BANCO CENTRAL DE RESERVA DEL PERÚ

Natural events in Peru: A multidimensional analysis

Renzo Castellares*, Maria Fe García** and Jhonatan Vicuña*

* Banco Central de Reserva del Perú.
** Paris School of Economics.

DT. N°. 2025-004
Serie de Documentos de Trabajo
Working Paper Series
September 2025

Natural events in Peru: A multidimensional analysis*

Jhonatan Vicuña† Maria Fe García‡ Renzo Castellares§

June 2025

Abstract

Natural hazard events are occurring at an increasing rate worldwide, posing significant challenges for Peru. Using data from the National Institute of Civil Defense (INDECI), this study describes the spatial and temporal evolution of natural events in Peru from 2003 to 2023. We examine the frequency and distribution of these events in Peru's territory and describe its impact on affected and displaced populations, relative to local and national populations. The descriptive analysis suggests that extreme precipitations represent the greatest risk for Peruvian households given their high frequency and geographic distribution, while low temperatures also show a significant capacity to affect the population. We introduce a multidimensional metric to identify the provinces most prone to experiencing natural events, located primarily in the southern Andes and the high jungle regions. We also compare this method for identifying the most affected areas with household reports of experiencing natural disasters, using data from Peru's National Household Survey (ENAHO). Our findings reveal a direct relationship between the frequency and intensity of natural events in the district of residence and the probability that a household reports experiencing this type of shock.

Keywords: Administrative data; climate change; disaster records; household survey data; natural disasters; natural events; shocks; socioeconomic indicators; spatial distribution

*Earlier versions of this paper were presented at the XX RIDGE Forum (Santiago, Chile, December 2024); Central Bank of Peru's *XLII Encuentro de Economistas* (Lima, Peru, October 2024); and the Vietnam Symposium in Climate Transition (December 2024). We thank participants for their helpful comments. The views expressed in this paper are those of the authors and do not reflect necessarily the position of the Central Reserve Bank of Peru.

†Social Policy Unit, Central Reserve Bank of Peru (BCRP). Email: `jhonatan.vicuna@bcrp.gob.pe`

‡Master in Public Policies and Development, Paris School of Economics (PSE). Email: `maria.fe.garcia.seminario@ens.psl.eu`

§Economic Policy Design Division, Central Reserve Bank of Peru (BCRP). Email: `renzo.castellares@bcrp.gob.pe`

1 Introduction

The frequency of natural phenomena is increasing throughout the world. Disasters associated with climatological events such as extreme rains and storms have become significantly more common compared to previous decades (CRED, 2015), a trend that has been intensified by population growth and climate change (UNDRR, 2022). Several studies project an increase in the frequency and intensity of natural events, as well as greater economic losses resulting from these events (IPCC, 2012; UNDRR, 2022; IPCC, 2021).

The higher frequency of natural phenomena poses a significant risk to vulnerable countries, including Peru. The Latin America and Caribbean region is particularly susceptible to the effects of such events, with more than 190 million people affected by more than 1 500 disasters between 2000 and 2022 (UNDRR & OCHA, 2023). Peru stands out in the region due to its location on the South Pacific coast, which makes the country prone to the effects of El Niño Southern Oscillation (ENSO). This phenomenon intensifies the frequency of heavy rains, floods, and droughts during the years it occurs (CEPLAN, 2023).

Frequent natural events can have a lasting effect on household income and living conditions, affecting their long-term development. Natural disasters cause long-term damage to human capital and income-generating mechanisms, especially among the poorest households (Baez et al., 2010). These events can also modify migration patterns and reinforce the cycle of poverty. Extreme weather conditions such as rains and floods induce forced displacement (Ronco et al., 2023). On the other hand, areas highly exposed to natural disasters often become the only housing alternative for poor households, especially in developing countries (Kaushik et al., 2024; Hallegatte et al., 2016).

The literature on Peru focuses on the economic losses generated by climate change and natural disasters. Chirinos (2021) estimates that deviations from the norm in temperature between 1970 and 2019 hindered economic growth. Several studies also predict that climate change will reduce output (CEPAL, 2014) and per capita income (Chirinos, 2021; Vargas, 2009) in the coming decades. Andersen et al. (2009) find that the effect of temperature increases on income and life expectancy in recent decades differs between districts with higher and lower initial temperatures. Regarding household-level effects, Kámiche and Pacheco (2010), using a difference-in-differences approach, estimate that households affected by natural disasters reduced their consumption by 4,5 to 11 percent.

These studies do not differentiate between types of natural events based on their impact in terms of the affected population or their expansion throughout the national territory. An analysis that goes deeper into these aspects could improve our understanding of the effect of natural phenomena on regional development in Peru and the living conditions of Peruvian households.

Therefore, this document studies the natural events in Peru between 2003 and 2023. A *natural hazard event*, abbreviated hereafter as a *natural event*, is the specific occurrence of a natural hazard in a given spatiotemporal domain[1]. The analysis is conducted using a multidimensional approach, considering the *temporal* and *spatial* evolution of natural events, as well as their human impact, measured as the negative effects on the population as a result of them[2]. Temporal evolution is described through the analysis of the frequency and periodicity of natural events in Peru, spatial evolution is studied by exploring their geographical distribution throughout different political-administrative divisions[3], and human impact is analyzed by quantifying the population that was affected and displaced as a result of these events.

This study employs various data sources to characterize natural events in the country. We use official emergency records from the National Institute of Civil Defense (INDECI), which register all meteorological phenomena between 2003 and 2023, as well as the number of affected and displaced people[4]. Emergency reports include their location at the district level and date of occurrence. We also retrieve the total population of each district from the 2017 Census, along with socioeconomic variables from the 2018 Poverty Map, both compiled by the National Institute of Statistics and Information (INEI). Lastly, information on disaster risk management from local municipalities is recovered from the National Registry of Municipalities (RENAMU).

We construct a *frequency, impact, and geographic distribution index (IFIDEN[5])* to identify the areas most prone to suffer the consequences of natural events. The index describes, in a single measurement, the temporal and spatial incidence of these events and their intensity in terms of human impact, for each province of Peru and each year of the study period. The methodology involves identifying the *spatiotemporal incidence* of different types of natural events in each province of Peru. This information is synthesized by weighing each type of emergency according to the magnitude of damage it causes to the local population, measured by a *human impact index*. The synthesis of the three dimensions of the incidence of natural events into a single indicator allows for the identification of the most affected provinces, becoming a tool for prioritizing prevention and containment efforts.

With the results of the multidimensional analysis, we rank Peru's provinces according to their IFIDEN value in each year of the sample and classify the provinces that most frequently top the ranking as the most affected by natural events. We identify the 18 most affected provinces, which are located in the southern Andes and high jungle regions, in the Apurímac, Ayacucho, Cusco, Junín, Huancavelica, and Pasco departments. These provinces show poverty levels above the national average (20,5 percent in 2018), more than doubling it in half of these cases, exposing the population to a higher risk of major setbacks in their development after natural events occur. Finally, it is also worth highlighting that the district municipalities in 10 out of these provinces

[1] This definition is present in De Angeli et al. (2022)

[2] The Sendai Framework for Disaster Risk Reduction considers the impact of a natural event as the negative and positive effects generated by it (UNDRR, 2015). This study focuses on the immediate and direct human impact of natural events

[3] We cover the main three political-administrative divisions in Peru, in order of hierarchy: departments, provinces and districts, as well as the three natural regions which expand across the national territory.

[4] In this study, we use disaggregated information provided by INDECI. The official records (Compendio Estadístico del Instituto Nacional de Defensa Civil - INDECI) are available up to 2023 (INDECI, 2023).

[5] Acronym in Spanish for "Indicador de Frecuencia, Impacto y Distribución Geográfica de los Eventos Naturales"

show lower-than-average efforts for disaster risk management; therefore, implementing and/or improving prevention measures among local governments in these highly exposed areas should become a priority.

Lastly, we contrast the identification of the most affected territories through the IFIDEN index with information from the National Household Survey (ENAHO), in which households report if they were affected by a natural disaster in the last 12 months. By integrating both data sources, it is possible to distinguish between two strategies to identify households affected by natural events: through the incidence of natural events in the area of residence and through the household's self-report of having faced a natural disaster. The analysis suggests a direct relationship between natural events occurring in the household's area of residence and their perception of having been affected by a natural disaster. Specifically, it is estimated that the probability that a household reports having been affected increases as the frequency and intensity of natural events increases, both measured by the IFIDEN value.

The rest of this document proceeds as follows. In Section 2, we describe the evolution of natural events over time and across the national territory, describing their frequency, periodicity, and geographical distribution. Subsequently, in Section 3, the human impact of natural events is analyzed through the quantification of the affected and displaced population. Section 4 introduces the frequency, impact, and geographic distribution index (IFIDEN), and identifies the most affected provinces under this measure. In Section 5, we contrast the identification of these affected territories with the household's self-report of having faced a natural disaster shock in recent months. The document concludes with remarks in Section 6.

2 Frequency and geographical distribution

This section presents various measures of the *frequency* of natural events, which describe how often a specific territory experiences a natural phenomenon, and their *geographical distribution*, which examines the number of districts or provinces that have experienced these phenomena over a given period. A measurement that integrates both units is developed to simultaneously evaluate the dimensions of time and space, referred to as *district-week*.

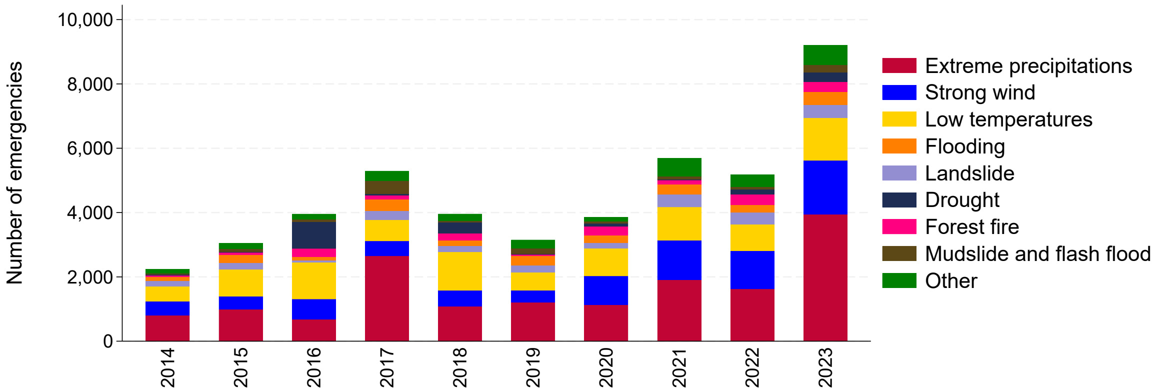
2.1 Frequency of natural events

Figure 1 illustrates the evolution of the number of natural events reported each year. A natural event is recorded if it occurs in a specific district at least once during a given week[6]. The main eight categories of events are shown in the figure[7], with the rest grouped into the "Others" category.

[6] If there is more than one record of a type of natural event in a single week in a specific district, this is counted as one sole occurrence, no matter how many times the event happened during said week.

[7] The eight categories with the highest number of records between 2003 and 2023.

Figure 1: Evolution of the number of natural events



Source: Authors, based on information from INDECI.

Extreme precipitations, low temperatures, and strong winds are identified as the most frequent categories during the study period[8]. Except for 2022, reported emergencies have increased consistently since 2019. The highest reported emergencies were recorded in 2017, 2021 and 2023. In the cases of 2017 and 2023, these were years of El Niño (ENSO) manifestation, characterized by increased frequency of heavy rains, floods, mudslides, and landslides.

2.2 Monhtly distribution of natural events

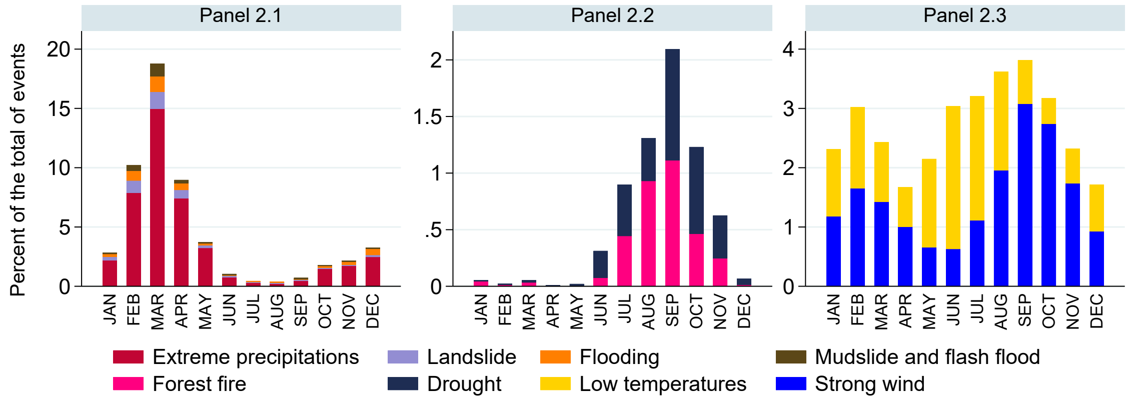
Figure 2 presents the monthly distribution of the different event categories during 2023. Panel 2.1 groups events that intensify with El Niño, while Panel 2.2 groups events associated with high temperatures and drier conditions. Finally, Panel 2.3 groups those categories related to lower temperatures and changes in wind patterns.

More than 20 percent of all events in 2023 occurred in March, mainly categories in Panel 2.1. Extreme precipitations, landslides, mudslides, and floods occurred more frequently between February and April. The first category was predominant, accounting for 43 percent of the total events of the year.

Forest fires and droughts (Panel 2.2) occurred more frequently in the second half of the year, mainly between July and October, but were the least frequent events during the year since they represented less than 7 percent of the total. Finally, Panel 2.3 shows that strong winds were most frequent between August and November, while low-temperature episodes were more common between May and August.

[8]Appendix 1 gives a detailed definition of the categories included in this study.

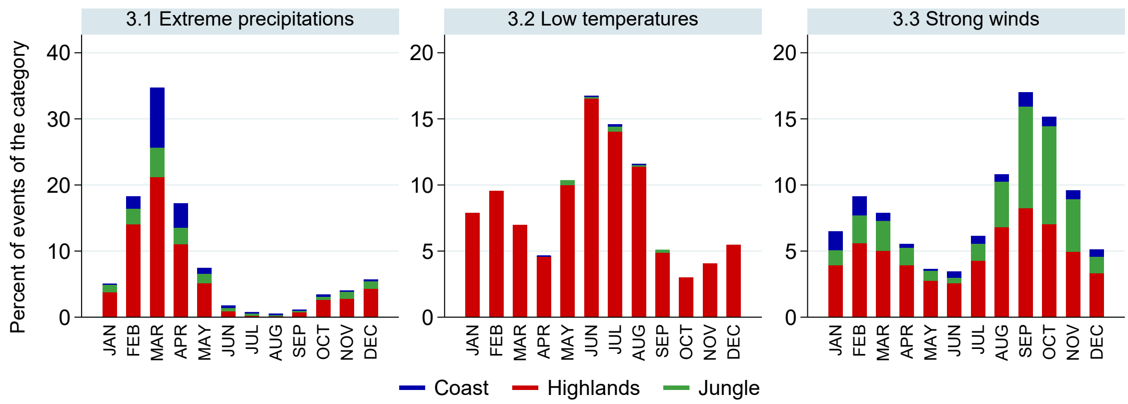
Figure 2: Monthly distribution of natural events in 2023



Source: Authors, based on information from INDECI.

Natural events occur with varying frequency throughout the year and across Peru's natural regions. Figure 3 presents the monthly distribution of the three main event categories by natural region, showing that 67 percent of extreme precipitation events occurred mainly in the highlands, especially between May and August (Panel 3.1). Low-temperature events took place almost entirely in the highlands between May and August (Panel 3.2), and strong winds manifested with similar frequency in the jungle and highland regions, with higher occurrence in September and October (Panel 3.3).

Figure 3: Monthly distribution of natural events in 2023, by natural region



Source: Authors, based on information from INDECI.

2.3 Geographical distribution: Number of affected districts

To analyze the spatial distribution of natural events, Table 1 summarizes their incidence between 2003 and 2023 among the 1 890 districts in Peru. Districts are the lowest-hierarchy political administrative division in Peru. A district is considered as *affected* by an event in a given year if it experienced the event at least once during the year.

Between 2003 and 2023, extreme precipitations affected between 235 and 1 242 districts at least once each year, reaching the maximum in 2023. Districts affected by extreme precipitations experienced them for 3,2 non-consecutive weeks and around 1,6 consecutive weeks on average in 2023. Low temperatures affected up to 715 districts in a year, while strong wind events reached between 214 and 642 districts in each year of the study period. Overall, 4 out of 9 categories of natural events reached the maximum number of affected districts in 2023.

Table 1: Incidence of natural events

Category	Number of districts affected at least once a year			Average number of weeks a district was affected, 2023[2]	Maximum number of consecutive weeks in which a district was affected, on average, 2023[2]
	2023	Minimum 2003-23[1]	Maximum 2003-23[1]		
Extreme precipitations	1 242	235	1 242	3,2	1,6
Low temperatures	566	99	715	2,3	1,2
Strong winds	642	214	642	2,6	1,2
Drought	200	1	597	1,5	1,1
Flooding	266	96	292	1,5	1,1
Landslide	264	55	264	1,5	1,2
Mudslide and flash flood	157	35	230	1,4	1,1
Forest fire	190	5	190	1,6	1,1
Other	372	83	411	1,7	1,1

Source: Authors, based on information from INDECI.
1/ Value of the year with the minimum/maximum number of affected districts for each emergency category.
2/ Average among all districts that suffered the event at least once in 2023.

Table 2 presents indicators of the frequency and geographical distribution of natural events for the 2003-2023 period. To analyze the frequency, the average number of weeks per year in which a district was affected, given that it experienced the natural, is presented. Throughout the study period, extreme precipitations and strong winds were the most frequent events. Regarding geographical distribution, the table shows the maximum number of districts affected by each emergency category in a single week and month as a percentage of the total districts in the country. Once again, extreme precipitation events stand out, since they affected up to 46,9 percent of districts in a single month and 23,7 percent in a week.

The last column in Table 2 shows the percentage of district-weeks affected by each event category k ($dist\_week_k$). This variable offers a measure of the incidence of natural events across time and space by aggregating the number of weeks in which a district was affected across all districts in the country. The calculation is given by:

$$dist\_week_k = \frac{\sum_i \sum_j Events_{ijk}}{\text{Total number of districts} \times \text{Total number of weeks}} \tag{1}$$

$Events_{ijk}$ represents the number of events of category k that occurred in district i during week j. The denominator represents the maximum possible number of district-week combinations, a hypothetical scenario where all districts in the country register the emergency category every week of the study period. Thus, the value of the indicator increases if events of the category occur more frequently (higher frequency) and/or in more districts (greater geographical distribution). Extreme precipitations show the highest bi-dimensional incidence, manifesting in 1,2 percent of the total possible district-weeks for the 2003-2023 period. In second place, while low-temperature events are less frequent than strong winds, their greater geographic distribution accounts for a similar bi-dimensional incidence.

Table 2: Frequency and geographical distribution: 2003-2023

Category	**Frequency**	**Geographical Distribution**		**District-weeks affected**[3] (% of total district-weeks)
	Average number of weeks that a district is affected[1]	**Maximum number of districts affected in a week**[2] (% districts)	**Maximum number of districts affected in a month**[2] (% districts)	
Extreme precipitations	2,1	23,7	46,9	1,2
Low temperatures	1,6	12,4	18,9	0,7
Strong winds	2,1	5,9	11,7	0,7
Landslide	1,4	2,0	5,8	0,2
Flooding	1,4	3,1	7,8	0,3
Drought	1,1	8,7	16,8	0,1
Forest fire	1,4	2,3	4,9	0,1
Mudslide and flash flood	1,2	4,9	7,7	0,1
Other	1,4	10,1	10,6	0,2

Source: Authors, based on information from INDECI.
1/ The number of weeks in which each category of emergency affected a district each year is calculated and averaged across all districts that reported any event of that category in that year. The table presents the average of the resulting values from 2003 to 2023.
2/ The week or month with the highest number of districts affected by each emergency is identified and shown as a percentage of the total number of districts in Peru (1 890 districts).
3/ This indicator corresponds to the number of weeks in which a district was affected by each type of emergency, aggregated for all districts in the country. The double summation is expressed as a percentage of the total number of district-week combinations possible, equivalent to a total of 52 weeks in a year x 1 890 districts x 10 years.

2.4 Incidence of events across natural regions

Table 3 presents the frequency and geographical distribution across the three natural regions of Peru[9]. Extreme precipitation events have affected up to 37,5 percent of districts on the coast, 24,2 percent in the highlands, and 16 percent in the jungle in a single week.

The table also shows regional variations: low-temperature events have taken place in up to 19,2 percent of districts in the highlands, while up to 13,1 percent of districts in the jungle experienced strong winds. Among less frequent categories, mudslides and floods affected up to

[9]The division of the national territory in the Coast, Highlands, and Jungle regions has long been used and is a common approach for political administration and policy analysis in Peru. The boundaries of these regions are determined by stark geographical differences between the desert, mountains, and rainforest areas, even though the territories within each region can be greatly heterogeneous. The INDECI database recovers the natural region where each occurrence happened, associated most likely with the district in the record.

11,8 and 11,2 percent of coastal districts in a single week respectively, while droughts manifested in up to 13,4 percent of districts in the highlands region.

Table 3: Frequency and geographical distribution: 2003-2023, by natural regions

Category \ Region	**Average number of weeks that a district is affected**[1]			**Maximum number of districts affected in a single week**[2]		
	Coast	**Highlands**	**Jungle**	**Coast**	**Highlands**	**Jungle**
Extreme precipitations	1,6	2,2	2,1	37,5	24,2	16,0
Low temperatures	1,1	1,6	1,2	1,1	19,2	4,5
Strong winds	2,4	1,9	2,3	3,8	6,3	13,1
Forest fire	1,2	1,3	1,3	1,1	2,8	4,5
Landslide	1,2	1,3	1,6	1,9	2,5	3,8
Drought	0,8	1,1	0,6	10,4	13,4	4,5
Flooding	1,3	1,3	1,5	11,2	3,7	12,5
Mudslide and flash flood	1,0	1,2	1,3	11,8	4,1	1,9
Other	1,7	1,3	1,4	17,3	9,4	30,8

Source: Authors, based on information from INDECI.
1/ The number of weeks in which each category of emergency affected each district of the region each year is calculated and averaged across all districts that reported any event of that category in that year. The table presents the average of the resulting values from 2003 to 2023.
2/ The week with the highest number of districts affected by each emergency in the natural region is identified and shown as a percentage of the total number of districts in each natural region.

2.5 Incidence across departments

Table 4 presents the bi-dimensional incidence of natural events using the district-week indicator, calculated for each department and the three most prevalent categories in each natural region. The department with the highest record is Pasco, where up to 4,1 percent of district-weeks recorded extreme precipitations, 2,6 percent low temperatures, and 2 percent strong winds. Other departments with high incidence are Apurímac, Tumbes, Ucayali, and Huancavelica.

2.6 Incidence across provinces and districts

This section further breaks down the analysis to identify the provinces and districts with the highest occurrence of natural events. To measure how often a province has been affected by a natural event during a year, the average number of weeks that a district in the province experienced the event is calculated, considering only those districts in the province that were affected by said event at least once during the evaluated year. The average of these values for the 2003-2023 period is then computed.

The ten provinces with the highest averages are listed in Table 5, along with additional information on the spatial distribution of the event within the province. The Daniel Alcides Carrion and Pasco provinces, which are among the ten most affected by extreme precipitations, are within the department of Pasco, which has also shown a high frequency of this type of event. The most affected province, Abancay in the Apurímac department, had 81,5 percent of its districts

Table 4: District-weeks affected between 2003 and 2023 (percentage of total possible district-weeks in the department).

Departments mainly in the highlands			
Department	**Extreme precipitations**	**Low temperatures**	**Strong winds**
Pasco	4,1	2,6	2,0
Apurímac	3,2	2,3	2,3
Huancavelica	2,3	1,9	0,9
Cajamarca	1,9	0,1	0,7
Ayacucho	1,9	0,8	0,7
Huánuco	1,3	1,0	0,7
Arequipa	1,1	0,8	0,1
Cusco	1,1	1,8	0,5
Áncash	0,9	0,1	0,1
Junín	0,5	0,5	0,4
Puno	0,4	1,3	0,5
Departments mainly in the jungle			
Department	**Strong winds**	**Extreme precipitations**	**Flooding**
Ucayali	3,5	0,6	1,6
Loreto	1,5	0,1	0,8
San Martín	1,4	0,4	0,8
Madre de Dios	1,0	0,8	1,5
Amazonas	0,7	1,6	0,2
Departments mainly in the coast			
Department	**Extreme precipitations**	**Strong winds**	**Flooding**
Tumbes	3,8	2,7	0,5
Piura	1,9	1,0	0,2
Moquegua	1,5	0,5	0,2
Lambayeque	1,1	0,5	0,1
La Libertad	0,7	0,2	0,1
Tacna	0,7	0,2	0,1
Ica	0,5	0,0	0,3
Lima[1]	0,3	0,0	0,1

Source: Authors, based on information from INDECI.
1/ Includes the Lima Metropolitan Area and Callao.
Note: This indicator corresponds to the number of weeks in which a district was affected by each type of emergency, aggregated for all districts in the department. The double summation is expressed as a percentage of the total number of district-week combinations possible.

experience extreme precipitations at least once a year on average, during 4,3 weeks in the year on average.

The provinces that were most affected by low-temperature events are mainly in the highlands, in the Apurímac, Cusco, Huancavelica, and Pasco departments. In the case of strong wind events, the ten most affected provinces do not belong to a single specific region and rather are located across the national territory. The list also includes all of the provinces in the department of Ucayali.

Table 6 lists the districts that experienced the highest frequency of the three main categories of natural events, based on the average number of weeks per year the district faced each type of event. Abancay (Apurímac), Huancavelica (Huancavelica), and Chachapoyas (Amazonas) are the districts with the highest frequency of extreme precipitations, with the first one reaching an average of more than 10 weeks of this phenomenon per year. Regarding low-temperature events, Yauli, Acoria, and Huancavelica present the highest prevalence, the first recording an average of 5,7 weeks of the event per year. Among the districts most affected by strong winds, the coastal districts of Tambo Grande (Piura) and San Jacinto (Tumbes) stand out, as well as Yauli, which also experience extreme precipitations often.

An alternative way to assess the geographic distribution criterion is to examine the number of districts unaffected by each type of natural event during the study period. The fewer unaffected districts by a type of event, the more widespread that phenomenon is. Table 7 presents this calculation for each type of event, disaggregated by natural region. Only 120 districts in the country have not been affected by extreme precipitations between 2003 and 2023, reflecting the high frequency of occurrence of this phenomenon. The next two events with the fewest unaffected districts are strong winds and low temperatures, which show differences in their regional spread. It is worth highlighting that only 7 districts were not exposed to any type of event throughout the entire period (see Table 8). Four of these districts are located in the Lima Metropolitan Area.

Table 5: Provinces with the highest frequency of natural events

	Natural region	Department	Province	Number of weeks per year a district of the province is affected, average[1]	Affected districts, average[2] (% of districts in the province)
			Extreme precipitations		
1	Highlands	Apurímac	Abancay	4,3	81,5
2	Highlands	Huancavelica	Huancavelica	3,9	47,9
3	Highlands	Pasco	Pasco	3,6	63,4
4	Highlands	Pasco	Daniel Alcides Carrión	3,5	57,1
5	Highlands	Cajamarca	Cajamarca	3,4	41,3
6	Highlands	Apurímac	Cotabambas	3,4	63,5
7	Highlands	Áncash	Huaraz	3,3	36,1
8	Jungle	Amazonas	Utcubamba	3,0	63,3
9	Highlands	Apurímac	Chincheros	2,9	53,6
10	Coast	Tumbes	Tumbes	2,8	65,1
			Low temperatures		
1	Highlands	Apurímac	Cotabambas	2,9	78,6
2	Highlands	Huancavelica	Huancavelica	2,3	62,2
3	Highlands	Cusco	Chumbivilcas	2,2	69,6
4	Highlands	Cusco	Canas	2,2	72,0
5	Highlands	Pasco	Pasco	2,1	67,0
6	Highlands	Pasco	Daniel Alcides Carrión	2,0	61,9
7	Highlands	Huancavelica	Angaraes	1,9	50,8
8	Highlands	Cusco	Quispicanchi	1,9	56,0
9	Highlands	Apurímac	Antabamba	1,9	78,2
10	Highlands	Huancavelica	Acobamba	1,8	64,3
			Strong winds		
1	Coast	Piura	Piura	5,6	26,7
2	Jungle	Ucayali	Padre Abad	4,5	36,7
3	Jungle	Loreto	Maynas	4,0	46,8
4	Coast	Tumbes	Contralmirante Villar	4,0	41,3
5	Coast	Tumbes	Tumbes	3,6	40,5
6	Jungle	Ucayali	Purús	3,5	57,1
7	Highlands	Huancavelica	Huancavelica	3,5	31,1
8	Highlands	Apurímac	Chincheros	3,2	60,3
9	Jungle	Ucayali	Coronel Portillo	3,1	60,5
10	Jungle	Ucayali	Atalaya	3,0	38,1

Source: Authors, based on information from INDECI.
1/ The number of weeks in which each category of emergency affected each district of the province each year is calculated and averaged across all districts that reported any event of that category in that year. The table presents the average of the resulting values from 2003 to 2023.
2/ The number of districts in the province that were affected by each emergency at least once a year is calculated, for each year of the study period. The table shows the average of these values as a percentage of the total number of districts in the province.

Table 6: Districts with the highest frequency of natural events

	Department	Province	District	Average weeks in a year[1]
		Extreme precipitations		
1	Apurímac	Abancay	Abancay	10,2
2	Huancavelica	Huancavelica	Huancavelica	9,6
3	Amazonas	Chachapoyas	Chachapoyas	8,8
4	Cajamarca	Cajamarca	Cajamarca	8,3
5	Áncash	Huaraz	Independencia	7,4
6	Apurímac	Cotabambas	Tambobamba	6,4
7	Apurímac	Andahuaylas	Andahuaylas	6,2
8	Pasco	Daniel Alcides Carrión	Yanahuanca	6,0
9	Huancavelica	Huancavelica	Yauli	5,9
10	Pasco	Pasco	Yanacancha	5,8
		Low temperatures		
1	Huancavelica	Huancavelica	Yauli	5,8
2	Huancavelica	Huancavelica	Acoria	3,7
3	Huancavelica	Huancavelica	Huancavelica	3,3
4	Apurímac	Cotabambas	Challhuahuacho	3,3
5	Apurímac	Cotabambas	Haquira	3,1
6	Huancavelica	Angaraes	Lircay	3,1
7	Pasco	Daniel Alcides Carrión	Yanahuanca	3,0
8	Apurímac	Cotabambas	Tambobamba	3,0
9	Huancavelica	Huaytará	Pilpichaca	2,8
10	Cusco	Chumbivilcas	Santo Tomas	2,6
		Strong winds		
1	Piura	Piura	Tambo Grande	7,6
2	Huancavelica	Huancavelica	Yauli	6,3
3	Loreto	Maynas	Punchana	6,0
4	Tumbes	Tumbes	San Jacinto	5,7
5	Ucayali	Padre Abad	Padre Abad	5,2
6	Apurímac	Antabamba	Antabamba	5,0
7	Loreto	Maynas	Belén	4,9
8	Loreto	Maynas	San Juan Bautista	4,9
9	Tumbes	Contralmirante Villar	Casitas	4,8
10	Piura	Piura	Las Lomas	4,6

Source: Authors, based on information from INDECI.
1/ The number of weeks in which each category of emergency affected each district each year is calculated. The table presents the average of the resulting values from 2003 to 2023.

Table 7: Districts that were not affected by a natural event between 2003 and 2023, by category

	Number of districts not affected by the event category between 2003 and 2023			
Category	**Coast**	**Highlands**	**Jungle**	**Total**
Extreme precipitations	42	37	41	**120**
Strong winds	218	311	26	**555**
Low temperatures	284	159	209	**652**
Flooding	132	587	29	**748**
Landslide	281	490	103	**874**
Drought	264	497	236	**997**
Forest fire	301	681	197	**1 179**
Mudslide and flash flood	231	678	199	**1 108**
Other	84	394	59	**537**
Total districts per region	**365**	**1 213**	**312**	**1 890**

Source: Authors, based on information from INDECI.

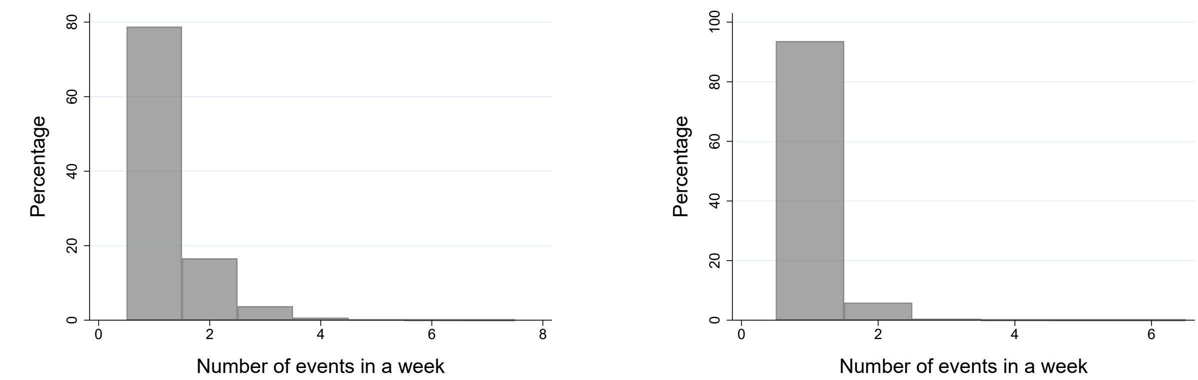
Table 8: Districts that were not affected by any natural event between 2003 and 2023

Region	**Department**	**Province**	**District**
Coast	Lima	Lima	Jesús María
Coast	Lima	Lima	Lince
Coast	Lima	Lima	San Luis
Coast	Lima	Lima	Santa María del Mar
Highlands	Ancash	Pallasca	Huacaschuque
Highlands	Puno	San Román	San Miguel
Jungle	Amazonas	Bongará	San Carlos

Source: Authors, based on information from INDECI.

Figure 4: Number of simultaneous events in a week

(a) Provinces **(b)** Districts



Source: Authors, based on information from INDECI.
Note: The distribution classifies every province-week and district-week combination during the 2003-2023 period in which at least one event was recorded, according to the number of different categories of events that occurred simultaneously in a given week.

2.7 Simultaneity of events

Figure 4 complements the previous analysis by showing the distribution of the number of simultaneous events affecting the provinces and districts of Peru in a given week. Considering all the weeks between 2003 and 2023 in which at least one event happened in a province, in more than 20 percent of cases, a province experienced two or more categories of natural events in the same week, while in the case of districts, this occurred in less than 7 percent of cases.

In this chapter, the most recurrent natural phenomena in Peru between 2003 and 2023 have been identified by presenting various measures of frequency and geographical distribution associated with these events. According to the different measures presented, extreme precipitations, low temperatures, and strong winds are the most frequent categories of events. While these events show varying seasonality, the high frequency of extreme precipitations between February and April predominates in the monthly distribution. Regarding geographical distribution, extreme precipitations, low temperatures, and droughts are the most widespread phenomena at the national level. The disaggregated analysis by natural regions and departments shows differences in the pattern of events across the national territory, revealing the highest incidence of natural events in the Pasco, Apurímac, Ucayali, Tumbes, and Huancavelica departments.

3 Human impact: People affected and displaced by natural events

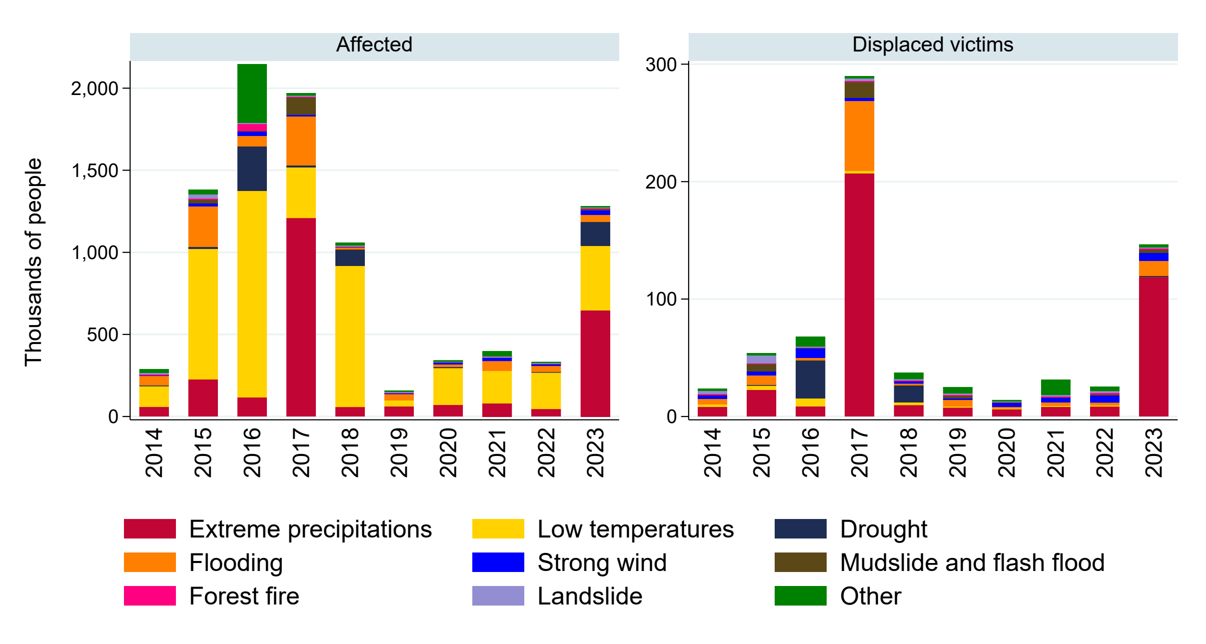
The frequency and geographical distribution indicators presented in the previous section show the historical exposure of a district or province to natural events. However, both dimensions are independent of *human impact*, which measures the effects of a natural event on the population.

A district can be consistently exposed to a natural phenomenon without registering significant damage regarding the number of affected or displaced individuals.

This section studies the human impact of natural events by analyzing the number of affected and displaced individuals caused by natural events. An *affected* person has experienced a disruption in their environment due to a natural event, while a *displaced* person has suffered damage or harm to their health or property, particularly their home, and could be unable to recover without additional support[10].

Figure 5 shows the number of affected and displaced individuals caused by each type of natural event in Peru. During the studied period, low-temperature emergencies caused the largest number of affected people, except in 2017 and 2023, when extreme precipitations associated with El Niño (ENSO) had a greater impact. The latter category, together with flooding and droughts, caused the highest number of displaced people throughout the study period.

Figure 5: Affected and displaced individuals, by emergency category



Source: Authors, based on information from INDECI.
Note: The number of affected and displaced individuals each year is calculated by identifying the maximum number recorded in each district and each week of the year, and adding these figures for every district in the country and every week of the year.

Table 9 presents the number of affected and displaced individuals and the frequency of natural events in 2023, to contrast these measures and evaluate whether more frequent events also have the greatest toll in terms of human impact. The figures suggest that the relationship between frequency and the number of affected and displaced people is not direct or linear. Extreme precipitation events evidenced a high frequency and great intensity, recording 3 949 occurrences in 2023, which caused the greatest number of displaced (118 854) and affected (645 682) individuals. However, the second most frequent category, strong winds, caused up to 27

[10] Appendix 2 presents a more detailed definition of affected and displaced individuals.

935 affected and 6 512 displaced individuals, smaller numbers than those caused by other less frequent categories such as low temperatures (392 826 affected), droughts (146 755 affected), and flooding (13 086 displaced).

Table 9: Affected and displaced individuals in 2023

Category	Number of emergencies	Displaced (number of people)	Affected (number of people)
Extreme precipitations	3 949	118 854	645 682
Strong winds	1 668	6 512	27 935
Low temperatures	1 329	808	392 826
Landslide	402	1 045	4 624
Flooding	402	13 086	43 875
Forest fire	310	413	1 256
Drought	308	31	146 755
Mudslide and flash flood	219	3338	12 396
Other	616	2 533	5 824

Source: Authors, based on information from INDECI.
Note: An *affected* individual has experienced a disruption in their environment due to a natural event. A *displaced* individual has suffered damage or harm to their health or property, particularly their home, and could be unable to recover without additional support (see Appendix 2). The number of affected and displaced individuals each year is calculated by identifying the maximum number recorded in each district and each week of the year, and adding these figures for every district in the country and every week of the year.

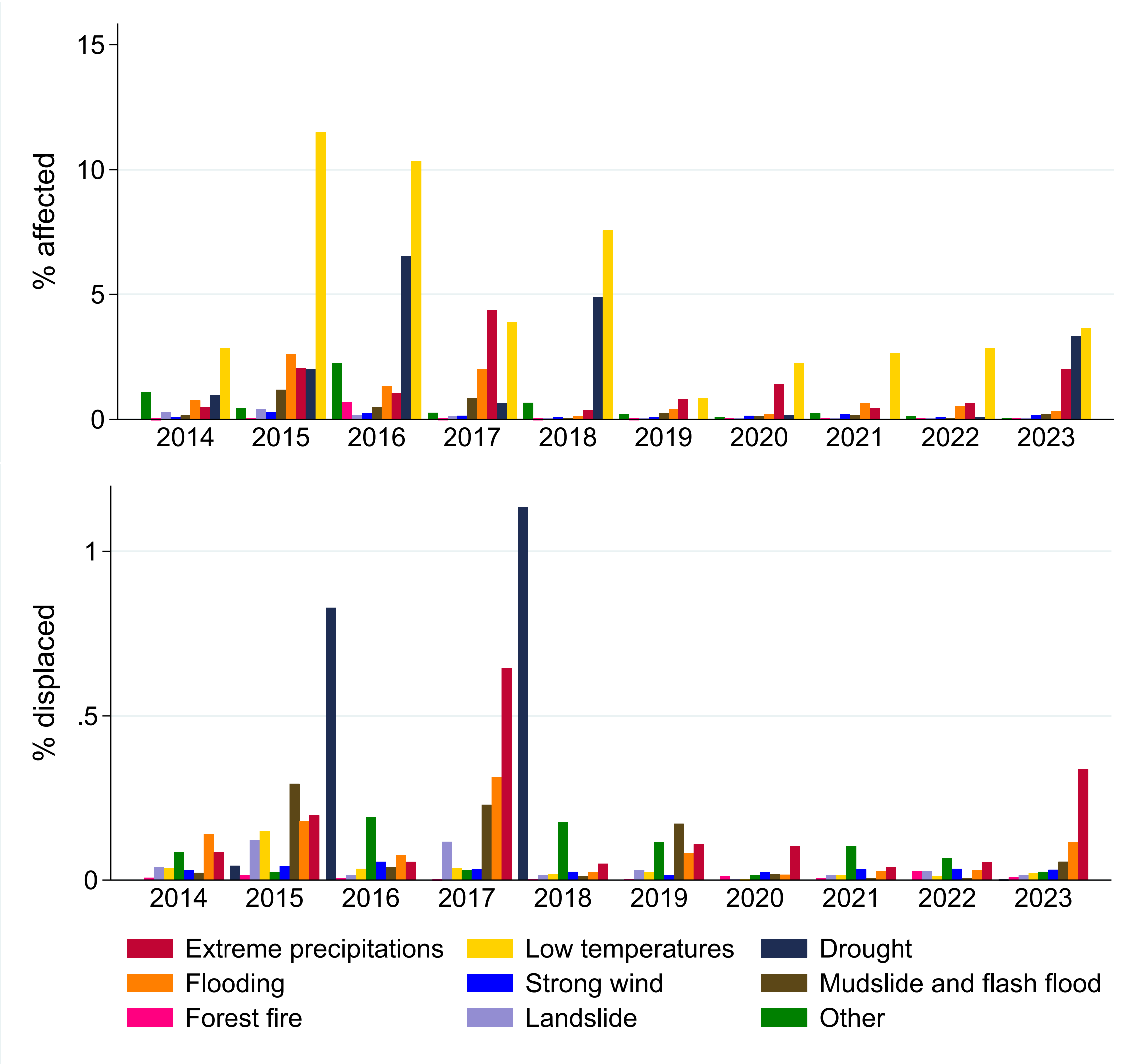
3.1 Local human impact

To determine which events represent the greatest potential damage to the population in the provinces of Peru, the *local human impact* of each emergency category is measured by the maximum number of affected or displaced people that can be reported in a province during one week for a given year[11]. Figure 6 shows the average of this value among all provinces that experienced each category at least once in the year, for each year between 2014 and 2023.

The figure reveals that low-temperature events and droughts affect the highest percentage of the local population, meaning these two types of emergencies cause the most affected individuals in the provinces where they occur. Low-temperature episodes affected over 10 percent of the local population in 2015 and 2016, while droughts affected up to 6,6 percent in 2016. Droughts and extreme precipitation events caused the highest percentage of displaced individuals, with droughts displacing over 1 percent of the local population in 2018.

[11] We analyze human impact at the province level to reduce discrepancies between INDECI records and population estimates at the district level, recovered from the National Census 2017.

Figure 6: Maximum population affected and displaced in a single week, province level



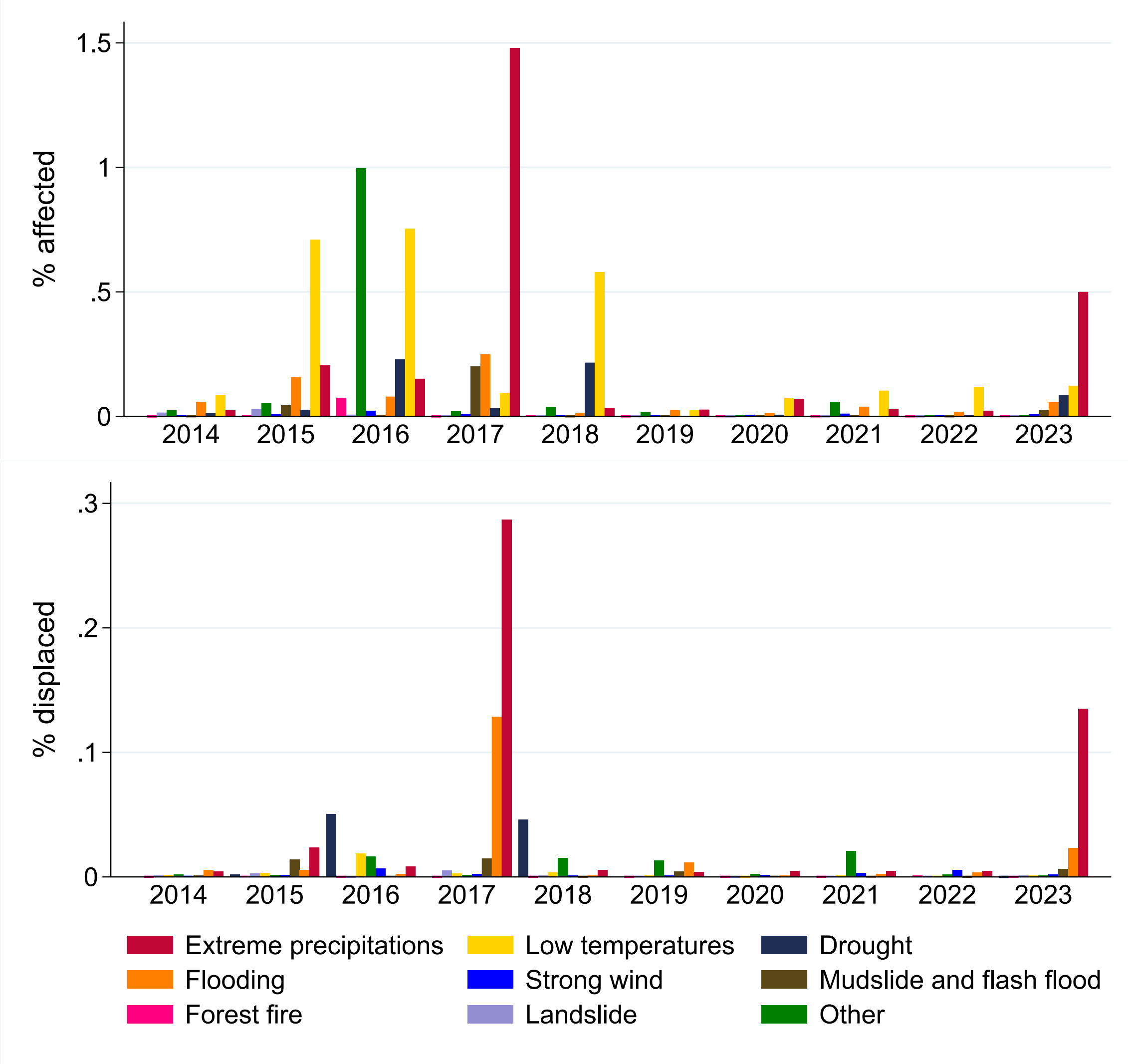
Source: Authors, based on information from INDECI and INEI.
Note: For each province, the week that registers the highest number of affected and displaced people caused by each category is identified, and these numbers are expressed as a percentage of the province's population. These values are averaged each year across all provinces that experienced the category of natural event at least once during the year.

3.2 National human impact

Additionally, *national human impact* is presented, quantifying the effect of natural events across the entire country during a given period. To calculate this, the number of affected and displaced individuals caused by each type of emergency nationwide during each week is identified, and the week with the maximum values is determined for each year of the study period. Figure 7 shows these values as a percentage of the national population.

Extreme precipitation events caused the largest number of affected individuals nationwide in 2017 and 2023, affecting up to 1,5 and 0,5 percent of the national population in a single week, respectively. Low temperatures also affect a significant number of individuals, between 0,5 and 1 percent of the national population in a single week, in 2015, 2016, and 2018. Regarding displaced population, extreme precipitations displaced around 0,3 percent of the national population in a single week in 2017 and more than 0,1 percent in 2023.

Figure 7: Maximum population affected and displaced in a single week, nationwide



Source: Authors, based on information from INDECI and INEI.
Note: The week that registers the highest number of affected and displaced people caused by each category nationwide is identified, and these values are expressed as a percentage of the national population. The national population is estimated from data in the 2017 National Census.

Table 10 summarizes the local and national human impact indicators studied for the 2003-2023 period. Analyzing each category of emergency separately, it is confirmed that low-temperature events generate the highest percentage of affected population at the local level, while extreme precipitation events do so at the national level. Meanwhile, drought events displaced the highest percentage of the population at the local level, while extreme precipitations and flooding did so when considering the national population.

Table 10: Local (province level) and national human impact indicators: 2003-2023

Category	Local human impact (province level)[1] (% of local population, average)				National human impact[2] (% of national population)	
	In a single week		In a single month		In a single week	
	Maximum affected	Maximum displaced	Maximum affected	Maximum displaced	Maximum affected	Maximum displaced
Low temperatures	5,55	0,10	6,70	0,10	0,75	0,10
Drought	4,53	0,33	4,72	0,34	0,96	0,07
Extreme precipitations	1,67	0,20	2,02	0,23	1,48	0,29
Flooding	1,02	0,23	1,15	0,27	0,41	0,18
Mudslide and flash flood	1,05	0,07	1,18	0,08	0,20	0,01
Strong winds	0,20	0,04	0,22	0,04	0,06	0,01
Landslide	0,33	0,05	0,33	0,05	0,12	0,01
Forest fire	0,06	0,02	0,07	0,02	0,08	0,00
Other	0,66	0,25	0,66	0,25	1,00	1,33

Source: Authors, based on information from INDECI and INEI.
1/ For each province, the week that registers the highest number of affected and displaced people caused by each category is identified, and these numbers are expressed as a percentage of the province's population. These values are averaged across all provinces that experienced the category of natural event at least once during the year, for each year of the study period. The table shows the average of these values from 2003 to 2023. The local population is estimated from data in the 2017 National Census.
2/ The week that registers the highest number of affected and displaced people caused by each category nationwide is identified, and these values are expressed as a percentage of the national population. The national population is estimated from data in the 2017 National Census.

3.3 Human impact by department

As analyzed in previous sections, Peru's natural regions are affected differently by each category of natural event, both in frequency and magnitude, which also affects their impact on the population. Table 11 presents human impact indicators for the 24 departments of Peru, grouped by their predominant natural region. The three most frequent categories of natural events for each are considered. The table shows, for each category, the maximum number of affected individuals registered in a single week and the average affected population in 2023, expressed as a percentage of the department population.

Table 11 confirms previous findings regarding the impact of extreme precipitation and low-temperature events. For departments predominantly on the coast, extreme precipitations exerted the greatest impact, affecting over 13 percent of the population of La Libertad and over 31 percent of the population of Tumbes in a single week. Among departments in the highlands, low temperatures affected up to 25,2 percent of the population in Huancavelica, 24,8 percent of the population of Pasco, and more than 13 percent of the population of Apurímac and Puno in a single week, while extreme precipitations affected up to 8,2 percent of the population in Apurímac. In the jungle region, extreme precipitations and floods affected up to 5,7 and 6,3 percent of the population in Madre de Dios, respectively. While strong winds are highly prevalent across all three natural regions, they do not significantly affect the population.

Table 11: Human impact indicators by department

Departments mainly in the coast

Category	Maximum population affected[1] (% of the department's population)			Average population affected in 2023[2] (% of the department's population)		
	Extreme precipitation	Strong winds	Flooding	Extreme precipitation	Strong winds	Flooding
Tumbes	31,51	0,62	1,21	0,35	0,01	0,00
La Libertad	13,88	0,15	0,35	0,10	0,00	0,00
Moquegua	8,71	0,36	0,22	0,07	0,00	0,00
Piura	5,08	0,96	2,47	0,42	0,01	0,02
Lambayeque	4,97	0,19	0,42	0,47	0,00	0,07
Ica	3,20	0,10	1,98	0,19	0,00	0,01
Tacna	2,57	1,95	0,52	0,17	0,03	0,00
Lima*	0,10	0,02	0,12	0,01	0,00	0,00

Departments mainly in the highlands

Category	Maximum population affected[1] (% of the department's population)			Average population affected in 2023[2] (% of the department's population)		
	Extreme precipitation	Low temperatures	Strong winds	Extreme precipitation	Low temperatures	Strong winds
Apurímac	8,23	13,96	0,99	0,01	0,27	0,00
Huancavelica	6,56	25,20	0,73	0,24	0,46	0,02
Huánuco	5,65	9,36	1,14	0,01	0,05	0,01
Áncash	5,33	0,25	0,04	0,08	0,01	0,00
Ayacucho	3,49	4,33	0,59	0,04	0,03	0,00
Cajamarca	3,22	0,36	0,07	0,02	0,00	0,00
Arequipa	2,14	1,56	0,42	0,05	0,04	0,00
Cusco	1,80	6,87	0,54	0,00	0,17	0,00
Pasco	0,73	24,76	0,27	0,01	0,30	0,01
Puno	0,71	13,95	0,09	0,01	0,09	0,00
Junín	0,16	1,63	0,06	0,01	0,15	0,00

Departments mainly in the jungle

Category	Maximum population affected[1] (% of the department's population)			Average population affected in 2023[2] (% of the department's population)		
	Strong winds	Extreme precipitation	Flooding	Strong winds	Extreme precipitation	Flooding
Amazonas	0,44	0,72	0,36	0,01	0,01	0,02
Madre de Dios	0,27	5,68	6,31	0,01	0,01	0,05
Ucayali	0,25	1,32	8,64	0,00	0,05	0,09
San Martín	0,13	1,37	2,74	0,00	0,03	0,07
Loreto	0,12	0,33	12,78	0,00	0,00	0,18

Source: Authors, based on information from INDECI and INEI.
* Includes the Lima Metropolitan Area and Callao.
1/ The number of affected individuals in the department is calculated for every week between 2003 and 2023, and the week with the highest value is identified. The value is presented as a percentage of the total population of the department.
2/ The number of affected individuals in the department is calculated for every week in 2023 in which the event category occurred in the department, and the average of these values is presented as a percentage of the total population of the department.

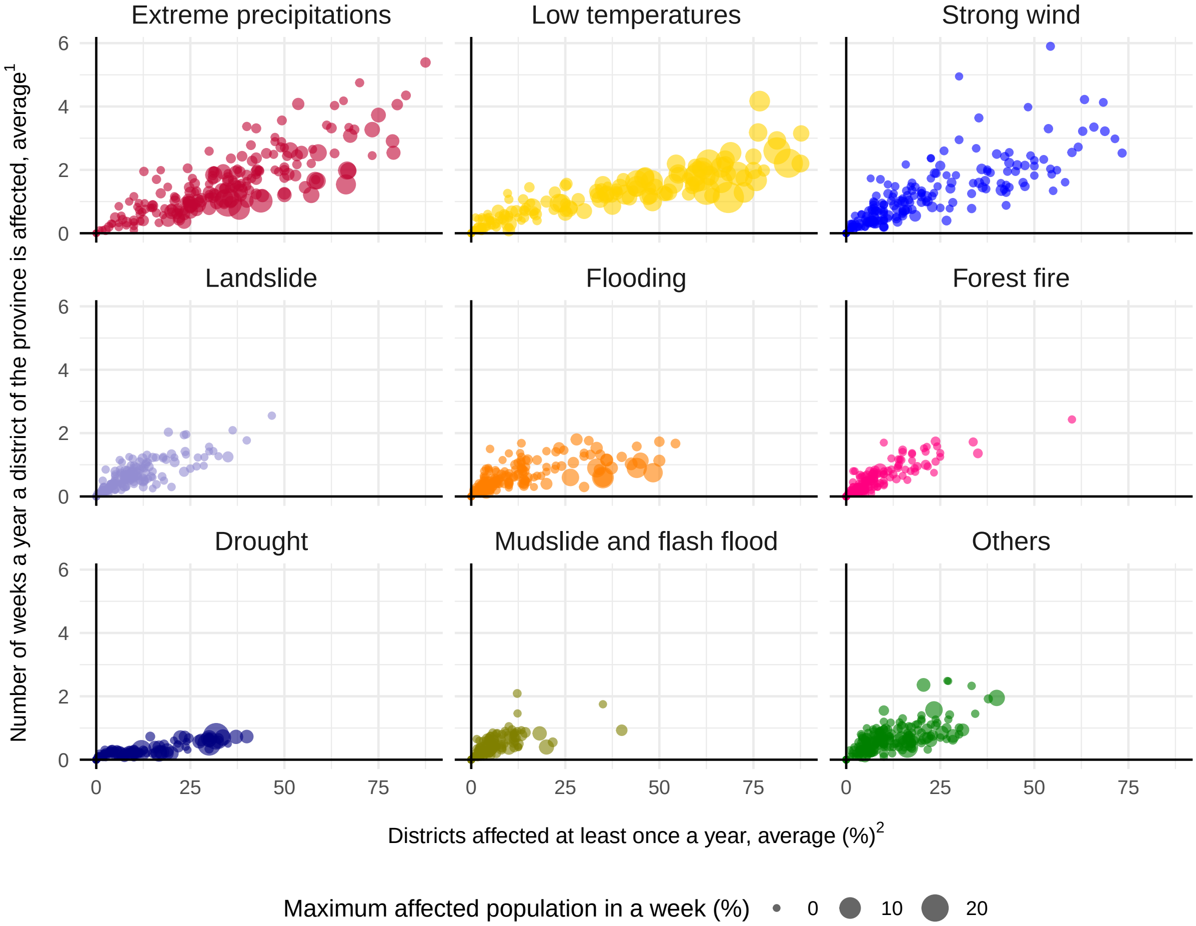
4 Multidimensional analysis: Frequency, Impact and Geographic Distribution Index

This section unifies the analysis of the three studied dimensions (time, space, and human impact) to determine which provinces reported the highest occurrence of natural events and the greatest harm to their population. Figure 8 shows the interaction between these dimensions in the provinces of Peru during the 2014-2023 period. Each point in the graph represents a province. The vertical axis represents the frequency of each event in the province, measured by the number of weeks per year in which a district of the province is affected, on average. The horizontal axis denotes the geographical spread of the natural event within the province, represented by the percentage of districts in the province that are affected by that event at least once per year, on average. The local human impact is measured by the maximum number of affected individuals that the province records in a single week, as a percentage of the province's population. The circle size represents this value for each observation.

Figure 8 reveals a positive correlation between the frequency and geographical distribution of natural events in the provinces. The more frequent a type of event, the greater the proportion of the province's territory affected by it. This relationship does not necessarily exist between these variables and the human impact of emergencies. The proportion of the local population affected by natural events does not increase as it moves along the horizontal or vertical axis, except in the case of low-temperature events. For example, strong wind events affect a similar proportion of the local population in provinces with different levels of geographical expansion. It is also observed, as described in previous sections, that low-temperature events generate the most affected individuals between the event categories.

To complement the analysis of this study, a *Frequency, Impact, and Geographical Distribution Index (IFIDEN)* is proposed in this section. The IFIDEN summarizes the occurrence and impact of natural events for every province of Peru, and for each year between 2003 and 2023. This indicator consists of two indices that capture the three dimensions of natural events analyzed in the document which are introduced in the subsections below: a *spatiotemporal index* and a *human impact index*.

Figure 8: Incidence and human impact of natural events: 2014-2023



Source: Authors, based on information from INDECI and INEI.
Note: Each dot corresponds to a province of Peru. The size of the dot in each observation is proportional to the maximum number of affected individuals that the province recorded in a single week during the 2014-2023 period, as a percentage of the local population. The number of affected individuals each week in a province is calculated as the sum of the maximum number of affected individuals registered in each district of the province during the week.
1/ Corresponds to the number of weeks each district in the province was affected in each year of the 2014-2023 period, averaged across all the districts in the province that presented the category in the year. The figure shows the average of this value for the ten years of the 2014-2023 period.
2/ Corresponds to the number of districts in the province that were affected by the emergency at least once during the year, for each year of the study period. The figure shows the average of these values as a percentage of the total number of districts in the province.

4.1 Spatiotemporal index

The *spatiotemporal index*, referred to as $index\_st_{ikt}$, captures the frequency and geographical distribution of the natural events in the province. For every province i, the number of district-weeks affected by each type of natural event k is expressed as a percentage of the total district-weeks in each year t. This calculation is denoted as $dist\_week_{ikt}$:

$$dist\_week_{ikt} = \frac{\sum_{s}\sum_{j} Events_{sj\_ikt}}{\text{Total Districts in Province } i \times \text{Total Weeks in Year } t} \tag{2}$$

In this equation, $Events_{sj\_ikt}$ represents the number of events of type k, occurring in district s (which is part of province i) during week j of year t. The denominator represents the maximum number of district-weeks possible in province i, where all districts of the province register the emergency of type k every week of year t. To obtain the spatiotemporal index $index\_st_{ikt}$, the calculated variable is normalized with respect to the minimum and maximum values reported for each type of natural event during the 2003-2023 period:

$$index\_st_{ikt} = \frac{dist\_week_{ikt} - \min_{k} dist\_week_{ikt}}{\max_{k} dist\_week_{ikt} - \min_{k} dist\_week_{ikt}} \tag{3}$$

Where $\max_{k} dist\_week_{ikt}$ and $\min_{k} dist\_week_{ikt}$ are the maximum and minimum values of the variable among all values associated with events of type k during the study period.

Table 12 presents the values of this index for the ten provinces with the highest average of this indicator between 2014 and 2023, for the extreme precipitations, low temperatures, and strong winds categories. The table reveals a difference in the dispersion over time of the index among the three categories: while extreme precipitation and low-temperature events register high values of the index throughout the ten years, the highest value for strong winds is observed in Purus (Ucayali) in 2021, and it is significantly higher than the rest of the sample.

4.2 Human impact index

To capture the human impact of natural events occurring in the province, the *human impact index* consists of the maximum number of affected and displaced individuals caused by each type k of natural event during a week, in province i and for each year t of the sample. This value is expressed as a percentage of the local population:

$$max\_affec_{ikt} = \frac{\max_{ikt} affected_{j\_ikt}}{population_i} \tag{4}$$

$$max\_disp_{ikt} = \frac{\max_{ikt} displaced_{j\_ikt}}{population_i} \tag{5}$$

Where $affected_{j\_ikt}$ and $displaced_{j\_ikt}$ represent the number of affected and displaced people due to type k emergencies in province i during week j of year t. The week with the highest record of affected and displaced people in the province is identified.

To properly capture the human impact of natural events, the construction of the index must consider that different categories of natural events affect and displace the population in varying

Table 12: Spatiotemporal Index – Most affected provinces

	Department	Province	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Extreme precipitation												
1	Pasco	Daniel Alcides Carrión	0,41	0,09	0,51	0,80	0,64	0,54	0,64	0,97	0,77	0,63
2	Pasco	Pasco	0,45	0,19	0,26	0,64	0,32	0,43	0,56	0,67	0,55	0,35
3	Apurímac	Cotabambas	0,14	0,47	0,18	0,33	0,31	0,39	0,65	0,74	0,53	0,45
4	Apurímac	Abancay	0,29	0,23	0,23	0,33	0,50	0,64	0,49	0,59	0,40	0,33
5	Tumbes	Zarumilla	0,03	0,31	0,34	0,86	0,09	0,15	0,18	0,37	0,52	0,89
6	Cajamarca	San Ignacio	0,00	0,18	0,12	0,40	0,19	0,16	0,21	0,74	0,74	1,00
7	Tumbes	Tumbes	0,00	0,25	0,47	0,94	0,10	0,14	0,10	0,33	0,49	0,70
8	Junín	Chanchamayo	0,27	0,10	0,27	0,14	0,12	0,45	0,33	0,61	0,37	0,63
9	Huancavelica	Acobamba	0,88	0,25	0,05	0,29	0,09	0,21	0,00	0,35	0,23	0,74
10	Piura	Huancabamba	0,28	0,14	0,14	0,48	0,15	0,18	0,05	0,32	0,38	0,81
Low temperatures												
1	Apurímac	Cotabambas	0,08	0,30	0,21	0,42	0,49	0,21	0,34	0,68	0,63	0,59
2	Pasco	Pasco	0,02	0,22	0,52	0,50	0,35	0,48	0,61	0,48	0,28	0,30
3	Pasco	Daniel Alcides Carrión	0,08	0,08	0,67	0,32	0,44	0,27	0,38	0,38	0,29	0,32
4	Cusco	Chumbivilcas	0,25	0,25	0,32	0,22	0,32	0,06	0,11	0,30	0,33	1,00
5	Cusco	Canas	0,22	0,22	0,33	0,25	0,46	0,03	0,16	0,24	0,32	0,63
6	Huancavelica	Acobamba	0,29	0,25	0,24	0,05	0,25	0,30	0,17	0,41	0,14	0,41
7	Apurímac	Antabamba	0,18	0,29	0,20	0,09	0,58	0,27	0,31	0,24	0,13	0,16
8	Cusco	Canchis	0,06	0,13	0,24	0,17	0,48	0,05	0,24	0,32	0,32	0,40
9	Huancavelica	Huancavelica	0,29	0,28	0,13	0,12	0,13	0,26	0,15	0,31	0,20	0,35
10	Cusco	Espinar	0,30	0,27	0,32	0,11	0,22	0,00	0,11	0,25	0,24	0,25
Strong winds												
1	Apurímac	Cotabambas	0,05	0,16	0,06	0,06	0,10	0,20	0,27	0,29	0,28	0,39
2	Ucayali	Padre Abad	0,08	0,20	0,25	0,09	0,12	0,16	0,20	0,30	0,14	0,22
3	Ucayali	Purús	0,00	0,00	0,00	0,00	0,00	0,06	0,38	1,00	0,13	0,00
4	Pasco	Daniel Alcides Carrión	0,03	0,07	0,16	0,06	0,09	0,08	0,16	0,38	0,29	0,16
5	Ucayali	Coronel Portillo	0,03	0,05	0,13	0,07	0,06	0,10	0,22	0,30	0,32	0,19
6	Apurímac	Chincheros	0,13	0,10	0,23	0,13	0,06	0,09	0,09	0,12	0,21	0,26
7	Apurímac	Antabamba	0,07	0,08	0,13	0,07	0,08	0,13	0,15	0,12	0,15	0,27
8	Ucayali	Atalaya	0,11	0,08	0,16	0,08	0,11	0,06	0,13	0,13	0,16	0,22
9	Tumbes	Tumbes	0,06	0,07	0,03	0,01	0,16	0,09	0,21	0,17	0,20	0,21
10	Amazonas	Condorcanqui	0,00	0,02	0,21	0,15	0,02	0,06	0,15	0,06	0,19	0,35

Source: Authors, based on information from INDECI.
Note: The spatiotemporal index is calculated as the percentage of district-weeks that registered an event of the respective category, normalized with respect to the minimum and maximum among all values during the study period.

magnitudes. To account for these differences, a greater weight is assigned to events that cause more affected or displaced individuals than others of the same category, as follows:

$$index\_human_{ikt} = (1+max\_affec_{ikt})^{2\Phi\left(\frac{disp_{k\_nat}/affec_{k\_nat}}{disp_{nat}/affec_{nat}}\right)-1} + (1+max\_disp_{ikt})^{2\Phi\left(\frac{affec_{k\_nat}/disp_{k\_nat}}{affec_{nat}/disp_{nat}}\right)-1} \tag{6}$$

Where $\Phi(x)$ is the cumulative distribution function of the standard normal distribution, $affec_{k\_nat}$ and $disp_{k\_nat}$ represent the weekly average of affected and displaced individuals caused by natural events of type k across the entire sample, and $affec_{nat}$ and $disp_{nat}$ are the weekly average of affected and displaced individuals across all categories during the entire period[12].

The exponent applying to the maximum percentage of the population that is affected in a single week (max_affec_{ikt}) is unique to each category k of natural events and is larger the fewer affected (or more displaced) people are caused by this type of emergency respect to the national average. Therefore, the index gives more weight to observations that affected individuals when their category does not typically generate many. The exponent operates similarly when counting the maximum percentage of the population that is displaced. This index ranges between 2 and 4 and reaches its maximum value if, in any week of the year, 100 percent of the province's population was affected and displaced by an event of category k.

Table 13 shows the values of the human impact index for the ten provinces with the highest average of this indicator between 2014 and 2023, for low-temperature, extreme precipitation, and drought events. For the low temperature and drought events, the highest values of the index were recorded before 2019, while high values of the index were recorded throughout the ten years for the extreme precipitation events.

4.3 Frequency, Impact and Geographical Distribution Index (IFIDEN)

The *frequency, impact, and geographical distribution index (IFIDEN)* consists of the product of the spatiotemporal and the human impact indices, aggregated for every category of natural event. This provides a unique value for each province i and year t:

$$IFIDEN_{it} = \sum_{k=1}^{9} index\_st_{ikt} \times index\_human_{ikt} \tag{7}$$

Based on this indicator, the most affected provinces during the study period are identified, considering those that ranked among the 20 most affected provinces most frequently[13]. Table 14 shows the provinces that ranked among the 20 most affected at least four times during the 2014-2023 period. The Abancay and Daniel Alcides Carrión provinces were consistently within

[12] Weekly averages are calculated by computing the number of affected/displaced individuals recorded in each province every week and averaging the values for every week of each year. Lastly, the resulting annual data are averaged

[13] From a total of 196 provinces, the 20 most affected provinces represent the top 10 percent.

Table 13: Human Impact Index – Most affected provinces

	Department	Province	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Low temperatures												
1	Apurímac	Antabamba	2,03	2,15	2,02	2,01	2,02	2,00	2,01	2,00	2,00	2,02
2	Tacna	Candarave	2,02	2,01	2,04	2,01	2,05	2,00	2,00	2,03	2,04	2,03
3	Moquegua	General Sánchez Cerro	2,01	2,08	2,03	2,03	2,04	2,00	2,00	2,01	2,01	2,02
4	Tacna	Tarata	2,00	2,01	2,02	2,03	2,02	2,00	2,00	2,02	2,03	2,03
5	Cusco	Canas	2,00	2,03	2,03	2,00	2,06	2,00	2,01	2,01	2,00	2,01
6	Huancavelica	Huaytará	2,01	2,05	2,03	2,00	2,01	2,01	2,00	2,02	2,01	2,01
7	Huancavelica	Castrovirreyna	2,01	2,07	2,01	2,01	2,01	2,00	2,01	2,00	2,01	2,01
8	Apurímac	Grau	2,03	2,02	2,02	2,00	2,00	2,00	2,01	2,00	2,00	2,01
9	Puno	Lampa	2,00	2,03	2,04	2,00	2,02	2,00	2,00	2,00	2,00	2,00
10	Huancavelica	Huancavelica	2,00	2,03	2,01	2,01	2,01	2,00	2,01	2,01	2,01	2,01
Extreme precipitation												
1	Tacna	Candarave	2,00	2,34	2,00	2,06	2,00	2,32	2,46	2,00	2,32	2,20
2	Tacna	Tarata	2,00	2,05	2,00	2,36	2,00	2,10	2,27	2,06	2,08	2,05
3	Ica	Palpa	2,00	2,24	2,00	2,39	2,00	2,01	2,03	2,00	2,00	2,05
4	Moquegua	General Sánchez Cerro	2,01	2,18	2,03	2,10	2,01	2,03	2,23	2,02	2,00	2,04
5	Áncash	Aija	2,00	2,00	2,00	2,28	2,00	2,02	2,01	2,00	2,01	2,16
6	Arequipa	La Unión	2,00	2,11	2,06	2,10	2,04	2,01	2,04	2,02	2,02	2,02
7	Tumbes	Contralmirante Villar	2,00	2,02	2,16	2,13	2,00	2,01	2,00	2,01	2,00	2,10
8	Huancavelica	Huaytará	2,00	2,05	2,00	2,24	2,00	2,01	2,01	2,01	2,00	2,07
9	Ayacucho	Páucar del Sara Sara	2,01	2,18	2,00	2,04	2,00	2,02	2,06	2,02	2,01	2,04
10	Piura	Paita	2,00	2,00	2,08	2,24	2,00	2,00	2,00	2,00	2,00	2,05
Drought												
1	Huancavelica	Churcampa	2,00	2,00	2,01	2,00	2,45	2,00	2,00	2,00	2,00	2,01
2	Huancavelica	Huaytará	2,00	2,00	2,22	2,00	2,13	2,00	2,00	2,00	2,00	2,00
3	Apurímac	Grau	2,00	2,00	2,31	2,00	2,03	2,00	2,00	2,00	2,00	2,00
4	Apurímac	Aymaraes	2,00	2,02	2,28	2,00	2,03	2,00	2,00	2,00	2,00	2,00
5	Ayacucho	Huanca Sancos	2,00	2,00	2,24	2,00	2,00	2,00	2,00	2,00	2,00	2,00
6	Puno	El Collao	2,00	2,00	2,16	2,00	2,00	2,00	2,00	2,00	2,00	2,01
7	Apurímac	Chincheros	2,00	2,03	2,08	2,00	2,02	2,00	2,00	2,00	2,00	2,00
8	Tacna	Candarave	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,09
9	Apurímac	Andahuaylas	2,00	2,00	2,06	2,00	2,02	2,00	2,00	2,00	2,00	2,00
10	Apurímac	Antabamba	2,02	2,00	2,00	2,00	2,04	2,00	2,00	2,00	2,00	2,00

Source: Authors, based on information from INDECI and INEI.
Note: To calculate the human impact index, the maximum percentage of the population affected and displaced by a natural event in a single week is calculated, for each category of natural event. Both values are aggregated, correcting the percentage of the population that is affected by the division of (1) the ratio of the weekly average of displaced people by events of the respective category with respect to that of affected people, and (2) the ratio of the weekly average of people displaced by any natural event respect to that of the people affected by them; and vice versa for the percentage of population that is displaced.

this group every year of the study period, due to the high frequency and significant impact of extreme precipitation and low-temperature events in these areas. Cotabambas (Apurímac) and Pasco (Pasco), ranked among the top 20 in 9 out of 10 years of the sample. Overall, the provinces displayed in the table are mainly located in the southern highlands and the upper jungle regions of Peru.

Table 14 also includes poverty and disaster risk management indicators for the most affected provinces. Poverty rates among these provinces ranged between 24 and 60 percent in 2018, higher in all cases than the national poverty rate in that year (20,5 percent), with 8 provinces even more than doubling this value. Furthermore, the last column presents the percentage of districts within each province whose municipalities reported counting with a Disaster Risk Management or a Civil Defense Office. Even though the average among the 18 most affected provinces is close to the national average, this hides disparities within them: 10 out of 18 provinces on the table performed below the national average in this indicator.

Figure 9 shows maps with the value of the IFIDEN for each province of Peru for selected years. In 2017 and 2023, characterized by higher occurrences of extreme precipitations, the most affected provinces were spread across various regions, with higher concentrations in the northern and central coast, southern highlands, and the Amazon jungle. In contrast, during 2016 and 2018, marked by a higher occurrence of low-temperature events, most affected provinces were concentrated in the central and southern highlands, where these events are more prevalent.

Finally, Table 15 presents the correlation of the IFIDEN with alternative models of the indicator. The alternative models include variations on the chosen model to assess its robustness, particularly modifying the configuration of the index spatiotemporal and human impact components. The IFIDEN shows a high correlation with alternative models, especially those whose configuration does not reduce the effect of natural events that do not record affected or displaced individuals (Models 2-4). Thus, a different choice regarding the methodology to compute the index would not substantially change the identified results.

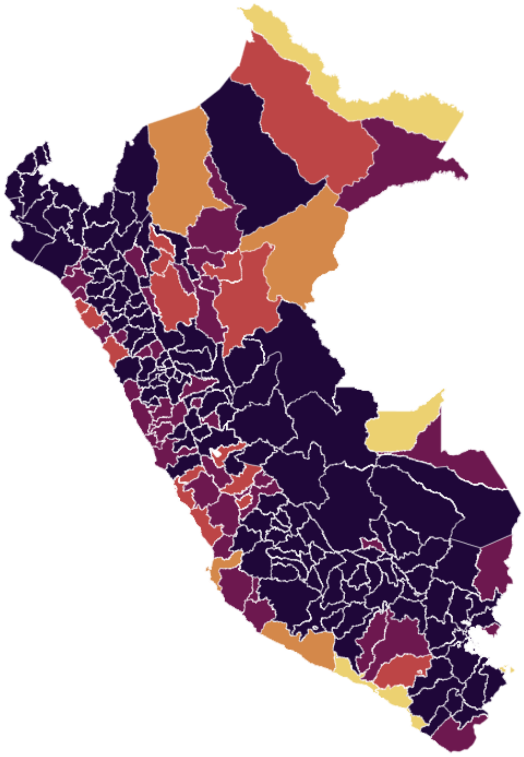
Table 14: Frequency, Impact and Geographical Distribution Index (IFIDEN) – Most affected provinces

Department	Province	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	% Poverty[1] (2018)	% Districts reporting Disaster Risk Management[2] (Average 2014-2023)
Apurímac	Abancay	**2,26**	**1,53**	**4,19**	**2,43**	**4,87**	**3,07**	**3,08**	**3,04**	**2,64**	**3,00**	24	81
Pasco	Daniel Alcides Carrión	**1,21**	**1,16**	**3,42**	**2,82**	**2,77**	**3,54**	**3,43**	**4,29**	**4,04**	**3,15**	60	89
Apurímac	Cotabambas	0,56	**1,89**	**2,80**	**1,77**	**2,86**	**1,83**	**3,31**	**3,88**	**4,35**	**3,64**	44	72
Pasco	Pasco	**1,13**	**1,20**	1,99	**2,51**	**1,79**	**4,86**	**2,97**	**3,25**	**2,74**	**3,02**	30	94
Apurímac	Antabamba	**0,96**	**1,44**	**2,77**	**1,71**	**3,04**	**1,45**	**2,44**	1,78	**1,95**	1,93	33	76
Apurímac	Chincheros	**0,97**	**1,59**	**2,51**	1,35	**1,74**	**2,00**	**1,98**	**1,99**	**2,48**	2,39	45	68
Huancavelica	Acobamba	**2,72**	**1,11**	**2,31**	0,99	**1,50**	**1,33**	1,07	**2,03**	**1,68**	**3,93**	41	81
Junín	Chanchamayo	**2,00**	**2,06**	1,60	0,93	**2,64**	**2,12**	**2,03**	**3,32**	**3,09**	**3,45**	25	95
Pasco	Oxapampa	0,22	**0,95**	1,25	1,23	**1,73**	**2,12**	**1,62**	**3,03**	**3,01**	**3,04**	34	96
Huancavelica	Huancavelica	**1,51**	**1,16**	1,67	1,28	**1,35**	**1,60**	1,17	**1,87**	1,50	**2,85**	34	70
Ayacucho	Cangallo	0,27	**0,96**	**2,47**	1,02	1,25	0,85	**1,49**	**2,05**	**3,85**	2,14	49	80
Ayacucho	La Mar	0,40	0,37	1,05	0,46	1,09	**1,08**	**1,65**	**3,51**	**3,44**	**3,44**	47	52
Cusco	La Convención	**0,96**	0,54	0,74	0,81	**1,58**	0,28	0,43	**2,23**	**1,95**	**3,02**	25	65
Huancavelica	Castrovirreyna	**1,34**	**1,04**	1,77	**2,13**	**1,77**	0,86	**1,31**	0,58	1,06	1,94	34	74
Apurímac	Andahuaylas	0,15	**1,30**	**2,64**	1,20	**2,68**	0,85	**1,25**	1,54	1,48	1,26	37	73
Ayacucho	Huanca Sancos	0,16	0,55	**2,26**	0,75	0,87	0,03	0,87	**1,92**	**2,06**	**2,89**	42	73
Cusco	Canas	**1,09**	0,90	1,67	0,67	1,04	0,12	**1,96**	1,49	**2,00**	**3,03**	50	95
Huancavelica	Churcampa	**1,79**	0,26	**2,64**	1,53	1,29	**1,16**	1,05	0,91	1,36	**4,08**	40	72
National average												**21**	**77**
Average among 18 most affected provinces												**39**	**78**

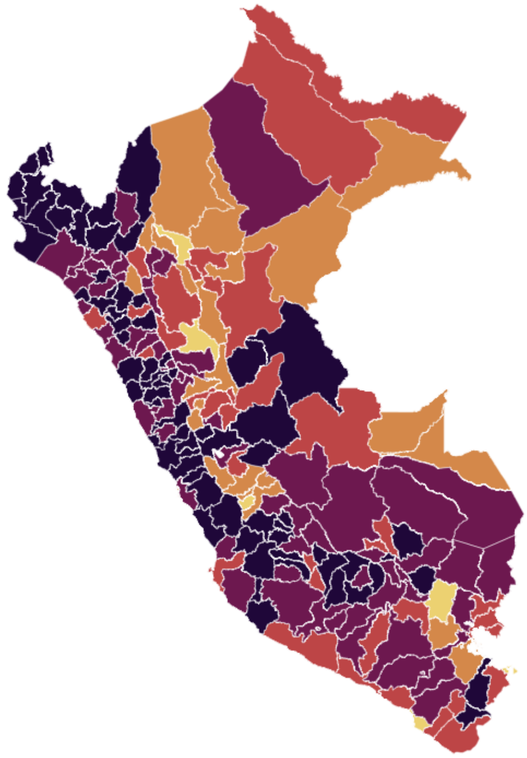
Source: Authors, based on information from INDECI and INEI.
Note: Blue cells indicate that the province ranked among the top 20 in the year of the column. The IFIDEN is calculated as the interaction between a spatiotemporal index and a human impact index, for each category of natural event. The spatiotemporal index consists of the percentage of district-weeks in the province in which an event was recorded for each category, while the human impact index incorporates the sum of the maximum percentage of the population that was affected and displaced in a single week by each category. The final index is the sum of the products of both indices, for all categories of natural events.
1/ Percentage of the province's population living in poverty according to the 2018 Poverty Map (INEI). The national average represents the poverty rate at the national level in 2018.
2/ Consists of the percentage of districts within the province whose municipalities reported counting with a Disaster Risk Management Unit or a Civil Defense Office, according to the National Registry of Municipalities (RENAMU). The value is calculated for each year, and the table presents the average of this data for the ten years of the study period. For provincial capital districts, the information of the provincial municipality is taken into account.

Figure 9: IFIDEN value - Map by province

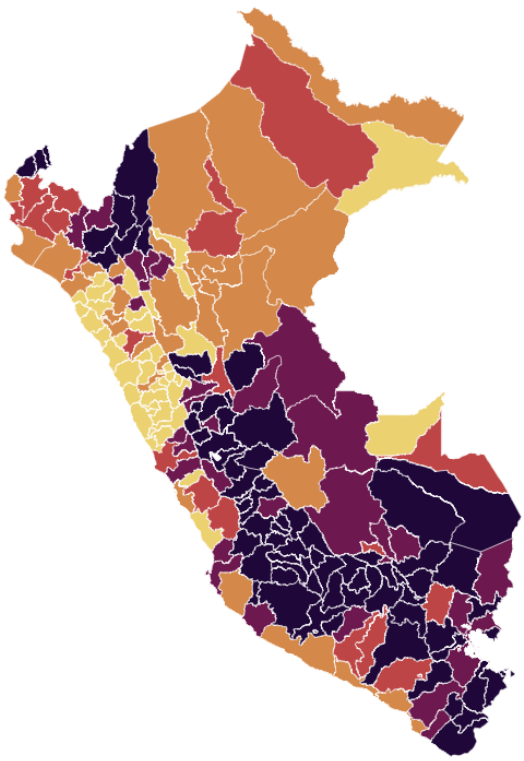
(a) 2023



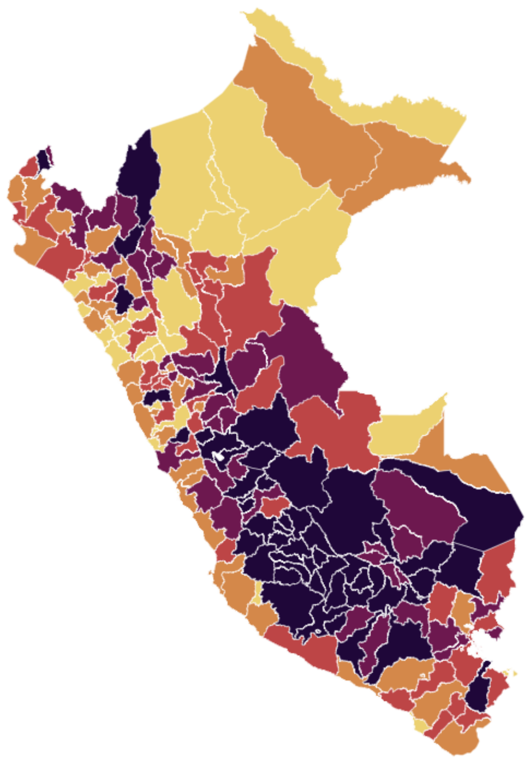
(b) 2017



(c) 2016



(d) 2018



Source: Authors, based on information from INDECI and INEI.

Table 15: IFIDEN - Correlation with alternative models

	Index components			Model								
Model	**Events with no human impact**	**Human impact measurement**	**Spatio-temporal index**	**IFIDEN**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
IFIDEN	Included	Maximum	One variable	**1,00**								
2	Included	Maximum	Two variables	0,92	**1,00**							
3	Included	Average	One variable	1,00	0,92	**1,00**						
4	Included	Average	Two variables	0,92	1,00	0,92	**1,00**					
5	Reduced effect	Maximum	One variable	0,41	0,35	0,39	0,34	**1,00**				
6	Reduced effect	Maximum	Two variables	0,33	0,35	0,32	0,34	0,89	**1,00**			
7	Reduced effect	Average	One variable	0,32	0,29	0,31	0,28	0,87	0,84	**1,00**		
8	Reduced effect	Average	Two variables	0,20	0,24	0,19	0,24	0,68	0,88	0,86	**1,00**	
9	Simple average of four normalized variables			0,92	0,99	0,91	0,99	0,40	0,43	0,34	0,32	**1,00**

Source: Authors, based on information from INDECI and INEI.
Note: Alternative models result from combining variations in the configuration of the IFIDEN components. The IFIDEN and Models 2, 3, and 4 apply a transformation to the number of affected and displaced people when constructing the index ($index\_human_{ikt}$), which includes events without human impact, that is, events that did not record affected and displaced individuals. In contrast, the transformation applied in Models 5, 6, 7, and 8 omits the effect of these events in the final calculation and, when the number of affected and displaced people is low, this effect is significantly reduced. Regarding the measurement of human impact for each province-year, the IFIDEN and models 2, 5, and 6 incorporate the maximum percentage of the population that was affected and displaced in a single week, while Models 3, 4, 7, and 8 use the average across the weeks in which the event occurred. The third variation is related to the spatiotemporal index, for which the IFIDEN and Models 3, 5, and 7 use the percentage of district-weeks that were affected, while Models 2, 4, 6, and 8 use the simple average of two normalized variables: (a) the average number of weeks that an emergency affects a district within the province, among districts where the event was recorded, and (b) the percentage of districts that were affected at least once during the year. Finally, Model 9 takes a different approach and consists of the simple average of four normalized variables: (1) the average number of weeks in which an emergency affected a district in the province, among those districts that experienced the event during the year, (2) the percentage of districts affected at least once during the year, (3) the maximum percentage of the population that was affected in a single week, and (4) the maximum percentage that was displaced in a single week. Further details on the construction of the alternative models are described in Appendix 3.

5 Impact of natural events on households

To study the impact of natural events on households' living conditions, it is key to identify how the occurrence of a natural event in a specific location translates into a shock the households face. For this purpose, the literature offers two different approaches to identifying whether a household was affected by a natural event.

In one approach, a household is identified as affected if it resides in a territory affected by a natural event (used in Anttila-Hughes and Hsiang, 2013). In this approach, the treatment variable is recorded at the territorial level where information about the evolution of natural events is available. Another approach is to identify a household as affected if one of its members reports having suffered a negative impact from a natural disaster in a recent period (used in Bui et al., 2014 and Kámiche and Pacheco, 2010). In this approach, the treatment variable is self-reported by each household, regardless of whether or not a natural event occurred in the territory where it resides.

In this section, data from two sources is used to combine both described approaches for identifying households affected by adverse natural events. The high frequency of official emergency records from INDECI is utilized to generate dynamic indicators of the incidence of natural events at the district level, such that the frequency and intensity in the spatiotemporal context where each household lives can be characterized. For this purpose, the Frequency, Impact, and Geographical Distribution Index (IFIDEN) developed in Section 4 is calculated for the districts of Peru. Additionally, data from the National Household Survey (ENAHO) is available, which includes households' self-reports of whether they were affected by a natural disaster in the last 12 months, as well as the socio-economic characteristics of the household and its members.

Combining both datasets enhances the identification of the impact of natural events on households. The inclusion of ENAHO data allows for a distinction between households that both reside in affected districts and were directly impacted by natural events, and those that, despite residing in affected areas, did not suffer direct harm. This approach also facilitates the analysis of the economic impact of these events on households. However, a limitation of ENAHO data is that it does not differentiate between the types of natural events that affect the household, nor their intensity regarding their effects on the population. INDECI data identifies reported emergencies by event category, as well as the affected and displaced population that they caused, among other indicators. This information provides a more precise description of the nature and magnitude of the shock experienced by households.

The rest of the section is structured as follows. The approaches for identifying affected households are described in detail, both the territorial and self-reporting approaches. These are further contrasted, and the relationship between the occurrence of natural events in the household's district of residence and the probability that the household reports being affected by them is examined. The INDECI data will serve for district-level identification, and the ENAHO Governance Module data will be useful for identification at the household level.

5.1 District-level identification: natural events in the past 12 months

To link the information from both data sources, it should be noted that ENAHO is conducted at different moments throughout the year, therefore the identification method using INDECI data should have at least a monthly frequency. For this purpose, for each month in the sample, the number of weeks each district recorded each type of natural event is calculated, for the corresponding month and the previous 11 months, a period referred to as a *moving year*. Table 16 contains the average and maximum number of weeks a district was affected across all moving years in the sample and the maximum population affected and displaced by each category of natural event.

Table 16 describes the frequency with which the different natural event categories occurred in the districts of Peru between 2003 and 2023. Districts were affected by at least one natural event for 1,8 weeks in 12 months on average; however, this figure can rise to 42 weeks or the equivalent of 81 percent of the weeks in a year. Extreme precipitation and strong wind were the most frequent categories: they occurred for 2,2 and 2,1 weeks on average in the moving years in

Table 16: Natural events and affected and displaced population in the last 12 months, by district

Category	Number of weeks with at least one natural event			Maximum population affected in a week[1] (% of district population)		Maximum population displaced in a week[1] (% of district population)	
	Average[2]	Average if> 0[2]	Maximum	Average	Maximum[3]	Average	Maximum
Extreme precipitations	0,6	2,2	32	2,3	100,0	0,3	100,0
Low temperatures	0,4	1,6	23	5,6	100,0	0,1	100,0
Strong winds	0,3	2,1	30	0,2	100,0	0,0	100,0
Flooding	0,1	1,4	27	0,6	100,0	0,1	100,0
Landslide	0,1	1,4	17	0,1	100,0	0,0	100,0
Drought	0,1	1,1	6	0,8	100,0	0,1	100,0
Forest fire	0,1	1,5	14	0,0	100,0	0,0	14,3
Mudslide and flash flood	0,0	1,3	11	0,2	100,0	0,0	78,5
Other	0,1	1,4	34	0,4	100,0	0,2	100,0
Any natural event	**1,8**	**3,1**	**42**				

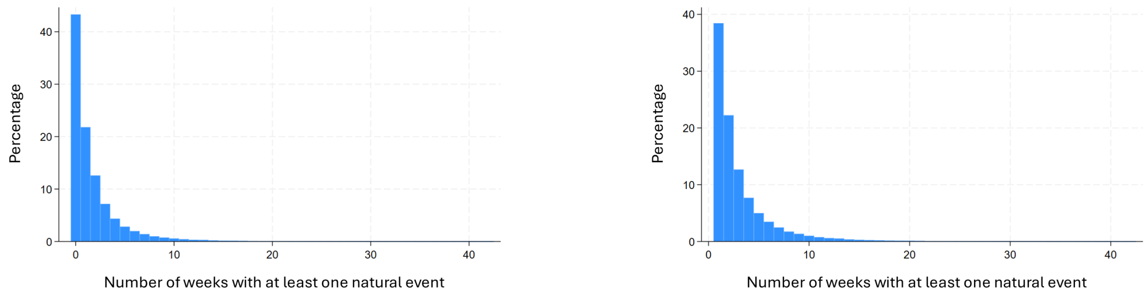
Source: Authors, based on information from INDECI and INEI.
Note: A *moving year* is defined as the 12 months consisting of the month of reference and the 11 preceding months. The table presents the average and maximum values across all districts in the sample and the 241 moving years between December 2003 and 2023.
1/ The definitions of affected and displaced population come from the INDECI Glossary of Terms. An *affected* individual has experienced a disruption in their environment due to a natural event. A *displaced* individual has suffered damage or harm to their health or property, particularly their home, and could be unable to recover without additional support (see Appendix 2). The maximum affected and displaced population in a given week is calculated by identifying, for each district and moving year in the sample, the week with the highest number of affected and displaced people, and presenting the maximum values from among these weeks.
2/ To calculate the average number of weeks with natural events in the last 12 months, the average of this indicator is calculated across all district-moving year combinations in the sample. The first column (average) includes all districts and moving years, while the second column (average if>0) includes only the district-moving year combinations with a number of weeks greater than zero.
3/ The maximum value recorded in the entire sample is presented. Observations representing more than 100 percent of the district population reported in the 2017 Census are censored at 100 percent.

which districts recorded these events. It is also worth noting that several categories have affected and displaced as many people as the district's total population. Extreme precipitation and low temperatures affected the largest proportion of the local population on average, reaching 2,3 and 5,6 percent of the local population respectively.

Figure 10 presents the histogram of the number of weeks with at least one natural event in the last 12 months for all district-moving year combinations in the sample. In more than half of cases, districts were affected by a natural event at least once in 12 months. The vast majority of these cases consist of districts that reported fewer than 4 weeks where they experienced an event, and the percentage of cases in which more than 10 weeks were recorded in the moving year is minimal.

Figure 10: Number of weeks in which a natural event occurred in the district, last 12 months

(a) All combinations **(b)** At least one natural event

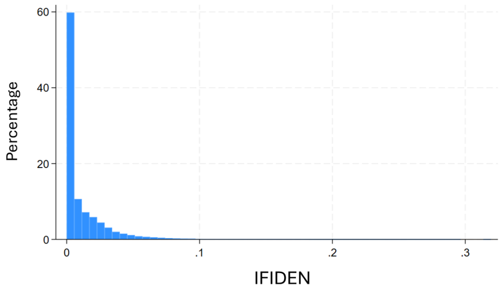


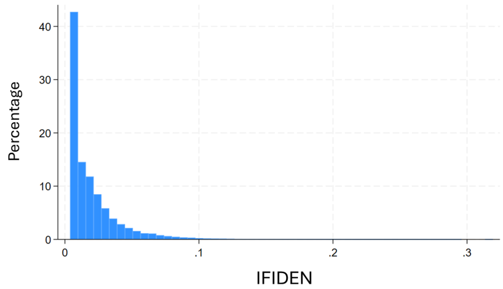
Source: Authors, based on information from INDECI and INEI.
Note: The left panel shows the distribution of the number of weeks with at least one natural event for all district-moving year combinations in the 2003-2023 period. The right panel shows this distribution for all combinations where at least one natural event was recorded.

To complete the identification of the most affected areas, the *Frequency, Impact, and Geographical Distribution Index (IFIDEN)* is calculated for every district of Peru, for all moving years between 2003 and 2023. The methodology used to calculate this indicator at the district level is described in Appendix 4. Figure 11 shows the histogram of the IFIDEN for all district-moving year combinations in the sample, as well as summary statistics. The index reaches a maximum value of 0,32, and the average is estimated to be 0,02 among all observations with at least one natural event recorded.

Figure 12 and 13 present the value of the IFIDEN for selected years, to describe the evolution of the index through time. The maps in Figure 12 include all districts of Peru, reflecting the extensive margin of change in the incidence of natural events in the country. Meanwhile, Figure 13 restricts the sample to districts that recorded a natural event in 2008 according to INDECI data, for better control over changes in the registry coverage and for analyzing the intensive margin of change in the incidence of natural events. Both figures confirm that not only the number of districts affected increased (extensive margin), but also the magnitude of its impact within these districts (intensive margin) over the past fifteen years.

Figure 11: Frequency, Impact, and Geographical Distribution Index (IFIDEN)





	All combinations					**IFIDEN > 0**			
	Average	$\mathbf{P_{25}}$	**Median**	$\mathbf{P_{75}}$	**Maximum**	**Average**	$\mathbf{P_{25}}$	**Median**	$\mathbf{P_{75}}$
District's IFIDEN	0,011	0,000	0,004	0,150	0,319	0,020	0,005	0,012	0,256

Source: Authors, based on information from INDECI and INEI.
Note: The left panel shows the distribution of the IFIDEN value of all district-moving year combinations between 2003 and 2023. The right panel shows the distribution of this value for all combinations where at least one natural event was recorded.

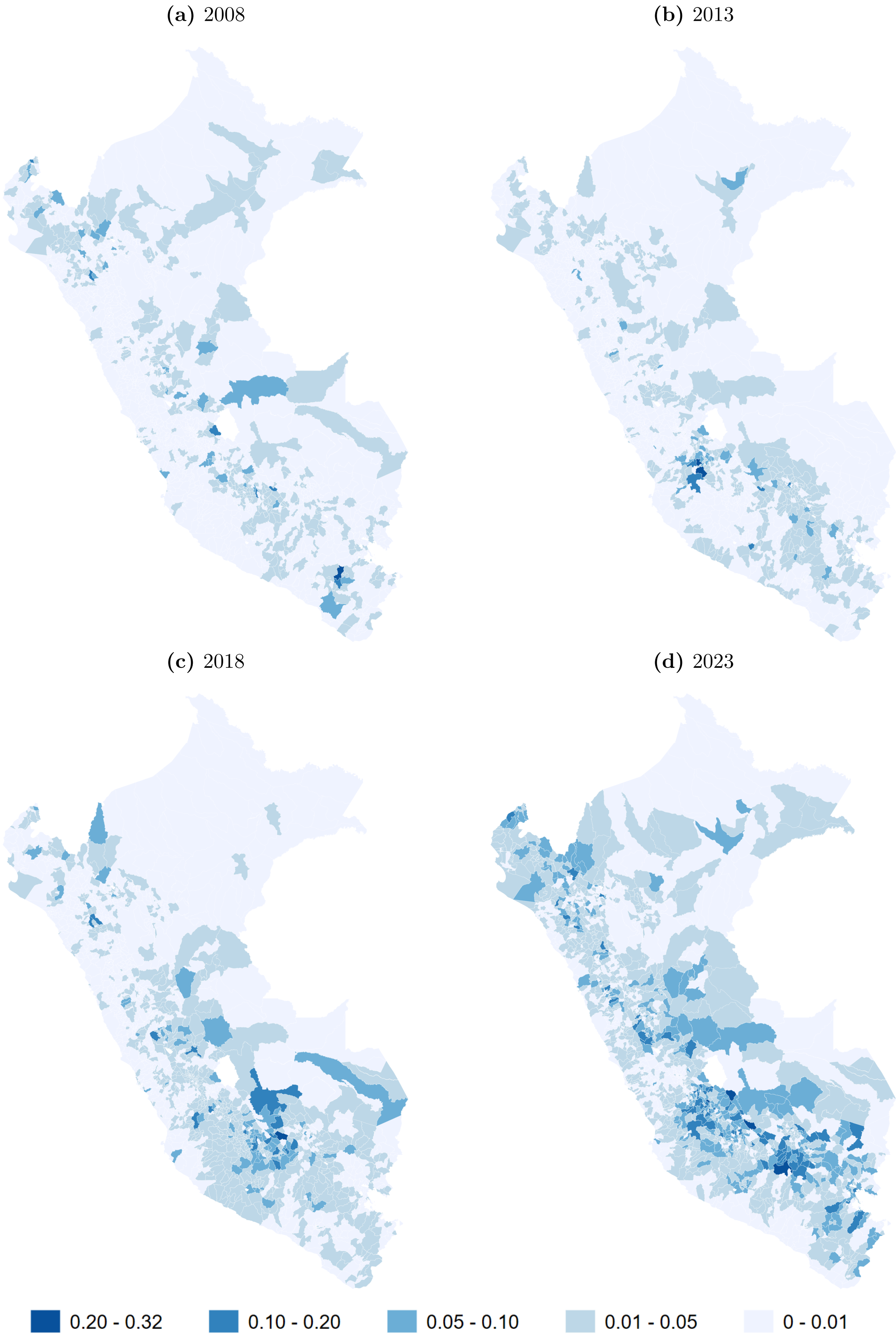
5.2 Household-level identification: household's self-reporting

The ENAHO survey, within the Governance, Democracy, and Transparency module, includes a questionnaire on the vulnerability of the household and adverse situations it has faced in the last 12 months before the survey date. In this module, the head of the household or the survey respondent can report if the household was affected by economic shocks (such as job loss or business failure), health shocks (such as serious illness or accidents), abandonment by the household head, theft or other criminal activity, or natural disasters[14]. Since the response is self-reported by the household, it helps identify the impact of adverse natural events as perceived by the household, regardless of their incidence in the household's spatial or temporal context.

The left panel of Figure 14 presents the percentage of households that *reported having faced a natural disaster shock* in the 12 months before the survey. Between 7 and 11 percent of households reported having faced this shock each year, and the highest records are observed in the years with major natural disasters (e.g., in 2008, due to the Pisco earthquake of August 2007; in 2017 and 2023, due to El Niño episodes in 2017 and 2023). Nevertheless, the national average hides geographical differences: up to 30 percent of households in rural areas reported having been affected by such disasters, suggesting that rural households are more exposed to these shocks, more vulnerable to their effects, or both.

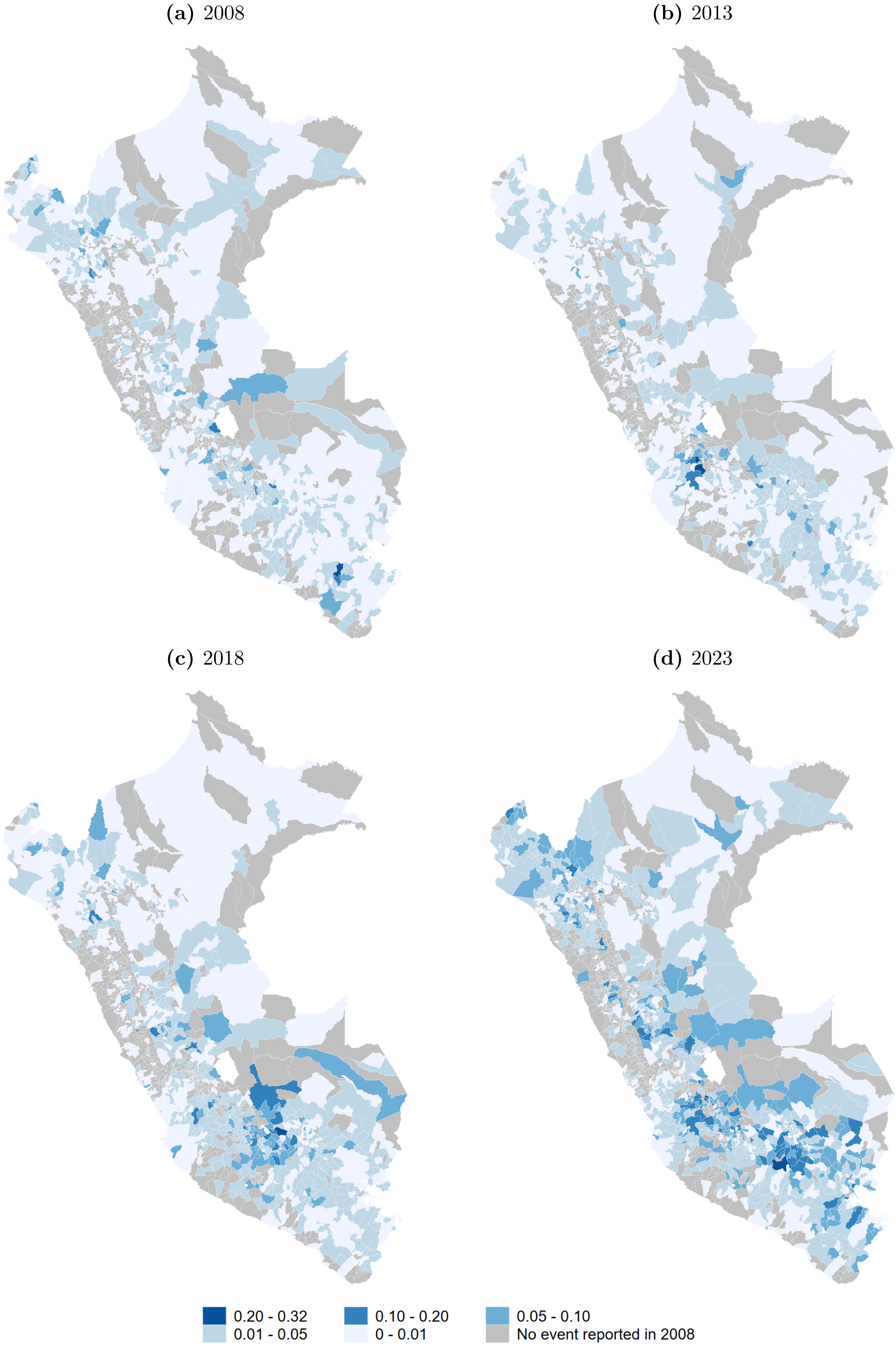
[14] The questionnaire does not ask the respondent what type of natural disaster the household faced.

Figure 12: IFIDEN by district: All districts



Source: Authors, based on information from INDECI and INEI.

Figure 13: IFIDEN by district: Districts that reported at least one natural event in 2008

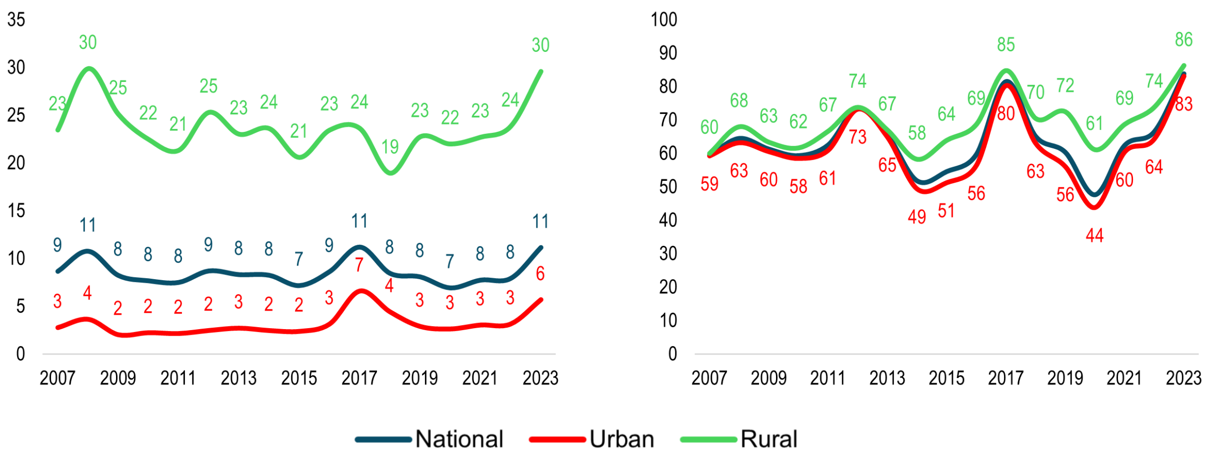


Source: Authors, based on information from INDECI and INEI.

Figure 14: Incidence of natural events in the district and household self-report

(a) ENAHO: Household reported having faced a natural disaster shock (% households)

(b) INDECI: Household resides in an affected district (% households)



Source: Authors, based on information from INDECI and INEI.
Note: The left panel presents the percentage of households in the National Household Survey (ENAHO) that reported having faced a natural disaster shock in the last 12 months, while the right panel shows the percentage of households that reside in a district that was affected in the last 12 months since the household was surveyed. A district is considered affected if a natural event occurred in the last 12 months, according to INDECI data. Values are calculated as a percentage of the total number of households, in urban and rural areas, respectively.

Figure 14 also shows the percentage of households that *resided in a district affected by a natural event* in the last 12 months at the time of the survey (right panel), based on INDECI data. This percentage is calculated from the district-level identification approach: a household in the sample resides in an affected district if at least one type of natural event was reported in that district during the last 12 months leading up to the survey month (i.e., the moving year that ends in that month). By identifying households within affected districts, it is possible to calculate the degree of exposure of these households to such shocks, regardless of their self-reporting.

When comparing both figures, the difference in magnitude between the two measurements stands out. In most years of the study period, more than 50 percent of households nationwide resided in a district affected by a natural event in the last 12 months and, therefore, may have experienced its consequences. As in the left panel, a higher percentage of rural households resided in an affected district at the time of the survey compared to urban households. However, this geographic difference is smaller than the observed when analyzing household self-reports. This suggests that, while rural households may be somewhat more exposed to natural events, greater exposure does not fully explain the differences between geographic areas, implying that other factors, such as household vulnerability, may also play a role in explaining them.

The analysis thus far has only considered whether a district has been affected by a natural event. However, the frequency and intensity of the events experienced by a district may influence households' perception that they were affected by them. To account for this, the value of the *Frequency, Impact, and Geographic Distribution of Natural Events Index (IFIDEN)* corresponding to each household in the sample is calculated, equivalent to the index value for the district in which the household resides and the month in which it was surveyed. Table 17 shows summary statistics of the IFIDEN distribution in the household sample.

Table 17: IFIDEN corresponding to households in ENAHO - Summary

	All combinations					**IFIDEN $>$ 0**			
	Average	**P_{25}**	**Median**	**P_{75}**	**Maximum**	**Average**	**P_{25}**	**Median**	**P_{75}**
District's IFIDEN	0,015	0,000	0,005	0,021	0,319	0,024	0,007	0,016	0,030

Source: Authors, based on information from INDECI and INEI.
Note: Each household is assigned the value of the IFIDEN corresponding to its district of residence and the month in which the household was surveyed. The table presents the distribution of this value in the sample from the National Household Survey (ENAHO).

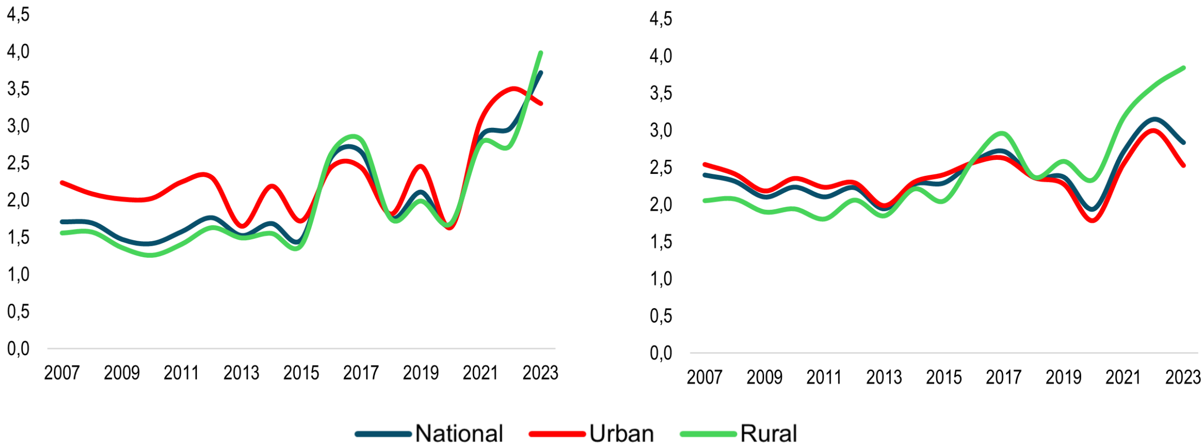
Figure 15 presents the average value of this index for both household classification methods. The left panel shows the average IFIDEN value for households that reported facing a natural disaster shock according to ENAHO. This value is higher among urban households than rural households, suggesting that the events affecting the former group of households either occurred more frequently during the evaluation period (the 12 months preceding the survey date), affected or displaced a greater number of people, or both. The trend reversed in 2017 and 2023, years in which the country experienced El Niño episodes, which increased the frequency and impact of extreme precipitation and related incidents in rural areas

The right panel shows the average IFIDEN value for households residing in districts affected by natural events according to INDECI. In contrast with the left panel, where the national average approaches that of households in rural areas, in the right panel it is closer to the average for households in urban areas, as they represent a larger proportion of the total number of households residing in affected districts nationwide. In the classification based on household self-reporting, households that reported experiencing a natural disaster shock in rural areas represent a larger share of the national total than those in urban areas.

Figure 15: IFIDEN corresponding to households, average by classification approach*

(a) Among households that reported facing a natural disaster shock according to ENAHO

(b) Among households residing in an affected district according to INDECI

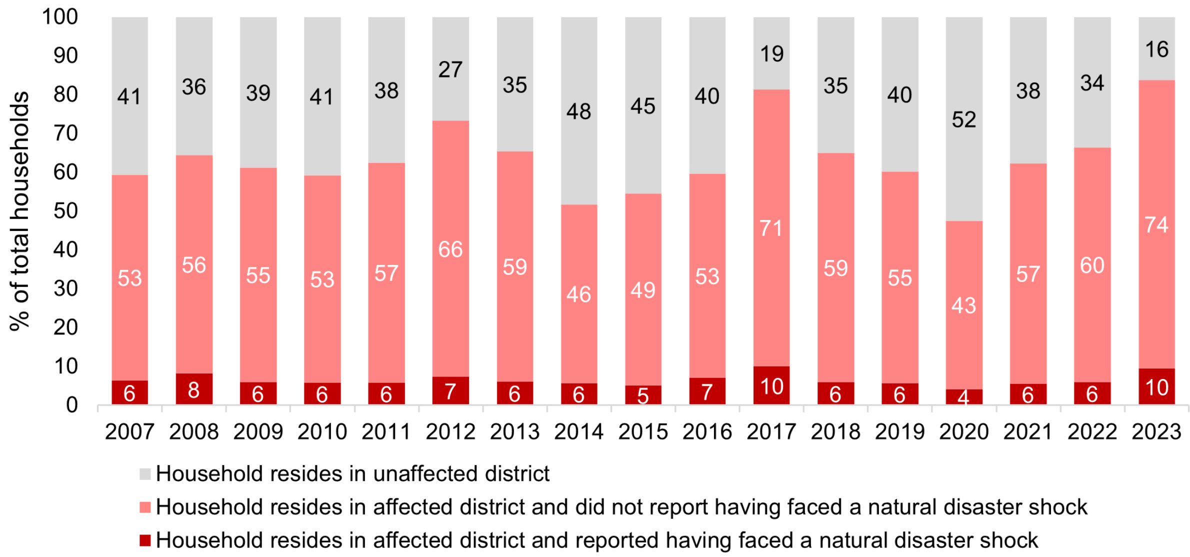


Source: Authors, based on information from INDECI and INEI.
* The figure shows the value of the index multiplied by 100.
Note: Each household is assigned the value of the IFIDEN corresponding to its district of residence and the month in which the household was surveyed. The left panel presents the average IFIDEN value for households in the National Household Survey (ENAHO) that reported experiencing a natural disaster shock in the last 12 months. The right panel presents the average IFIDEN value for households residing in districts affected by a natural event in the last 12 months according to INDECI.

5.3 Relationship between district-level incidence and household's self-reporting

After analyzing both classification systems separately, this section integrates both approaches, describing their relationship. By combining the two approaches, three categories can be considered to identify households affected by natural events. The first category includes households that reside in *districts affected* by natural events according to INDECI and also *reported having faced a natural disaster shock* according to ENAHO. The second category includes households that reside in an affected district according to INDECI but did not report being directly impacted in ENAHO. Finally, households living in unaffected districts according to INDECI are grouped into a third category.

Figure 16: Households affected by natural disasters in the last 12 months, by category



Source: Authors, based on information from INDECI and INEI.
Note: The first category (in red) includes households that reside in districts affected by natural events according to INDECI and reported having faced a natural disaster shock according to ENAHO. The second category (in pink) includes households that reside in an affected district according to INDECI but did not report being directly impacted in ENAHO. The third category consists of households living in unaffected districts according to INDECI.

Table 18: Households affected by natural disasters in the last 12 months, by category and area of residence

Category	Resides in affected district according to INDECI				Resides in unaffected district according to INDECI			
	2013	2017	2023	Average 2007/23	2013	2017	2023	Average 2007/23
Urban (% of total households nationwide)								
Household reported facing natural disaster (I)	1,6	4,6	3,9	2,0	0,4	0,2	0,5	0,4
Household did not report facing natural disaster (II)	45,3	54,0	60,2	44,1	25,1	14,2	12,6	27,3
Rural (% of total households nationwide)								
Household reported facing natural disaster (III)	4,6	5,5	5,6	4,6	1,7	0,9	1,1	1,6
Household did not report facing natural disaster (IV)	13,9	17,4	14,1	13,5	7,4	3,3	2,0	6,5
National (% of total households nationwide)								
Household reported facing natural disaster (I + III)	6,2	10,1	9,6	6,6	2,1	1,1	1,6	2,0
Household did not report facing natural disaster (II + IV)	59,2	71,3	74,2	57,5	32,5	17,5	14,6	33,9

Source: Authors, based on information from INDECI and INEI.
Note: The table shows the number of households in each category as a percentage of the total number of households in the sample nationwide, in the respective year or period.

Figure 16 shows the percentage of households in each category described, between 2007 and 2003, and Table 18 details the composition of each category across geographic areas. The percentage of households *residing in a district affected by a natural event* (based on INDECI data) and simultaneously *reported having faced a natural disaster shock* (based on ENAHO data) ranges between 5 and 10 percent of total households each year. The percentage of households residing in affected districts but not reporting facing a natural disaster shock is more variable over time, ranging from 43 to 74 percent of the sample. Once again, geographical differences are revealed: rural households that reported experiencing a natural disaster shock represent a larger proportion of the total than those in urban areas, even though rural populations contribute less to the overall total.

5.4 Probability that a household reports facing a natural disaster shock

Based on the classification systems discussed, the *change in the probability of a household reporting having faced a natural disaster shock* associated with residing in a district that experienced a natural event recently is estimated. For this purpose, a *probit* specification is used to model the conditional probability that a household reports having faced a natural disaster shock ($Y_{it} = 1$) using the standard normal cumulative distribution. Two models are considered for the two variables of analysis: the household's *residence in an affected district* and the *IFIDEN value* corresponding to the district where the household resides.

The regression equations are described below:

Model 1 - Household reports having faced a natural disaster shock | resides in affected district:

$$\mathbb{P}(Y_{it} = 1 \mid X_{it}, DistAffec_{it}) = \mathbb{E}(Y_{it} \mid X_{it}, DistAffec_{it}) = \Phi(X_{it}'\beta_1 + \gamma_1 DistAffect_{it}). \quad (8)$$

Model 2 - Household reports having faced a natural disaster shock | IFIDEN value:

$$\mathbb{P}(Y_{it} = 1 \mid X_{it}, IFIDEN_{it}) = \mathbb{E}(Y_{it} \mid X_{it}, IFIDEN_{it}) = \Phi(X_{it}'\beta_2 + \gamma_2 IFIDEN_{it}), \quad (9)$$

where X_{it} groups control variables to account for the household's socioeconomic characteristics, $DistAffec_{it}$ is the key variable in Model 1 and is 1 if the household resides in a district affected by a natural event in the last 12 months, according to INDECI, and $IFIDEN_{it}$ is the variable of interest in Model 2, which is the value of the index corresponding to the household's district and survey month.

Table 19 shows the marginal effects estimation results of the *probit* specification for the described models. Households *residing in affected districts* according to INDECI were 1,4 percentage points more likely to report having faced a natural disaster shock between 2007 and 2023, and 1,6 percentage points more likely between 2015 and 2023. This result holds even after including socioeconomic control variables, confirming the positive relationship between the incidence of natural events in the district of residence and the household's self-report of having faced a natural disaster shock.

The results also show that the probability of a household reporting having faced a natural disaster shock increases with the *frequency* and *impact* of natural events in the district, as measured by the IFIDEN. An increase of one unit in the IFIDEN for the district of residence raises the probability that the household is affected by 12 to 14 percentage points. In the context

Table 19: Probability that a household reports facing a natural disaster shock - Marginal effects

	Dependent variable: Probability of reporting having faced a natural disaster					
	Model 1			Model 2		
	2007/23	2015/23	2015/23, controls	2007/23	2015/23	2015/23, controls
Natural events incidence in the district						
Household resides in affected district	0.014***	0.016***	0.016***			
IFIDEN				0.117***	0.151***	0.145***
Household lives in rural area	0.112***	0.110***	0.091***	0.112***	0.110***	0.092***
Poverty						
Household under the poverty line			0.012***			0.013***
Demographic characteristics						
Age of head of household			0.000***			0.000***
Head of household is male			0.018***			0.018***
Number of household members			0.003***			0.003***
Children between 0 and 5 years old			-0.009***			-0.009***
Children between 6 and 15 years old			-0.000			-0.000
Head of household's human capital						
Employed			0.041***			0.041***
Years of education			-0.002***			-0.002***
Physical disability			0.004			0.004
Fixed effects[1]	✓	✓	✓	✓	✓	✓
Number of observations	460 811	271 887	271 809	460 811	271 887	271 809

Source: Authors, based on information from INDECI and INEI.
Note: *: p-value<0,10; **: p-value<0,05; ***: p-value<0,01.
1/ Includes binary variables for year, department, and natural region (coast, highlands, and jungle).

of the IFIDEN distribution in the sample, moving from the 25th to the 75th percentile of the index increases the probability of reporting having faced a natural disaster by up to 0.32.

It is worth noting that certain household characteristics increase the probability of reporting having faced a natural disaster. In both models, the coefficients show that this probability is higher for households below the poverty line, indicating that economic vulnerability impacts the total effect of the shock on the household. The probability is also higher in households where the head is male or employed at the time of the survey. Finally, the probability increases with the number of household members but decreases with the number of children aged 0 to 5 years, suggesting that the presence of young children has a differentiated effect.

The analysis developed in this section argued that there is a direct relationship between the occurrence of natural events in a given area and their perceived impact on Peruvian households, as reported directly by the head of the household. It also identified differences between classification systems and between urban and rural households. Finally, the marginal effect of residing in an affected district on the probability of being affected by a natural disaster, as well as the effect of the frequency and intensity of natural events occurring in the district (through the IFIDEN), were estimated. The integration of these identification approaches serves as a tool for calculating the impact of natural events on households' economic well-being and vulnerability, providing a better understanding of the factors that make a household more vulnerable to the effects of a natural disaster.

6 Conclusions and remarks

This document proposes an analytical framework to enhance our understanding of the areas in Peru most prone to experiencing natural events. This framework analyzed three dimensions of the incidence of natural events: frequency, geographical distribution, and human impact. By studying each dimension separately, differences between types of natural events and their impact across the Peruvian territory are identified. However, some common trends stand out: extreme precipitation events pose the greatest risk for Peruvian households due to their high frequency, considerable geographic spread, and capacity to affect and displace the population. Among other frequent categories, low temperatures cause the most affected individuals, while strong wind events are more widely distributed across the national territory.

We develop a Frequency, Impact, and Geographic Distribution Index (IFIDEN) to assess the interaction between the three dimensions. This index helped identify the most affected provinces in the country, mainly located in the southern highlands and upper jungle regions. Finally, the identification of the most affected areas is contrasted with the households' self-reporting of experiencing a natural disaster shock. In this exercise, a relationship is described between the multidimensional incidence of natural events in a territory and a higher probability that the resident households report having experienced the consequences of these events.

Some considerations should be taken into account when interpreting the results of this report. The geographical distribution of natural events has been analyzed based on the country's political-administrative divisions, with districts representing the lowest level of analysis. This interpretation is useful since local authorities, responsible for managing disaster risk and emergency response, are organized under this structure. However, districts in Peru are not homogeneous in their extension area, and the area affected by each type of natural event can vary. Further analysis considering the extension area specifically affected by each emergency could enhance the understanding of the geographical distribution of natural events.

The descriptive analysis in this document contributes to the literature on the impact of natural events on household living conditions and the policy responses governments can implement to address their consequences. As described when contrasting methods to identify affected households, the occurrence of a natural event in the geographical area where they reside does not necessarily imply that the household's well-being has been affected by it. This relationship is influenced by how much this event represents an unusual incident in the district, and what potential losses it could cause. Understanding the differences in how the natural events manifest in the national territory provides a better tool for studying this impact.

Future research can put greater emphasis on the duration or persistence of natural events in a territory, beyond the analysis of consecutive weeks in Section 2. Even though the number of consecutive weeks is low on average, it may hide heterogeneity between districts frequently affected by natural events and those that experience them more sporadically. A deeper analysis of the duration of natural events can better inform the policy response before a disaster.

References

Andersen, L. E., Suxo, A., & Verner, D. (2009). *Social Impacts of Climate Change in Peru: A District Level Analysis of the Effects of Recent and Future Climate Change on Human Development and Inequality* (tech. rep. No. WPS 5091). World Bank Group. Washington, D.C. http://documents.worldbank.org/curated/en/689261468045043845/Social-impacts-of-climate-change-in-Peru-a-district-level-analysis-of-the-effects-of-recent-and-future-climate-change-on-human-development-and-inequality

Anttila-Hughes, J., & Hsiang, S. (2013). Destruction, Disinvestment, and Death: Economic and Human Losses Following Environmental Disaster. *SSRN Electronic Journal*. https://doi.org/https://doi.org/10.2139/ssrn.2220501

Baez, J., Fuente, A., & Santos, I. (2010). Do natural disasters affect human capital? An assessment based on existing empirical evidence. *Institute for the Study of Labor (IZA), IZA Discussion Papers*. https://doi.org/10.2139/ssrn.1672172

Bui, A. T., Dungey, M., Nguyen, C. V., & Pham, T. P. (2014). The Impact of Natural Disasters on Household Income, Expenditure, Poverty and Inequality: Evidence from Vietnam [CitationKey: Bui2014]. *Applied Economics*, *46*(15), 1751–1766. https://doi.org/https://doi.org/10.1080/00036846.2014.884706

CEPAL. (2014). *La economía del cambio climático en el Perú*.

CEPLAN. (2023). Aumento de la frecuencia de eventos climáticos extremos. Observatorio CEPLAN. https://observatorio.ceplan.gob.pe/ficha/t57

Chirinos, R. (2021). *Efectos económicos del cambio climático en el Perú* (Working Paper No. 2021-009). Banco Central de Reserva del Perú. https://www.bcrp.gob.pe/docs/Publicaciones/Documentos-de-Trabajo/2021/documento-de-trabajo-009-2021.pdf

CRED. (2015). The human cost of natural disasters: A global perspective: Centre for Research on the Epidemiology of Disasters (CRED). https://www.cred.be/sites/default/files/The_Human_Cost_of_Natural_Disasters_CRED.pdf

De Angeli, S., Malamud, B. D., Rossi, L., Taylor, F. E., Trasforini, E., & Rudari, R. (2022). A multi-hazard framework for spatial-temporal impact analysis. *International Journal of Disaster Risk Reduction*, *73*, 102829. https://doi.org/https://doi.org/10.1016/j.ijdrr.2022.102829

Hallegatte, S., Vogt-Schilb, A., Bangalore, M., & Rozenberg, J. (2016). *Unbreakable: Building the resilience of the poor in the face of natural disasters* (tech. rep.). World Bank Group. Washington, D.C. http://documents.worldbank.org/curated/en/512241480487839624/Unbreakable-building-the-resilience-of-the-poor-in-the-face-of-natural-disasters

INDECI. (2020). Glosario de Términos y Siglas Utilizadas - Compendio Estadístico del INDECI 2020. https://portal.indeci.gob.pe/wp-content/uploads/2021/02/CAPITULO-VIII-Glosario-de-T%C3%A9rminos.pdf

INDECI. (2022). Aprende sobre la temporada de Bajas Temperaturas - Campañas - Instituto Nacional de Defensa Civil - Plataforma del Estado Peruano. Retrieved September 8, 2024, from https://www.gob.pe/institucion/indeci/campa%C3%B1as/7854-aprende-sobre-la-temporada-de-bajas-temperaturas

INDECI. (2023). *Compendio Estadístico del INDECI 2023 - Gestión Reactiva. Instituto Nacional de Defensa Civil.*

IPCC. (2012). *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change* (C. Field, V. Barros, T. Stocker, D. Qin, D. Dokken, K. Ebi, M. Mastrandrea, K. Mach, G.-K. Plattner, S. Allen, M. Tignor, & P. Midgley, Eds.). Cambridge University Press.

IPCC. (2021). *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (V. Masson-Delmotte, P. Zhai, A. Pirani, S. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J. Matthews, T. Maycock, T. Waterfield, O. Yelekçi, R. Yu, & B. Zhou, Eds.). Cambridge University Press.

Kámiche, J., & Pacheco, A. (2010). ¿Cuánto es afectado el consumo de los hogares cuando ocurre un desastre de origen natural? Un análisis empírico para el Perú, 2004-2006. *Apuntes. Revista De Ciencias Sociales*, (67), 67–107. https://doi.org/https://doi.org/10.21678/apuntes.67.609

Kaushik, R., Parida, Y., & Naik, R. (2024). Human development and disaster mortality: Evidence from India. *Humanities and Social Sciences Communications*, *11*(1), 814. https://doi.org/10.1057/s41599-024-03353-2

Ronco, M., Tárraga, J. M., Muñoz, J., Piles, M., Marco, E. S., Wang, Q., Espinosa, M. T. M., Ponserre, S., & Camps-Valls, G. (2023). Exploring interactions between socioeconomic context and natural hazards on human population displacement. *Nature Communications*, *14*(1), 8004. https://doi.org/10.1038/s41467-023-43809-8

UNDRR. (2015). Sendai Framework for Disaster Risk Reduction 2015-2030. United Nations Office for Disaster Risk Reduction (UNDRR). https://www.undrr.org/media/16176/download?startDownload=20240907

UNDRR. (2022). Global Assessment Report on Disaster Risk Reduction 2022: Our World at Risk: Transforming Governance for a Resilient Future. United Nations Office for Disaster Risk Reduction. https://www.undrr.org/gar/gar2022-our-world-risk-gar

UNDRR & OCHA. (2023). Panorama de los Desastres en América Latina y el Caribe: 2000 - 2022. Oficina de las Naciones Unidas para la Reducción del Riesgo de Desastres (UNDRR) y Oficina de las Naciones Unidas de Coordinación de Asuntos Humanitarios (OCHA). https://www.undrr.org/media/89902/download?startDownload=20240907

Vargas, P. (2009). *El cambio climático y sus efectos en el Perú* (Working Paper No. 2009-14). Banco Central de Reserva del Perú. https://www.bcrp.gob.pe/docs/Publicaciones/Documentos-de-Trabajo/2021/documento-de-trabajo-009-2021.pdf

A Appendix 1: Natural events categories

The definitions presented in Appendix 1 and 2 are found in the Glossary of Terms and Acronyms used in INDECI's Statistical Compendium (INDECI, 2020) and the Low-Temperature Season Learning Campaign (INDECI, 2022).

- **Extreme precipitation:** Precipitation of liquid water in the form of drops larger than a drizzle, falling rapidly and continuously, exceeding 60 mm within an hour, typically originating from thick nimbostratus clouds. Extreme precipitations often provoke other hazards such as floods, mudslides, avalanches, lahars, collapses, and landslides.

- **Low temperatures:** Phenomenon associated with decreasing air temperatures. Includes: (1) Frosts: an air temperature decrease to 0°C or less in the Andes highlands between April and September, (2) Snowfalls: solid precipitation in the form of snowflakes more than 20 cm thick in the Andes highlands above 3 600 meters above sea level, when the air temperature remains below 2 to 3°C, (3) Cold front: a sudden drop in air temperature in the Amazon, associated with a cold air mass coming from Antarctica, where temperatures drop from 22°C to 33°C to values between 11°C and 22°C, with an average duration of 3 to 5 days.

- **Strong winds:** Air currents produced in the atmosphere due to variations in atmospheric pressure. They are characterized by their intensity, with speeds exceeding 30 kilometers per hour (km/h) (Beaufort Scale, used to measure wind intensity). Paracas winds are strong sea breezes (ranging from 25 to 60 km/h). They usually occur in winter, from August to October, but have also been observed throughout the year.

- **Flooding:** Lateral overflows of water from rivers, lakes, and seas, temporarily covering lowlands adjacent to their banks, known as flood zones. They typically occur during periods of heavy rainfall, waves, and tsunamis.

- **Droughts:** Absence of rainfall that affects agriculture. The criteria for rainfall amount and days without precipitation vary when defining a drought. A drought is considered absolute if no precipitation greater than 1 mm has been recorded in 15 days. A partial drought occurs when the average daily rainfall is less than 0.5 mm in 29 consecutive days. Droughts are further defined when insufficient rainfall is related to agricultural activity.

- **Landslide:** Rupture and displacement of small or large masses of soil, rocks, artificial fills, or a combination of these on a natural or artificial slope. It always presents a sliding plane or fault along which the downward movement occurs. The landslide material consists of a mass corresponding to a portion of the slope or the slope itself. The displacement occurs downhill and outward, falling onto a cleared plane.

- **Forest fire:** Uncontrolled and unplanned spread of fire over vegetation (trees, grasslands, weeds, and shrubs) in forests, jungles, and arid and semi-arid areas. It affects and degrades natural forests, forest plantations, vegetation cover, and crops; it also affects wild or domestic animals. It is mainly caused by human activity as well as climatic conditions.

- **Mudslide and flash flood:** Flows with large volumes of water and material of various sizes. They occur as a result of intense rains that then descend through ravines. They occur quickly, with loud noises and a smell of mud. They are triggered by extreme precipitation and significantly contribute to floods since the flows discharge into rivers, causing them to overflow. Also known as llocllas in Quechua.
- **Others:** Remaining categories of natural events in the INDECI database, including Erosion, Earthquakes, Hill collapse, Thunderstorms, Swells, Avalanches, Volcanic activity, and others not classified by INDECI.

B Appendix 2: Definitions used by INDECI

- **Displaced:** A person partially or entirely affected by an emergency or disaster, who has suffered significant damage or loss of health or property. They usually have lost their housing or shelter, partially or entirely, permanently or temporarily, and therefore require temporary shelter and humanitarian aid. They cannot recover the original state of their property and assets on their own.
- **Affected:** A person, animal, territory, or infrastructure whose environment has been disturbed due to the effects of a natural or human-induced phenomenon. Immediate support may be required to eliminate or reduce the causes of the disturbance and resume activities as usual.
- **Emergency:** A state of damage to life, property, and the environment caused by the occurrence of a natural or human-induced phenomenon that disrupts the normal functioning of the affected area.

C Appendix 3: Robustness tests – Alternative models

Variation 1: Events with no human impact

To construct the human impact index ($index\_human_{ikt}$), the IFIDEN and Models 2, 3, and 4 apply the following transformation to the number of affected and displaced people:

$$index\_human_{ikt} = (1+max\_affec_{ikt})^{2\Phi\left(\frac{disp_{k\_nat}/affec_{k\_nat}}{disp_{nat}/affec_{nat}}\right)-1}+(1+max\_disp_{ikt})^{2\Phi\left(\frac{affec_{k\_nat}/disp_{k\_nat}}{affec_{nat}/disp_{nat}}\right)-1} \tag{10}$$

Where $\Phi(x)$ is the cumulative distribution function of the standard normal distribution, $affec_{k\_nat}$ and $disp_{k\_nat}$ represent the weekly average of affected and displaced individuals caused by natural events of type k across the entire sample and $affec_{nat}$ and $disp_{nat}$ are the weekly average of affected and displaced individuals across all categories during the entire period. This way, the theoretical minimum value of the index is 2, occurring when the maximum weekly number of affected and disaster victims is zero[15], implying that events of type k caused no impact in province i during year t. However, this does not necessarily mean that events of type k did not occur in that province and year, as they could have taken place without causing an impact on the population.

Models 5, 6, 7, and 8, on the other hand, apply the following transformation:

$$index\_human_{ikt} = (max\_affec_{ikt})^{1.5-\Phi\left(\frac{disp_{k\_nat}/affec_{k\_nat}}{disp_{nat}/affec_{nat}}\right)} + (max\_disp_{ikt})^{1.5-\Phi\left(\frac{affec_{k\_nat}/disp_{k\_nat}}{affec_{nat}/disp_{nat}}\right)} \tag{11}$$

Here, the theoretical minimum index value is zero, achieved when both the affected and displaced counts are zero. In this case, events without human impact on province i during year t do not affect the final value of the index.

Variation 2: Human impact measurement

To measure the human impact of natural events in each province, the IFIDEN and Models 2, 5, and 6 consider the maximum number of affected and disaster victims generated in a week by each event type:

$$max\_affec_{ikt} = \frac{\max\limits_{ikt} affected_{j\_ikt}}{population_i} \tag{12}$$

$$max\_disp_{ikt} = \frac{\max\limits_{ikt} displaced_{j\_ikt}}{population_i} \tag{13}$$

[15]Given the ratio $\frac{disp_{k\_nat}/affec_{k\_nat}}{disp_{nat}/affec_{nat}}$ has a minimum value of zero, the power to which the maximum percentage of affected people is elevated is at least zero.

where $affected_{j\_ikt}$ and $dsiplaced_{j\_ikt}$ represent the number of affected and displaced individuals caused by emergencies of type k in province i during week j of year t, and $population_i$ represents the total population of province i. Conversely, Models 3, 4, 7, and 8 use the weekly average of affected and displaced individuals in the province, considering only those weeks in which the category of event occurred in the province:

$$avg\_affec_{ikt} = \frac{\sum_{j=1}^{J^{ikt}} affected_{j\_ikt}/J^{ikt}}{population_i} \tag{14}$$

$$avg\_disp_{ikt} = \frac{\sum_{j=1}^{J^{ikt}} displaced_{j\_ikt}/J^{ikt}}{population_i} \tag{15}$$

where J^{ikt} is the number of weeks in year t in which province i experienced an event of type k. By using the weekly average, information from all weeks is included, not just the week with the highest value, even if that includes weeks with insignificant or zero values.

Variation 3: Construction of the spatiotemporal index

The third variation corresponds to the construction of the spatiotemporal index ($index\_st_{ikt}$). The IFIDEN and Models 3, 5, and 7 use the normalized percentage of district-weeks affected, as presented in Section 4. This variable, known as $dist\_week_{ikt}$, is constructed as follows:

$$dist\_week_{ikt} = \frac{\sum_{s}\sum_{j} Events_{sj\_ikt}}{\text{Total Districts in Province } i \times \text{Total Weeks in Year } t} \tag{16}$$

where $Events_{sj\_ikt}$ represents the number of events of type k that occurred in district s (part of province i) during week j of year t. The denominator represents the maximum number of possible district-weeks in province i, for which all the districts of the province should register the type k emergency every week of year t. The spatiotemporal index $index\_st_{ikt}$ is obtained by normalizing the $dist\_week_{ikt}$ variable relative to the minimum and maximum values reported for each type of natural event throughout the period from 2003 to 2023:

$$index\_st_{ikt} = \frac{dist\_week_{ikt} - \min_k dist\_week_{ikt}}{\max_k dist\_week_{ikt} - \min_k dist\_week_{ikt}} \tag{17}$$

Meanwhile, Models 2, 4, 6, and 8 use the simple average of two normalized variables: (a) the *average number of weeks* in which an emergency affected a district in the province, among the districts where the event was recorded (num_weeks_{ikt}), and (b) the *percentage of districts* in the province that were affected at least once a year (num_dist_{ikt}). This variation of the spatiotemporal component allows the calculation of the temporal and geographical expansion dimensions independently. The variables are calculated as follows:

$$num\_weeks_{ikt} = \frac{\sum_{s}\sum_{j} Events_{sj\_ikt}}{S_{ikt}} \tag{18}$$

$$num\_dist_{ikt} = \frac{\sum_{s}\sum_{j} Events_{sj\_ikt}}{\text{Total Districts in Province } i} \tag{19}$$

where S_{ikt} is the number of districts in province i where an event of type k was recorded at least once in year t. Both variables are normalized with respect to the minimum and maximum values reported for each type of event through the period:

$$num\_weeks^{n}_{ikt} = \frac{num\_weeks_{ikt} - \min_{k} num\_weeks_{ikt}}{\max_{k} num\_weeks_{ikt} - \min_{k} num\_weeks_{ikt}} \tag{20}$$

$$num\_dist^{n}_{ikt} = \frac{num\_dist_{ikt} - \min_{k} num\_dist_{ikt}}{\max_{k} num\_dist_{ikt} - \min_{k} num\_dist_{ikt}} \tag{21}$$

In this case, the index $index\_st_{ikt}$ is constructed as the simple average of both normalized variables:

$$index\_st_{ikt} = 0.5 \times num\_sem_{ikt} + 0.5 \times num\_dist_{ikt} \tag{22}$$

Simple average of four normalized variables

Finally, Model 9 includes a simplified version of the index, in which four variables are averaged, each normalized to their maximum value over the study period: (1) the number of weeks an emergency affected a district of the province, among districts where the event was recorded ($num\_weeks^{n}_{ikt}$), (2) the percentage of districts in the province that were affected at least once a year ($num\_dist^{n}_{ikt}$), (3) the maximum number of affected individuals generated in a week by event type k, as a percentage of the population of province i ($max\_affec^{n}_{ikt}$), and (4) the equivalent measure for the number of displaced individuals ($max\_disp^{n}_{ikt}$):

The index for each province i and year t is calculated as follows:

$$index_{it} = \sum_{k=1}^{9} 0.25 \times [num\_weeks^{n}_{ikt} + num\_dist^{n}_{ikt} + max\_affec^{n}_{ikt} + max\_disp^{n}_{ikt}] \tag{23}$$

D Appendix 4: Frequency, Impact, and Geographic Distribution Index (IFIDEN) at the district level

The calculation of the *Frequency, Impact, and Geographic Distribution Index (IFIDEN) at the district level* is similar to the index at the province level presented in Section 4. Like its province-level counterpart, the district-level IFIDEN summarizes the incidence of natural disasters across districts, capturing their frequency, geographic spread, and impact on the population. The same components are included in the construction of this indicator: a *spatiotemporal index* and a *human impact index*. In this case, the 16 categories of natural events are considered, without grouping less frequent categories together[16].

The *spatiotemporal index* ($index\_st_{ikt}$) captures the frequency with which each category of natural events has affected the district analyzed within the relevant time frame for each household. This index is calculated as the percentage of weeks that district i experienced a natural event of category k in the past 12 months to month t, normalized to the maximum and minimum values in the sample:

$$index\_st_{ikt} = \frac{nb\_weeks_{ikt} - \min\limits_{k} nb\_weeks_{ikt}}{\max\limits_{k} nb\_weeks_{ikt} - \min\limits_{k} nb\_weeks_{ikt}}$$

where nb_weeks_{ikt} is the percentage of weeks in which district i registered an event of category k during the 12 months up to month t, $\max\limits_{k} nb\_weeks_{ikt}$ y $\min\limits_{k} nb\_weeks_{ikt}$ represent the minimum and maximum values of the variables across all values associated with event type k over the entire study period. This index ranges from 0 to 1.

The *human impact index* ($index\_human_{ikt}$) is calculated based on the maximum number of affected individuals and disaster victims in each district by category over the past 12 months:

$$max\_affec_{ikt} = \frac{\max\limits_{ikt} affected_{j\_ikt}}{population_i}$$

$$max\_disp_{ikt} = \frac{\max\limits_{ikt} displaced_{j\_ikt}}{population_i}$$

where $affected_{j\_ikt}$ and $displaced_{j\_ikt}$ represent the number of affected and displaced people caused by emergencies of type k in district i during week j of moving year t. The week with the highest value in each year is identified, and this value is presented as a percentage of the district's population estimated from the 2017 Census. If the number of affected individuals or disaster victims exceeds the district's population estimate, the value is capped at 1. Thus, the

[16] The 16 categories of natural events considered to compute the district-level IFIDEN are: Extreme precipitations, Low temperatures, Strong Wind, Flooding, Landslide, Drought, Forest fire, Mudslide and flash flood, Erosion, Earthquakes, Hill collapse, Thunderstorms, Swells, Avalanches, Volcanic activity, and others not classified by INDECI. Appendix 1 shows a detailed definition of these categories.

human impact index is calculated as follows:

$$index\_human_{ikt} = (1+max\_affec_{ikt})^{2\Phi\left(\frac{disp_{k\_nat}/affec_{k\_nat}}{disp_{nat}/affec_{nat}}\right)-1} + (1+max\_disp_{ikt})^{2\Phi\left(\frac{affec_{k\_nat}/disp_{k\_nat}}{affec_{nat}/disp_{nat}}\right)-1}$$

Where $\Phi(x)$ is the cumulative distribution function of the standard normal distribution, $affec_{k\_nat}$ and $disp_{k\_nat}$ represent the weekly average of affected and displaced individuals caused by natural events of type k across the entire sample and $affec_{nat}$ and $disp_{nat}$ are the weekly average of affected and displaced individuals across all categories during the entire period[17]. This index theoretically ranges between 2 and 4.

To obtain the **IFIDEN**, the product of the spatiotemporal index ($index\_st_{ikt}$) and the human impact index ($index\_human_{ikt}$) is calculated for each category, and this result is aggregated across all categories, resulting in a single indicator for each district i and moving year t.

$$IFIDEN_{it} = \frac{\sum_{k=1}^{16} index\_st_{ikt} \times index\_human_{ikt}}{16}$$

With this, the indicator has a theoretical value range between 0 and 4, reaching its maximum value if district i experienced each natural event type for the highest number of weeks during moving year t, with 100 percent of the population affected and impacted by these natural events during the corresponding period.

[17] Weekly averages are calculated by computing the number of affected/displaced individuals recorded in each province every week and averaging the values for every week of each year. Lastly, the resulting annual data are averaged