This section presents the main results. First, we characterize the study case in terms of descriptive statistics of features that might predict cold wave-related disaster risk. Second, we present the main results of Machine Learning model training including model selection

**Descriptive characterization of Puno**

According to historical data, the urban public infrastructure in Puno is poor. Whether households are settled in rural areas or not: 15.94% of them have inlaid walls, 52.43% have tracks of which 21.93% are paved, and 40.94% are settled near a lighting pole. Regarding ownership, 82.55% of households are owned, but 22.17% have title of ownership. Housing infrastructure is fragile: 27.49% of households have walls of concrete. Most households in Puno are settled in rural areas (59.04%) at an average altitude of 3880 meters above sea level.

In terms of access to basic services, 34.28% of households are connected to a water and drainage network, 55.39% have daily access to water for consumption. Nevertheless, access to electricity has improved, with 89.33% of households with electric lighting compared to 74.18% in 2017. Households without electricity uses candle (7.14%) or other lighting (3.53%). The main cooking methods are cooking by GLP (60.58%) and cooking by manure (39.86%). Manure cooking is a characteristic of rural livelihoods (Sagastume-Gutiérrez et al., 2022), thus the prevalence of manure cooking is explained by the prevalence of rurality. Regarding access to Information and Communications Technologies, 14.05% of households have internet access, but 83.05% have cellphone.

Households are equipped with assets like color TV (47.36%), bicycle (32.05%), motorcycle (24.35%) and DVD (24.38%). Just 6.54% of households have a particular car, which is explained by the observed poor urban infrastructure. In the modern society, ICTs grant opportunities and capabilities for individuals (Oyelami et al., 2022), however just 18.14% of households have a computer or laptop. Just 8.68% of households have a refrigerator. The annual per capita expenditure approximates short-term household nominal income. The average annual per capita expenditure is US$1634.29. The average expenditure is below Latin America's principal cities, such as Lima, Bogotá, Buenos Aires, and Rio de Janeiro. It is worth mentioning that the mean income is above the median, meaning that more than half of the per capita expenditure distribution is below the average, showing some degree of income inequality.

It is common to find old adults (51 to 65 years old) and old (more than 65 years old) household heads (59.95%). Even though Puno is not densely populated, 38.47% of households are overcrowded, that means they have more inhabitants than bedrooms. The 40.68% of households’ heads are married. Puno has a poor development of human capital: the 19.56% of households’ heads are illiterate, 63.02% have no education, and just 2.25% have a postgraduate degree.

Last but not least, the population faces a high prevalence of acute illness (96.24%), and chronic illness (87.52%). More than half of the households in the sample have at least one member that searched for medical attention (67.14%), and 73.32% have a subsidized health insurance regime. 32.79% of households have at least one member with one or more disabilities.

**Table 1.** Multidimensional vulnerability features

|  |  |
| --- | --- |
| **Category** | **Variable** |
| Household exterior and access to public goods | Household with inlaid walls, Household with painted walls, Outside tracks are paved, Outside tracks are terrain, Outside paths, Lighting pole, No public good |
| Ownership and physical characteristics | Independent house, Household is a house, Household is totally owned, Tittle of ownership, Concrete walls, Concrete floor, Concrete roof, Overcrowded bedrooms, No other rooms than bedrooms |
| Access and use of basic services | Water network, Potable water, Quality water (chlorine), Daily access to water, Drainage network, Electric lighting, Candle lighting, Other lighting, GLP cooking, Wood cooking, Other cooking, Manure cooking, Phone, Cellphone, Cable TV, Internet |
| Household income and assets | Per capita expenditure, Radio, Color TV, Black-White TV, Sound equipment, DVD, Computer or laptop, Electric iron, Electric blender, Gas stove, Refrigerator, Cloth washing machine, Microwave oven, Sewing machine, Bicycle, Car, Motorcycle, Tricycle |
| Socio-demographics | The head is employed, The head is a woman, The head is married, The head is literate, The head has no education, The head achieved basic education, The head achieved technic education, The head achieved college education, The head achieved pos-graduate education, The head is a young adult (17-35), The head is an adult (36-50), The head is an old adult (51-65), The head is old (more than 66) |
| Health and insurance  (for household members) | Illness (last month), Accident (last month), Healthy (last month), Chronic illness, Medical intervention (last month), Contributory health insurance, Subsidized health insurance, Disabilities |
| Geographical context | Household is located in a rural area, Altitude |

Figure 5 shows the correlation heatmap of features listed in Table 1. Statistical correlation between features was estimated using Spearman’s Rank-Order Correlation. There is no visual evidence of high correlation between features, however it is worth mentioning that both ENLR and RFC have mechanisms to handle correlated predictors.

Following results from spearman correlation matrix (see annex), households with concrete walls and concrete floors tend to have a connection to a water and drainage network and are located in urban areas. Rural households tend to have less assets, lower educational level, access to health and tend to have lower prevalence of acute illness. We next report model training results.

Graphical user interface, chart

Description automatically generated

**Figure .** Features’ correlation heatmap

**Machine learning model training results**

As optimal hyperparameters were selected based on performance on training dataset, it is important to analyze how trained models perform on unseen data. We use data from 2021 as test dataset to perform this analysis. Table 2 summarizes the main results regarding model performance.

**Table 2.** Models’ performance on test dataset

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **ROC-AUC** | **Accuracy** | **F1-Score** | **MCC** | **Sensitivity** |
| ENLR | 73.76 | 73.5 | 73.31 | 47.48 | 77.75 |
| RFC | 74.24 | 73.82 | 74.3 | 48.64 | 80.9 |

RFC was selected as the best predictive model for the case of cold wave-related disaster risk in Puno. The RFC produced more accurate results than ENLR, and it achieved higher Sensitivity that makes it less prone to misclassify households at risk of being affected by cold wave-related disasters. We next report the optimal hyperparameter configuration in Equation 5:

(5)

For reproductible purposes, the trained model was saved to a file, so that it can be loaded in software to reproduce the results or use the model for practical implementations or further research.

We report below the corresponding confusion matrix:

Chart, treemap chart

Description automatically generated

Figure . Confusion matrix for Random Forest Classifier

As expected, the RFC produced more False Positives than False Negatives. However, negative classes (households that are not at risk) are more frequent than positive classes. The model is clearly focusing on positive classes, and the proposed objective function is helping to reduce False Negatives, which is the desired characteristic for the case of disasters. We next report complementary results regarding False positives and False Negatives

**Complementary descriptive analysis**

We carried out a descriptive analysis of False positives and False Negatives to complement the results above.