer screening among adults aged 45–75 years
	pr_core_screenings_male_prevalence	Older adults aged 65+ years who are up to date on a core set of clinical preventive services, male
	pr_core_screenings_female_prevalence	Older adults aged 65+ years who are up to date on a core set of clinical preventive services, female
	hr_binge_drinking	Binge drinking among adults
	hr_current_smoking	Current cigarette smoking among adults
	hr_no_leisure_time	No leisure-time physical activity among adults
	hr_short_sleep_duration	Short sleep duration among adults
	hs_physical_health_status_poor	Frequent physical distress among adults
	hs_mental_health_status_poor	Frequent mental distress among adults
OpenFema Disaster Declaration Summaries	incident_Fire	Disaster declared as fire type
	incident_Flood	Disaster declared as flood type
	incident_Hurricane	Disaster declared as Hurricane type (including Tropical Storms during 2023 - 2025Q2 out-of-time period)

Continued on next page

Table A1: Data descriptions and transformations (Continued)

Source	Variable	Description and Transforms
	incident_Severe Ice Storm	Disaster declared as severe ice storm
	incident_Severe Storm	Disaster declared as severe storm
	incident_Tornado	
FEMA IHP	total_need	Count of households per disaster and per county registering any type of need with the US Federal Emergency Management Agency's Individual and Households Program
	outcome_home_damage	Count of households that reported home damage.
	outcome_auto_damage	Count of households that reported auto damage.
	outcome_food_need	Count of households that reported need for food
	outcome_shelter_need	Count of households that reported need for shelter
	outcome_access_need	Count of households that required special accommodations
	outcome_hab_repair_need	Count of households that require repairs to make a dwelling habitable
	outcome_emergency_need	Count of households that report needs for emergency, life-sustaining items under Critical or Serious Needs assistance, such as water, food, first aid, prescriptions, infant formula, diapers, hygiene items, fuel, etc.

Note. Census ACS and CDC Places data are proportion of unit within a county. Census is scaled 0 to 1, CDC Places 0 to 100. Scaling differences are immaterial for Random Forest and XGBoost architectures. Exceptions to scaling are hou_units_mortgage_pymt_median, hou_units_gross_rent_median, hou_units_value_median_2022, and eco_income_mean_wages_2022 , which are adjusted from relative year of disaster to 2022 USD dollars using the US Bureau of Labor Statistics CPI, then have a log transform applied. Counties with FIPS codes 02261, 02063, and 02066 were removed due to inconsistent definition during time period. Connecticut counties (FIPS 09110, 09120, 09130, 09140, 09150, 09160, 09170, 09180, 09190 in 2022 are re-weighted to maintain consistency up through 2021 using AP News crosswalk. Counties 15001, 48301, 48261, 48269, 48301, 15051, 35059 each had between one and three fields that were missing for mortgage, rent, home value, or wages, and were filled with the field minimum populated value. ACS and CDC Places include 3,141 counties total, data treatment applied before combining to outcome data reported in Table 4.

Appendix B: Model Training Fit Statistics

This appendix reports model training and validation results, including in-sample and out-of-sample MAE, MAPE, R^2, and RMSE across all need types and model architectures.

Table B1: Model Training Results

Need	Model	Feature set	CV MAE	CV MAE σ	R^2	RMSE	MAE	MAPE
Accessibility	RF	SVI	1.304271	0.072161	0.385500	1.725348	1.302756	40.036400
	XGBoost	SVI	1.275307	0.066160	0.377618	1.736379	1.314030	39.684000
	RF	LIVA	1.182688	0.070941	0.489384	1.572761	1.171210	34.673300
	XGBoost	LIVA	1.167228	0.070419	0.499152	1.557647	1.167285	34.593800
Auto damage	RF	SVI	1.295517	0.056456	0.428086	1.667579	1.306766	48.249600
	XGBoost	SVI	1.260609	0.051552	0.475714	1.596633	1.231995	45.436500
	RF	LIVA	1.167910	0.060467	0.512144	1.540163	1.182622	42.045900
	XGBoost	LIVA	1.126864	0.074218	0.530756	1.510499	1.112570	39.460500
Emergency items	RF	SVI	1.498880	0.090026	0.443482	1.890685	1.480227	51.770000
	XGBoost	SVI	1.450210	0.083762	0.452302	1.875643	1.461966	51.790800
	RF	LIVA	1.277337	0.088757	0.565600	1.670415	1.244116	45.490700
	XGBoost	LIVA	1.291733	0.079160	0.581191	1.640164	1.204961	44.715800
Food	RF	SVI	1.560076	0.057043	0.435081	1.961869	1.538606	52.306100
	XGBoost	SVI	1.516792	0.075189	0.485545	1.872194	1.431270	48.541800
	RF	LIVA	1.302275	0.065394	0.568348	1.714920	1.296901	45.850900
	XGBoost	LIVA	1.315835	0.069837	0.567928	1.715755	1.301683	45.897600
Hab. repair	RF	SVI	1.295698	0.070373	0.321842	1.706097	1.264378	32.353600
	XGBoost	SVI	1.300952	0.082708	0.319031	1.709629	1.275004	32.465000
	RF	LIVA	1.172462	0.076325	0.425090	1.570862	1.138288	28.685200
	XGBoost	LIVA	1.199066	0.078072	0.388564	1.619995	1.189890	30.464000
Home damage	RF	SVI	1.337741	0.061980	0.378344	1.703264	1.280582	36.477300

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Table B1: Model Training Results (Continued)

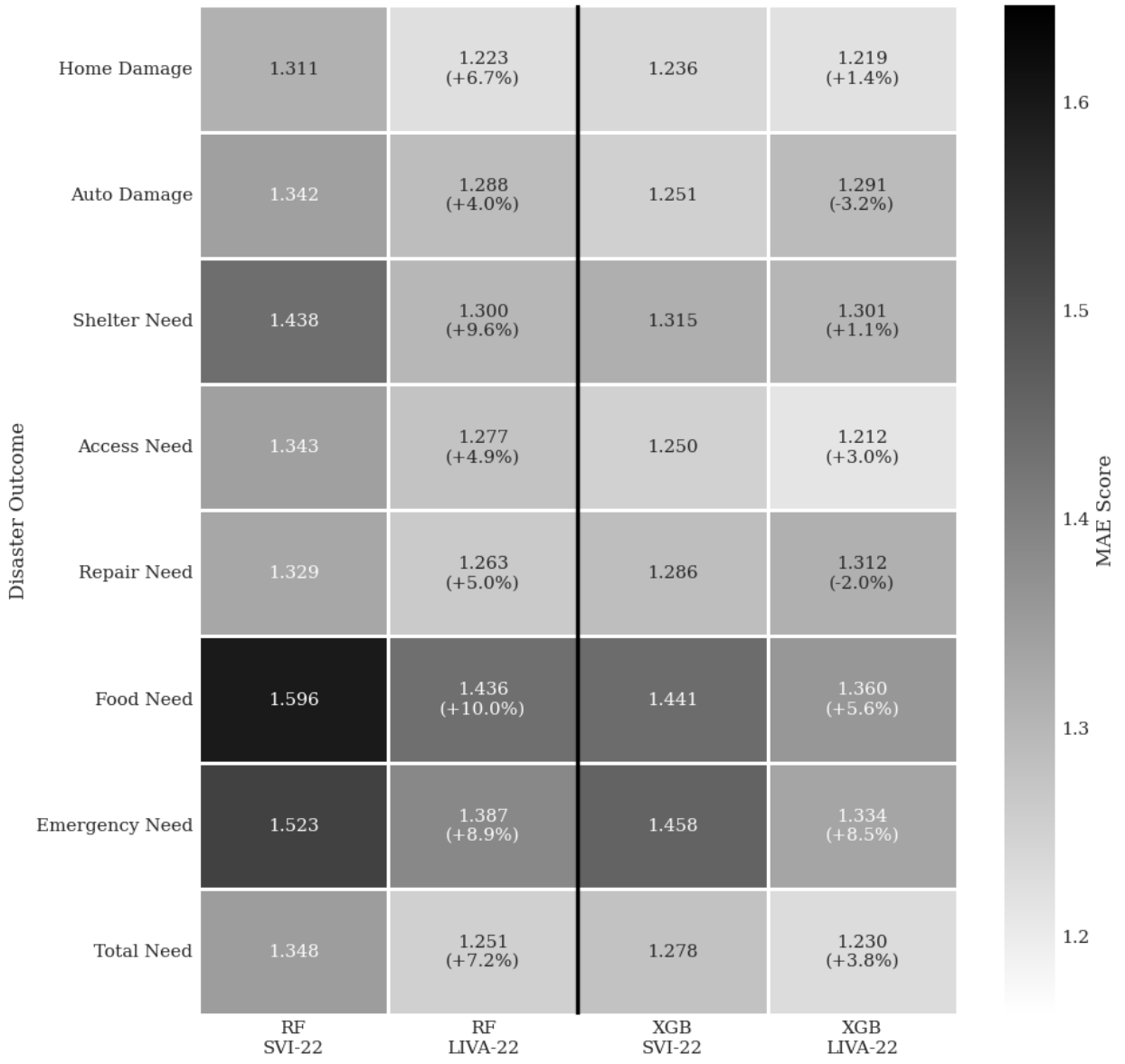
Need	Model	Feature set	CV MAE	CV MAE σ	R^2	RMSE	MAE	MAPE
	XGBoost	SVI	1.314332	0.062473	0.395769	1.679223	1.256483	36.492900
	RF	LIVA	1.155421	0.066970	0.499570	1.528194	1.092852	34.328400
	XGBoost	LIVA	1.177689	0.078987	0.487146	1.547047	1.086201	34.920400
Shelter	RF	SVI	1.424392	0.058792	0.439027	1.778747	1.356176	47.948800
	XGBoost	SVI	1.389756	0.061200	0.489758	1.696413	1.277656	46.161900
	RF	LIVA	1.262812	0.061112	0.540986	1.609001	1.203270	42.795600
	XGBoost	LIVA	1.255857	0.075491	0.566929	1.562871	1.161380	41.431900
Total Need	RF	SVI	1.357571	0.063387	0.379495	1.736925	1.304648	35.282700
	XGBoost	SVI	1.332627	0.088422	0.397252	1.711891	1.258372	35.289500
	RF	LIVA	1.168668	0.071447	0.498042	1.562219	1.122159	33.122400
	XGBoost	LIVA	1.180421	0.068914	0.492657	1.570577	1.102133	33.365100

Note. CV fit statistics (MAE, $MAE\sigma$) are calculated from 5 folds and 3 randomized repetitions. Statistics not labeled as CV are from the Test dataset.

Appendix C: Robustness and Sensitivity Analyses

We conducted a controlled comparison where both LIVA and SVI use exactly 22 features, in order to parsimoniously match the number of potential features at the same count and show whether LIVA performs better simply due to more features. In this equal-feature-count comparison, LIVA-Top22 (using Random Forest-selected features) outperforms SVI-22 across nearly all outcomes, demonstrating that the improvement comes from identifying better predictors, not just having more of them. LIVA retains 4-6 of SVI's 22 features, replacing 16-18 of SVI's traditional vulnerability indicators with more predictive alternatives. The SVI features kept were race/ethnicity, mobile homes, and mortgage payments, while LIVA identifies predictors such as professional industry employment, preventive care screening rates (as health access proxies), and housing economic indicators. The outcomes can be seen in Figure C1.

Figure C1 MAE Comparison for LIVA and SVI restricted sets.



Note. Improvements shown in parentheses.

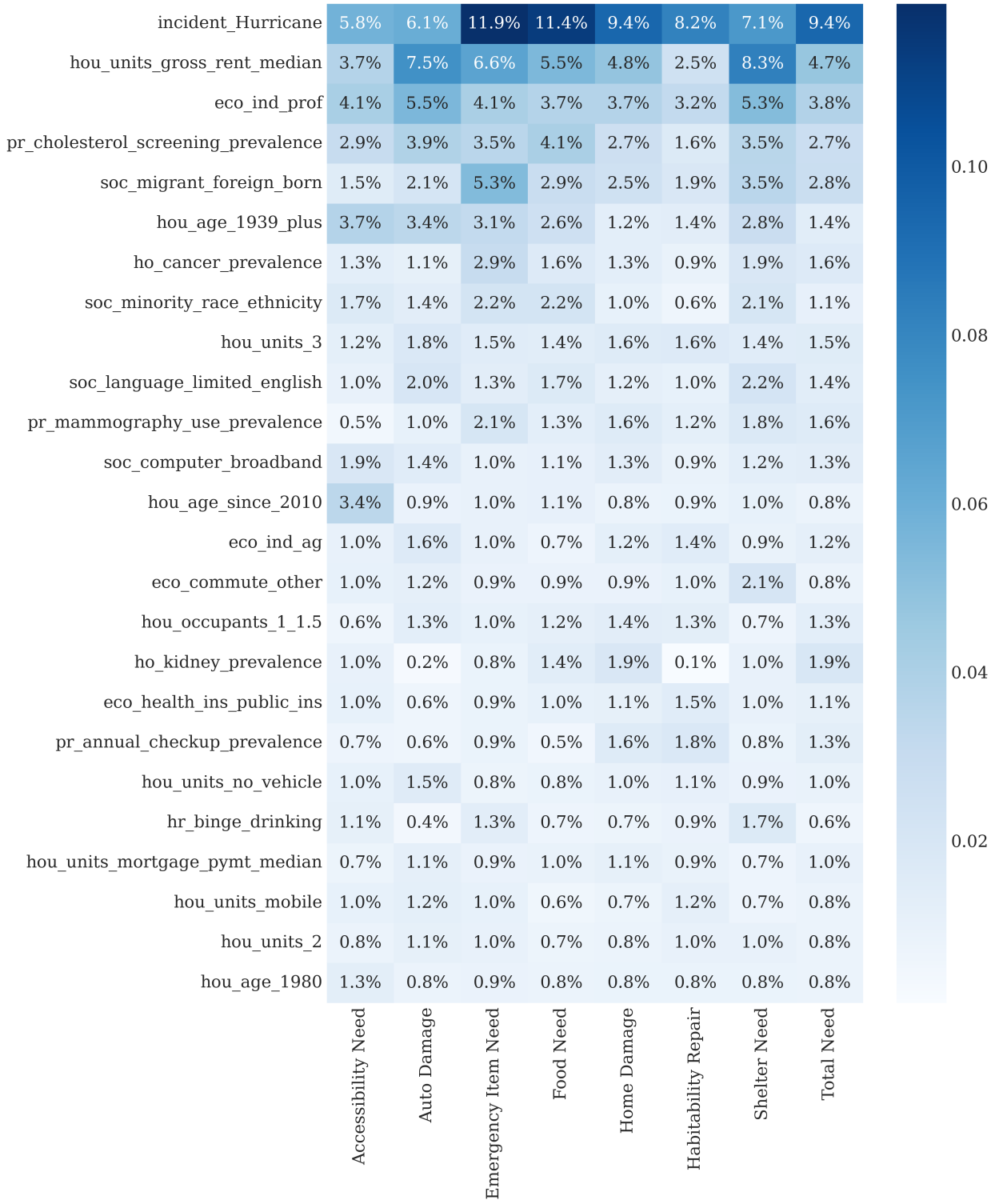
Appendix D: Interpretability and Diagnostics

In this section, we provide exhibits related to model interpretability, including feature importance, SHAP, and PDP plots.

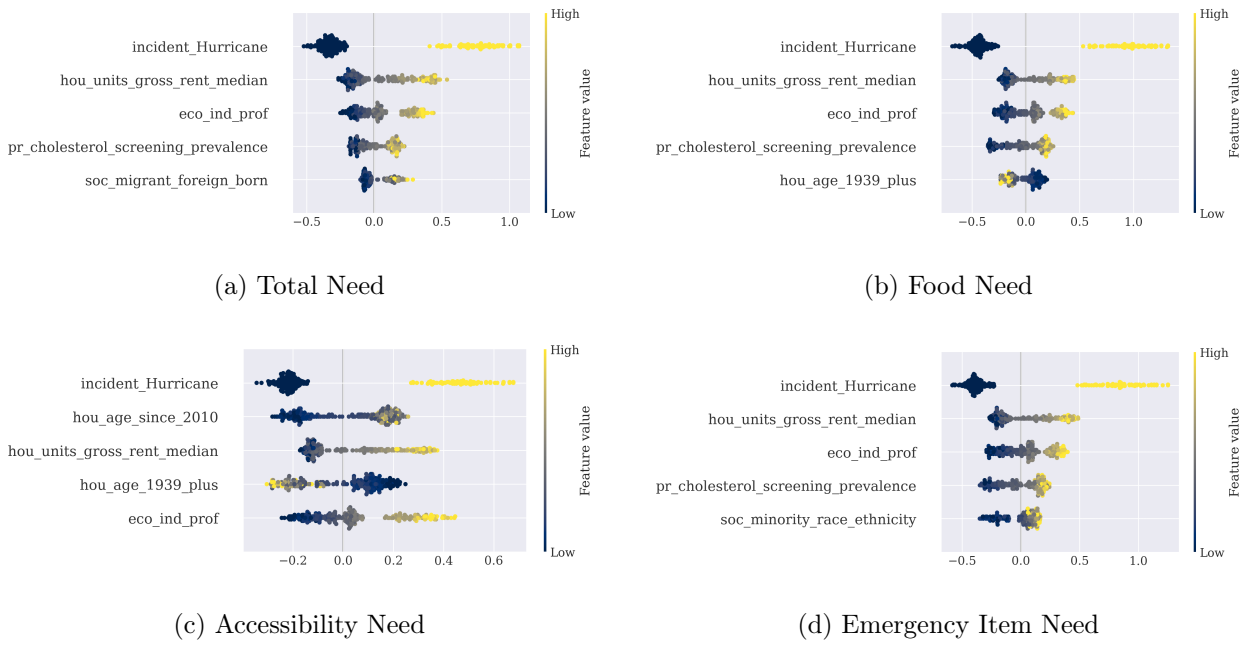
The top 25 variables, identified by average mean feature importance across all LIVA models, are presented in Figure-D1. The values shown are the average importance across model architectures (Random Forest and XGBoost), and show that different features have significant differences in feature importance. This highlights that each LIVA need–hazard model draws on a distinct set of drivers, yet several predictors repeatedly rank highly across tasks (e.g., hurricane incident exposure, median gross rent, employment in professional industries, foreign-born population share, preventive-care utilization, and housing age). To guard against metric-specific artifacts, we corroborate these rankings with permutation-based importance and SHAP attributions, which yield overlapping top predictors and consistent directionality. Importances are model-based summaries and should be interpreted as relative contributions to prediction rather than causal effects.

Shapley values reveal how different forms of need are driven by distinct community features. Figure-D2 displays the top five predictors for a sample of the need's Random Forest models, organized by type of need. In all cases, a Hurricane incident strongly increase predicted need. Beyond this, the features diverge considerably across need types: models for Accessibility Need emphasize household-related variables such as housing age and rental costs (e.g., hou_units_gross_rent_median, hou_age_1939_plus), while Food, Emergency Items, and Total Needs surface social and health-related factors, including screening rates and foreign-born populations (e.g., pr_cholesterol_screening_prevalence, soc_migrant_foreign_born). The SHAP plots also illustrate directionality and interaction: when high-value records (lighter coloring) cluster on the right, the feature acts monotonically to increase need; when colors are mixed (gray color) on both sides, effects are more heterogeneous. This variation suggests that while hazard exposure is a common base, each type of need reflects distinct social and spatial vulnerabilities.

Figure D1 Feature Importances for LIVA-22 and SVI-22 restricted sets.



Note. Average Feature importance across Random Forest and XGBoost architectures for each need and for each feature in the top 25 features.



(a) Total Need

(b) Food Need

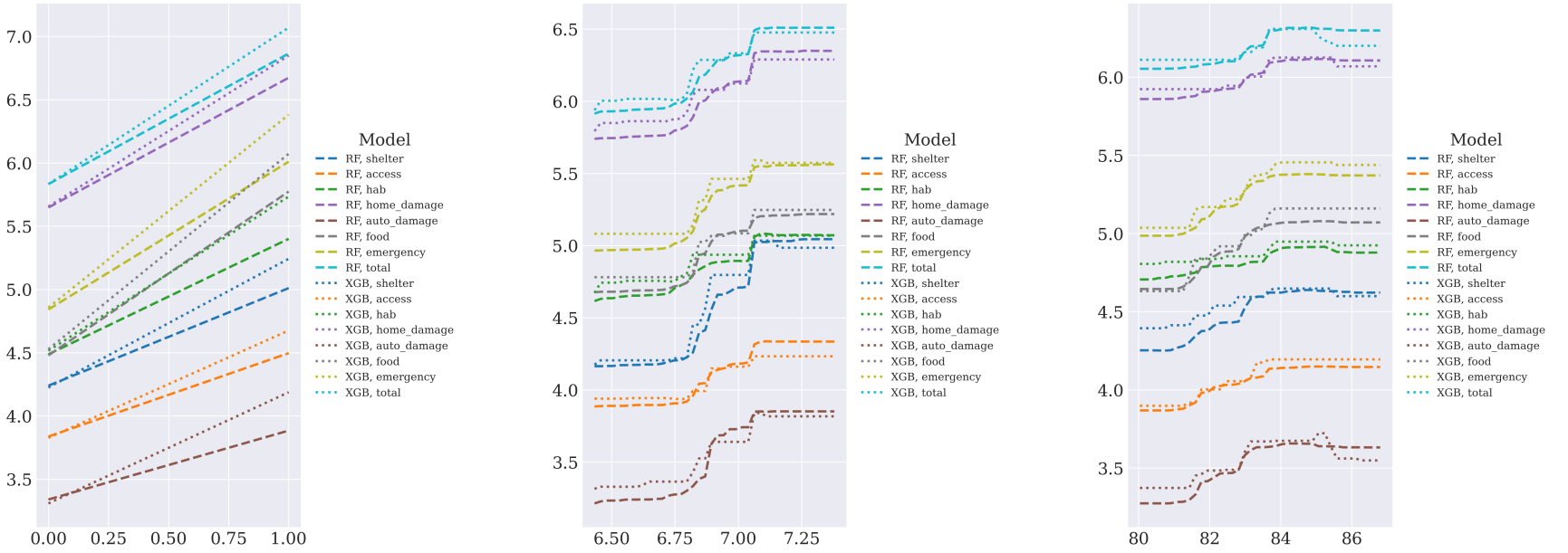
(c) Accessibility Need

(d) Emergency Item Need

Figure D2 **Shapley values for LIVA Random Forest for Total Need, Food Need, Accessibility Need, Emergency Item Need.**

We finish this section by presenting partial dependence plots (PDPs) for three variables that appeared frequently among the top features across models and need types. These plots illustrate how predicted need varies on average as the value of each variable changes, marginalizing over other features. Figure D3 shows PDPs for: (a) the binary indicator for hurricane exposure, (b) median gross rent (log-transformed), and (c) the prevalence of cholesterol screening. Each curve represents a different model–need pairing, allowing comparison across both architecture and outcome type.

The hurricane indicator shows a consistent and steep increase in predicted need across all models, reaffirming its dominant role in need prediction. The effect of housing cost (log rent) is nonlinear: moderate rent values are associated with slightly elevated need, but very high rent correlates with decreasing need, possibly reflecting wealthier and more resilient areas. In contrast, cholesterol screening shows a monotonic and inverse relationship—higher prevalence is associated with lower predicted need—indicating that access to preventive care acts as a strong proxy for social and health resilience, particularly in the food and emergency need models.



(a) Hurricane incident indicator

(b) Median rent (log, 2022 USD)

(c) Cholesterol screening prevalence

Figure D3 **Partial dependence plots for three top features across LIVA models and need types. Each line represents a model–need combination. (a) Hurricane exposure increases predicted need. (b) Median rent shows a nonlinear relationship with need. (c) A higher prevalence of cholesterol screening reduces the predicted need.**

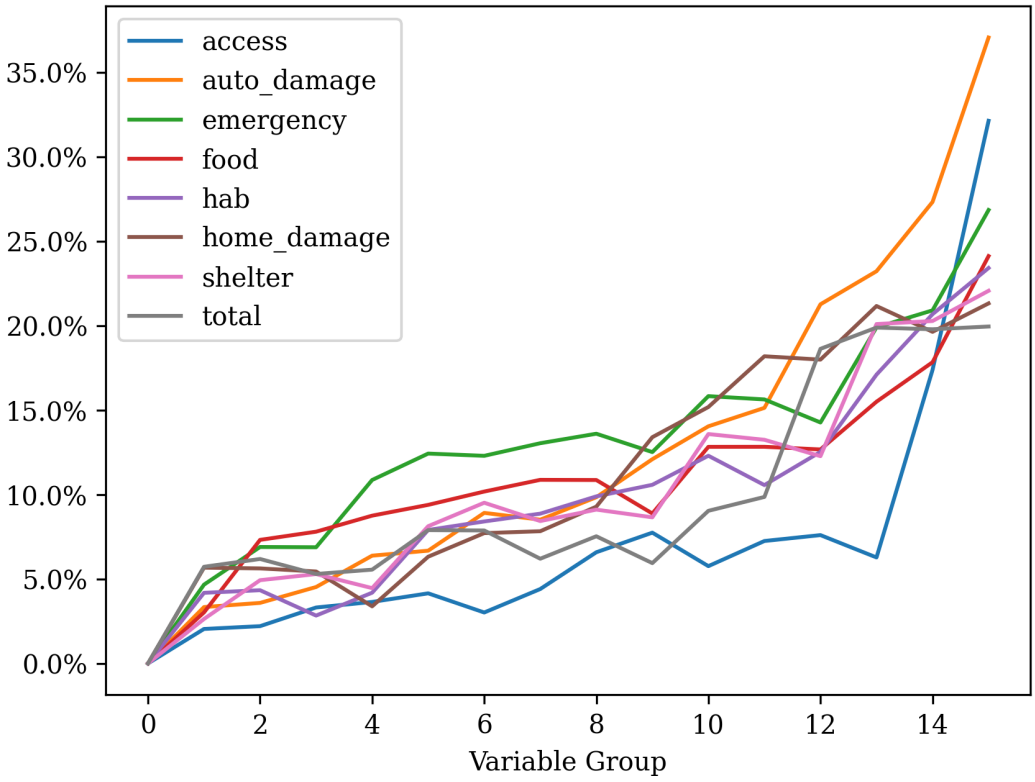
Appendix E: Ablation Analysis

As a complementary extension of the ablation analysis, Figure E1 illustrates how model performance deteriorates as groups of features are cumulatively removed from the Random Forest models across all need types. The x-axis represents the progressive exclusion of feature groups (e.g., housing, socioeconomic, health, hazard), while the y-axis tracks the resulting increase in mean absolute error (MAE). This cumulative ablation curve serves as a diagnostic to reveal the marginal value of each group in the predictive stack.

The shape of the curve highlights the relative importance of the feature sets, which were ranked by total group feature importance on the full model. An initially flat trajectory followed by steep increases indicates that the earliest-removed groups were less critical, while subsequent removals degrade performance more sharply. This indicates that the model was not reliant solely on the most important feature groups.

While the plot focuses on Random Forest models, similar patterns are observed for XGBoost, suggesting robustness across architectures. Together, these curves reinforce that predictive strength is not aligned with specific feature domains, but jointly excluding the groups can significantly reduce performance.

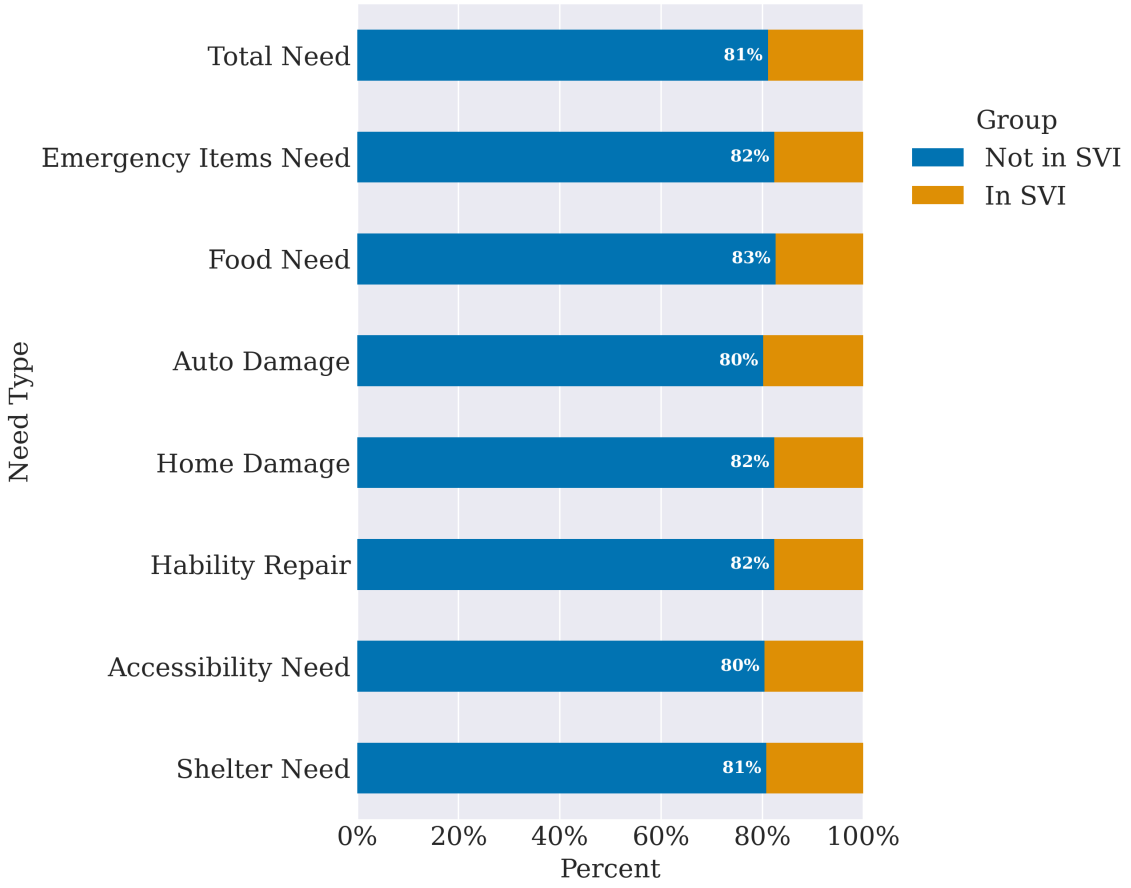
Figure E1 Cumulative MAE change across need models as groups are removed.



Appendix F: SVI vs. Non-SVI Feature Importance

This section examines the relative cumulative importance of features that are part of the CDC SVI versus those that are not, based on the feature importance rankings from the full LIVA model used during the ablation study. The SVI group comprises 22 features that constitute the CDC-defined SVI domains, including socioeconomic status, household composition, minority status, and housing type/transportation.

Figure F1 Proportion of features sourcing from SVI.



As shown in Figure F1, the SVI feature set consistently accounts for approximately 20% of total feature importance across all ablation study models and outcome types. This indicates that while SVI-based features contribute meaningfully, the bulk of predictive power comes from non-SVI variables—such as housing age, health behavior indicators, or disaster context—not included in the CDC index. Note that this comparison reflects only the contribution of the features as used in the full model, not causality.

These results suggest that while SVI variables remain relevant, the models rely more heavily on broader feature sets to explain variation in need. This underscores the value of extending beyond predefined indices like the CDC SVI when building data-driven models for post-disaster response.

Appendix G: Binary Risk Classification Results

One possible use for LIVA is to assign *a priori* classifications of need (e.g., high vs. low) based on predicted scores. To demonstrate this use, we define a binary risk classifier by applying a threshold of 0.5 to a min–max normalized transformation of the relevant training set field (e.g., log-transformed need, LIVA RF/XGBoost predictions, SVI, or SoVI scores).

Table G1 reports classification performance, averaged across all identified need types. Both LIVA models (XGBoost) achieve a favorable balance of precision and recall, with F1-scores near 0.80 and AUC values between 0.843 and 0.882 in testing and out-of-time datasets. By contrast, the SVI score attains higher recall but at the expense of precision, reflected in lower overall F1 and AUC values. The SoVI has poor precision and recall across both test and out-of-time datasets.

Table G1 Classification metrics for high or low identified need

Model - OOT	**Precision**	**Recall**	**F1**	**AUC**
LIVA RF	0.821	0.738	0.772	0.847
LIVA XGB	0.795	0.798	0.794	0.843
SVI	0.645	0.837	0.726	0.711
SoVI	0.279	0.116	0.160	0.509
Model - Test				
LIVA RF	0.821	0.8055	0.807	0.882
LIVA XGB	0.759	0.841	0.796	0.874
SVI	0.556	0.832	0.666	0.612
SoVI	0.152	0.106	0.122	0.405

Metrics aggregated across need types.