MODELLING SOCIETAL LANDSLIDE RISK IN ITALY

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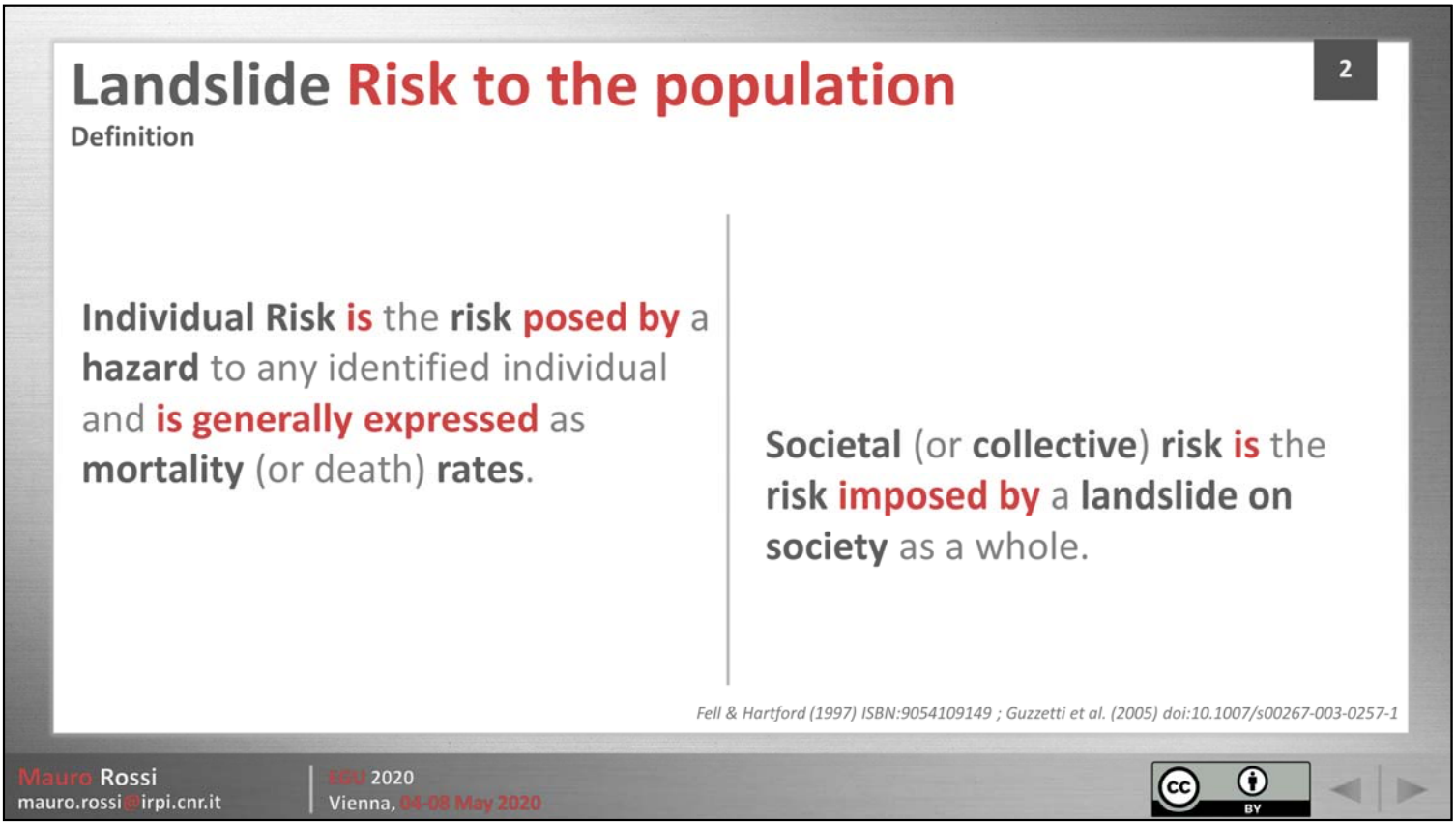
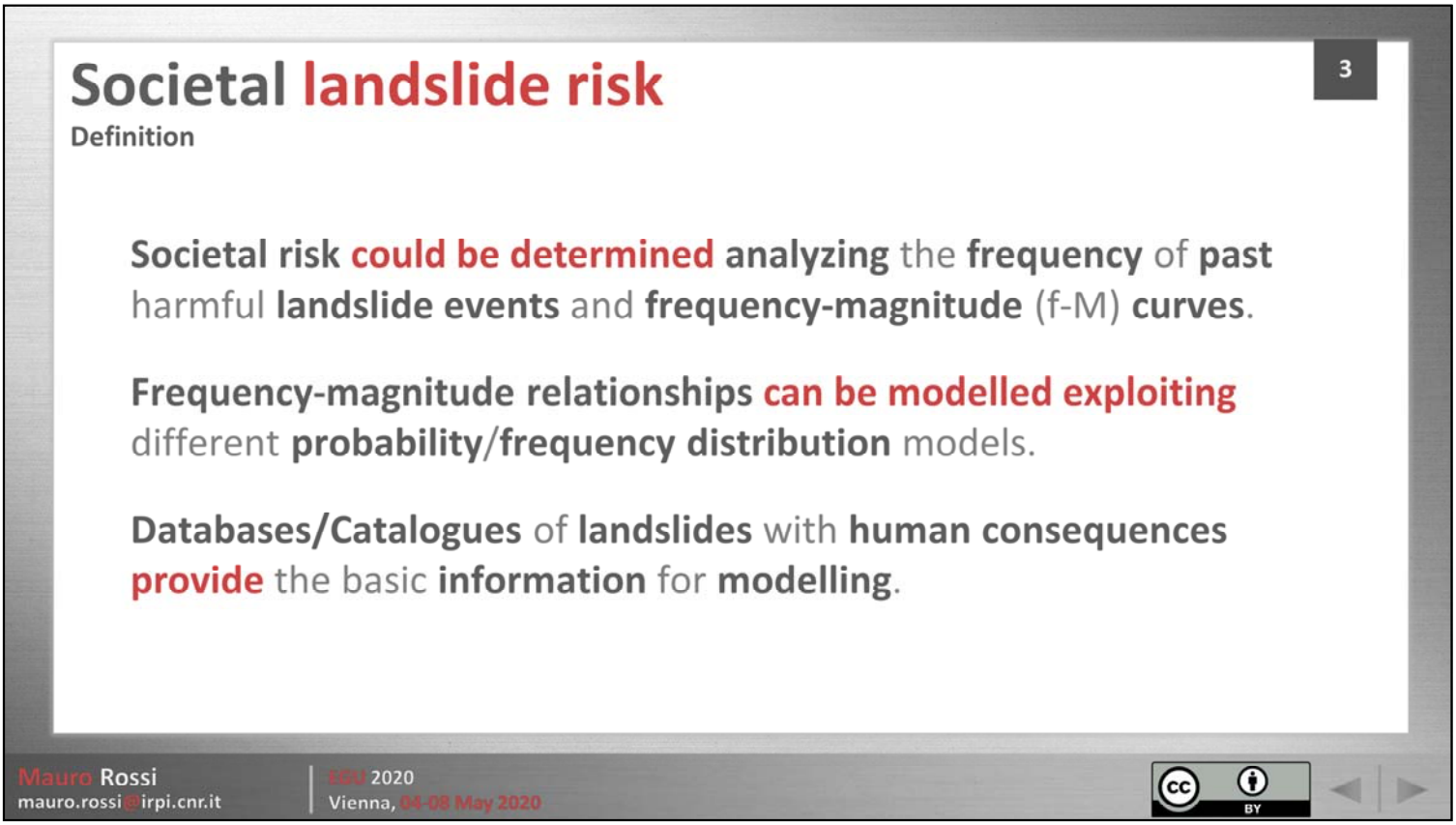


Individual Risk is the risk posed by a hazard to any identified individual and is generally expressed as mortality (or death) rates.

(Mortality is the number of deaths per 100,000 of any given population over a pre-defined period, usually one year)

Societal (or collective) risk is the risk imposed by a landslide on society as a whole.



Societal risk could be determined analyzing the frequency of past harmful landslide events and frequency-magnitude (f-M) curves.

Frequency-magnitude relationships can be modelled exploiting different probability/frequency distribution models.

Databases/Catalogues of landslides with human consequences provide the basic information for modelling.

Fatal Landslides

Landslide impact on the population in Italy

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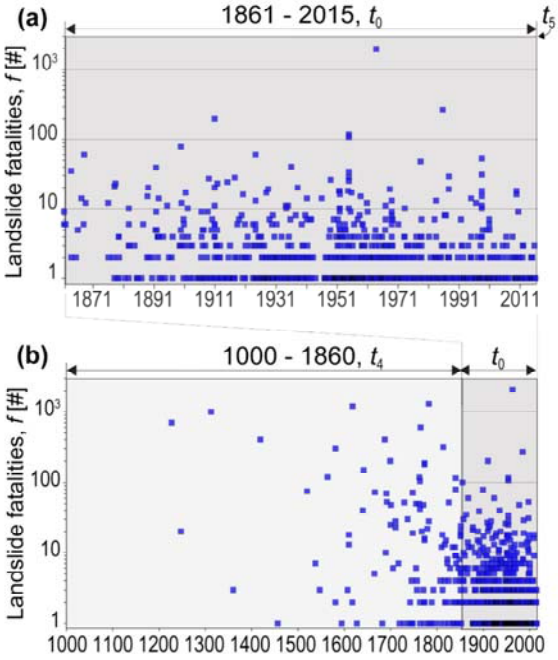
CNR IRPI collected information on the **fatal landslide** (and also flood) **events in Italy**. For every events, the catalogue reports:

- **Location** and **timing** of landslide;
- Landslide **type**;
- **Natural** or **anthropic trigger** (e.g. rainfall, earthquake, dam break, …)
- **Number** of **fatalities** and, when know, of **injured people**;
- **Death circumstances**.



Guzzetti (2000) doi:10.1016/S0013-7952(00)00047-8; Salvati et al. (2010) doi:10.5194/nhess-10-465-2010

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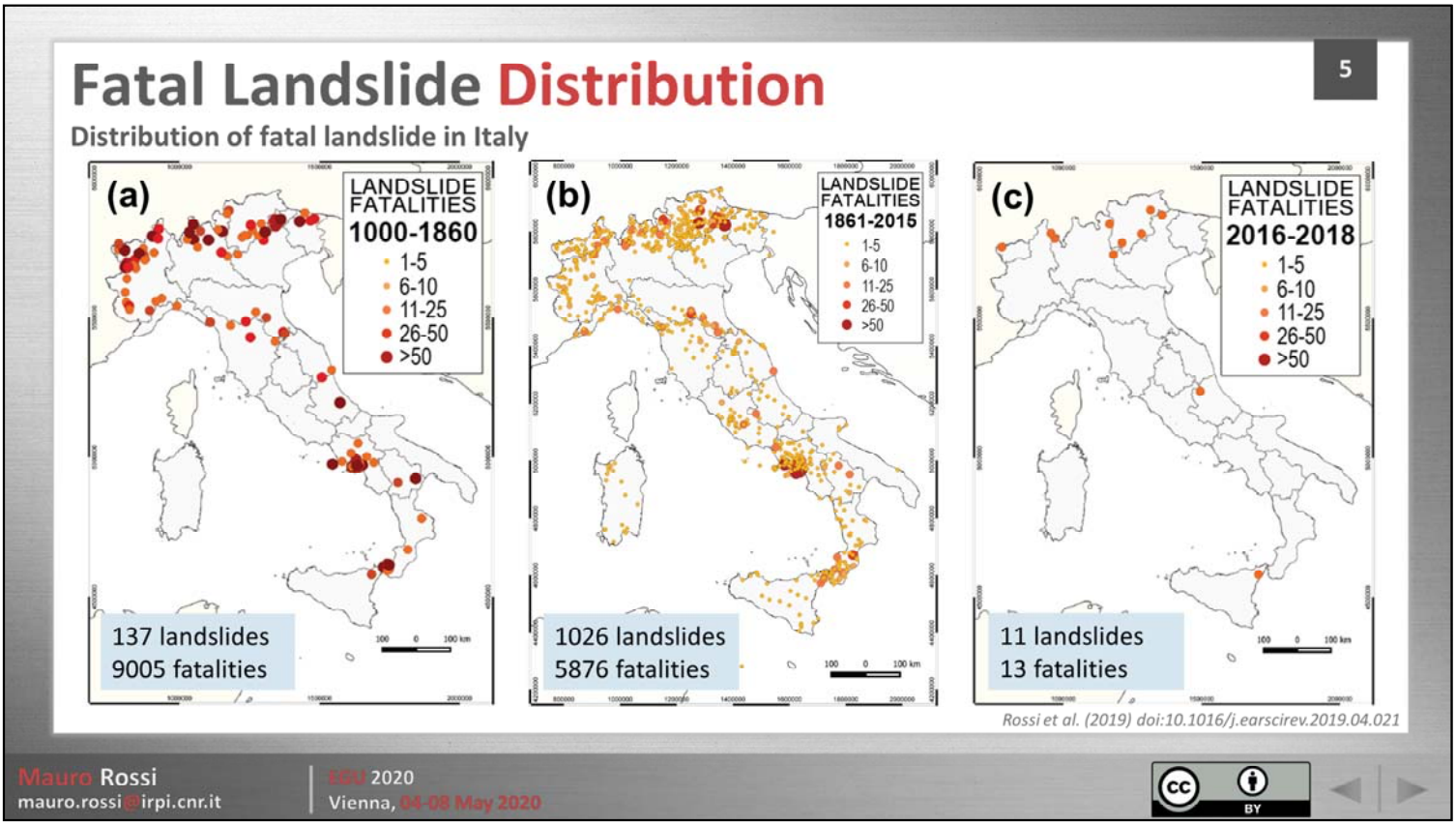
CNR IRPI collected data on such fatal landslide events in Italy, compiling a detailed catalogue extended for more that 1000 years and reporting information on

- Location and timing of landslide;
- Landslide type;
- Natural or anthropic trigger (e.g. rainfall, earthquake, dam break, …)
- Number of fatalities and, when know, of injured people;
- Death circumstances.

In particular, the plots show the distribution of landslide fatalities per event in time.



The figure shows the distribution of the fatal landslide events for three period respectively from 1000 to 1860 (the oldest and less complete portion of the catalogue listing 137 landslide with at least 9005 fatalities), from 1861-2015 (used in this study listing 1026 landslide with 5876 fatalities) and from 2016-2018 (the most recent period used to verify our modelling results listing 11 landslides causing 13 fatalities.

As we see in the figure those data are sparse but are well distributed over the Italian reliefs.

Distribution Models

Different types of distributions for frequency-Magnitude analysis

Pareto model

$$p(x;k,x_m) = k x_m^k x^{-(k+1)}$$

$x,\ k,\ x_m \in \mathbb{R}^+$

$x \geq x_m$

Zeta model

$$p(x;z) = \frac{1}{x^{z+1}\xi(z+1)}$$

with $\xi(z+1) = \sum_{n=1}^{\infty} \frac{1}{n^{z+1}}$

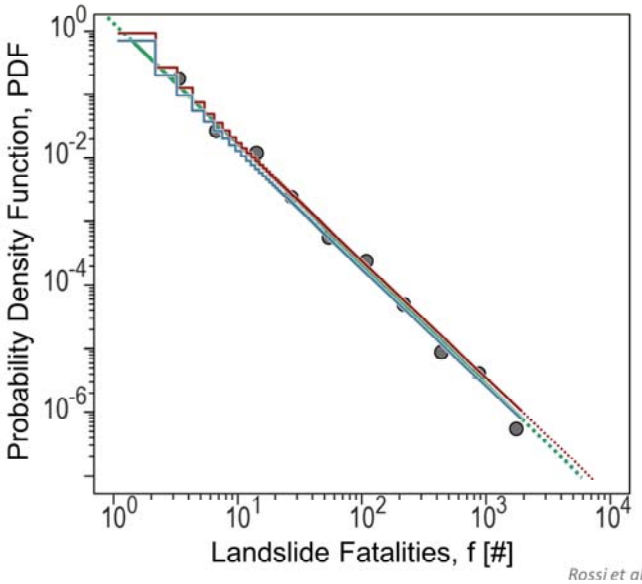
$z \in \mathbb{R}^+;\ x \in \{1, 2, \ldots, \infty\}$

Zipf model

$$p(x;s,N) = \frac{1}{x^s H_{N,s}}$$

with $H_{N,s} = \sum_{n=1}^{N} \frac{1}{n^s}$

$s \in \mathbb{R}^+;\ x \in \{1, 2, \ldots, N\}$



Rossi et al. (2010) doi:10.1002/esp.1858

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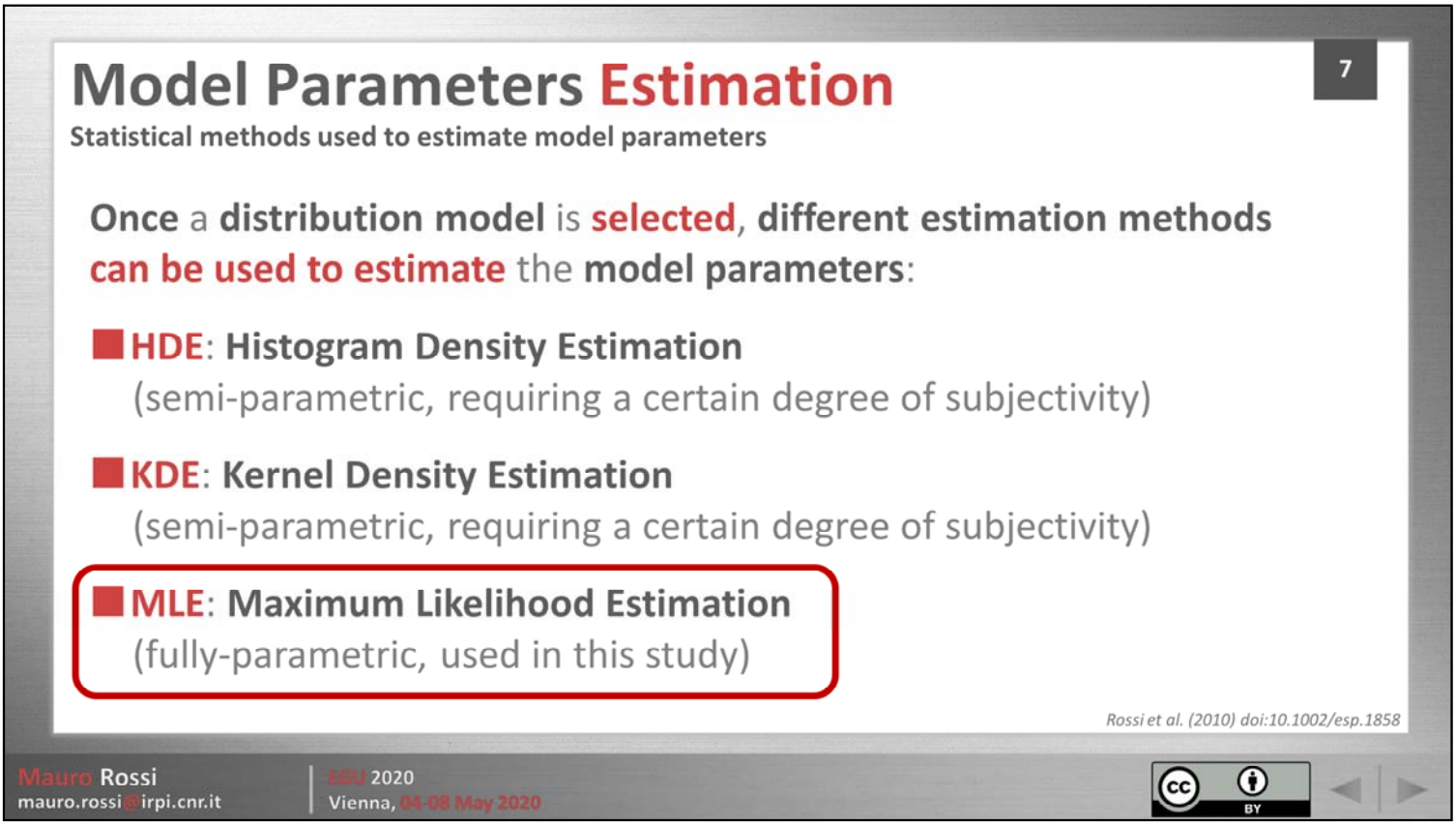
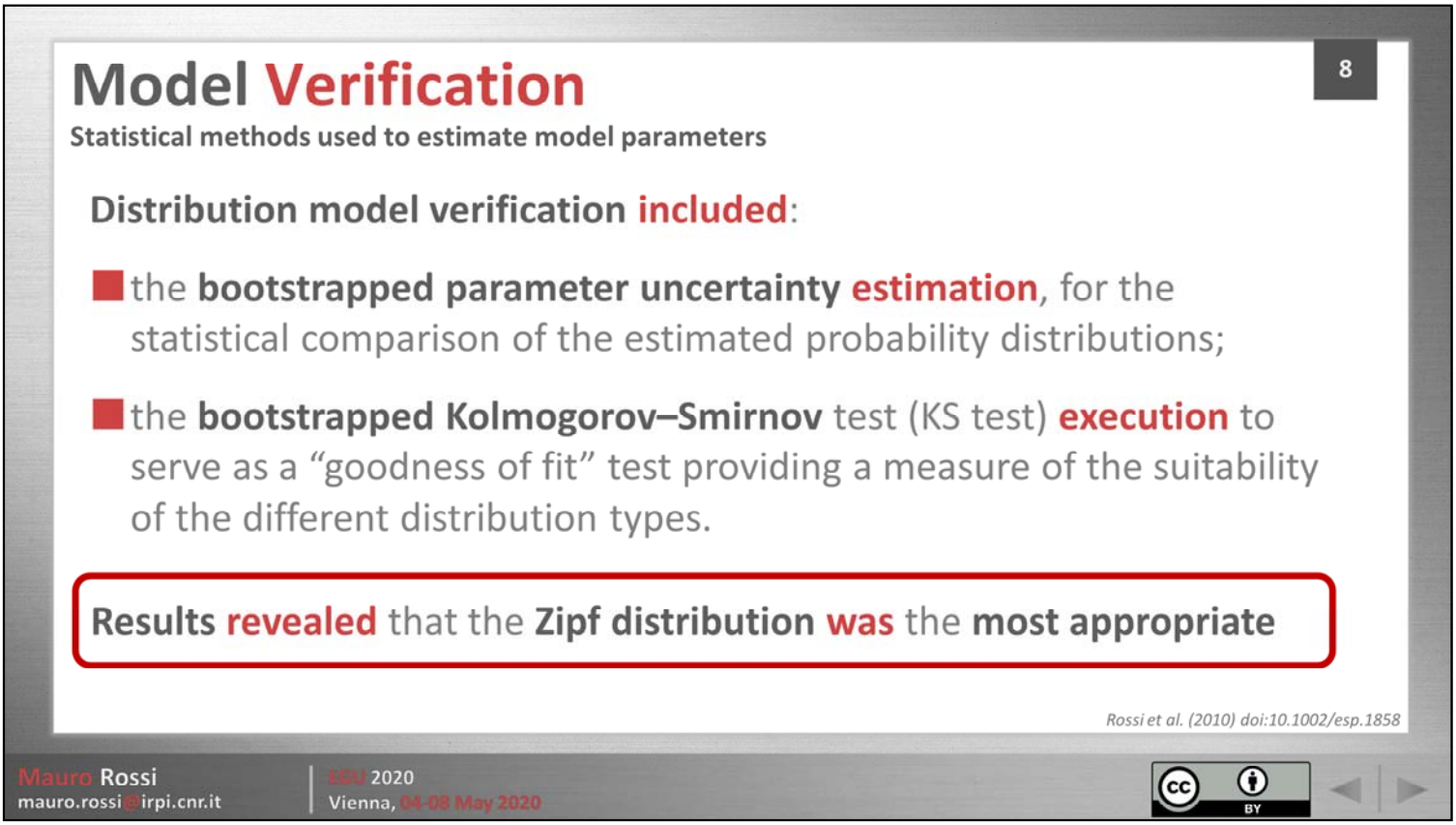
Different types of distribution can be used for modelling societal landslide risk. Here we show 3 type of distributions the Pareto, the Zeta and the Zipf distribution that can be used for modelling the probability/frequency of landslide events which were found to show a power low behavior (i.e. a linear probability/magnitude relation in log-log scale). The plots on the right show an application of the 3 distribution to model the probability of landslides in Emilia Romagna. Among them, the best model was the Zipf distribution, which is defined for discrete variable with a maximum value.



Once a distribution model is selected, different estimation methods can be used to estimate the model parameters:

- HDE: Histogram Density Estimation (semi-parametric, requiring a certain degree of subjectivity)
- KDE: Kernel Density Estimation (semi-parametric, requiring a certain degree of subjectivity)
- MLE: Maximum Likelihood Estimation (fully-parametric, used in this study)



Distribution model verification included:

the bootstrapped parameter uncertainty estimation, for the statistical comparison of the estimated probability distributions;

the bootstrapped Kolmogorov–Smirnov test (KS test) execution to serve as a "goodness of fit" test providing a measure of the suitability of the different distribution types.

Results revealed that the Zipf distribution was the most appropriate.

Zipf Model Interpretation

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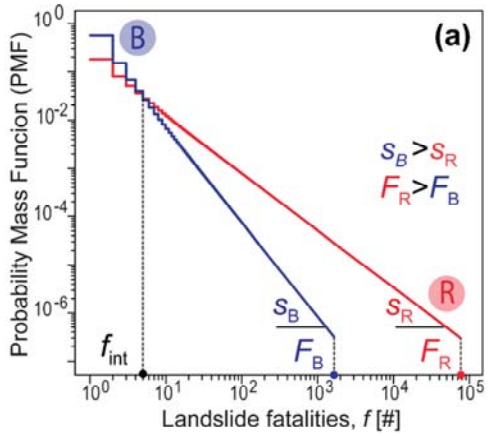
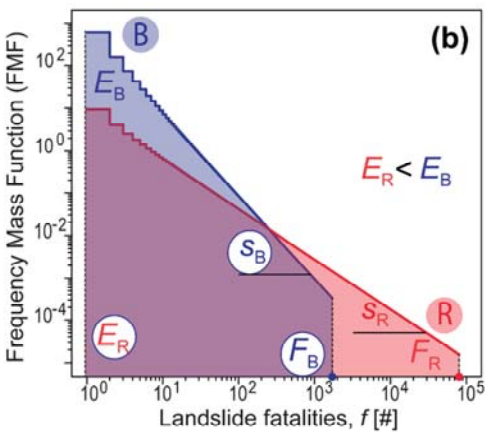
Interpretation of Zipf model applied to landslide fatalities

$$\mathrm{PMF} = \frac{1}{f^s \sum_{f=1}^{F} \frac{1}{f^s}}$$

$$\mathrm{FMF} = \mathrm{PMF} \times E = \int_0^1 \frac{1}{f^s \sum_{f=1}^{F} \frac{1}{f^s}} \times E$$





Rossi et al. (2019) doi:10.1016/j.earscirev.2019.04.021

The Zipf model is appropriate to describe the distribution of the number of landslide fatalities in an event, which is commonly used to quantify the societal landslide risk in an area.

In the model equation f ∈ {1, 2, … , F} is the number of the fatalities caused by a landslide i.e., the magnitude of the fatal event, F is the largest number of fatalities caused by a single fatal landslide in the empirical record, and s ∈ ℝ+ is the scaling exponent of the Zipf distribution model that measures the proportion of small versus large magnitude fatal events in the record.

Both the PMF (PDF) and the FMF (FDF) provide useful information for quantitative risk evaluations.

Zipf Model Derivatives

Different derivatives of the Zipf distribution model usable for societal landslide risk analysis

CCDF	Complementary Cumulative Distribution Function	$\mathrm{CCDF} = 1 - \mathrm{CDF}$
CCFDF	Complementary Cumulative Frequency Distribution Function	$\mathrm{CCFDF} = 1 - \mathrm{CFDF}$ with $\mathrm{CFDF} = \int_0^1 FMF$
CDF	Cumulative Distribution Function	$\mathrm{CDF} = \int_0^1 \mathrm{PMF}$
FMF	Frequency Mass Function	$\mathrm{FMF} = \mathrm{PMF} \times E = \int_0^1 \frac{1}{f^s \sum_{f=1}^{F} \frac{1}{f^s}} \times E$
PMF	Probability Mass Function	$\mathrm{PMF} = \frac{1}{f^s \sum_{f=1}^{F} \frac{1}{f^s}}$
yCCFDF	Yearly Complementary Cumulative Frequency Distribution Function	$\mathrm{yCCFDF} = \frac{\mathrm{CCFDF}}{T}$
yFDF	Yearly Frequency Mass Function	$\mathrm{yFDF} = \frac{\mathrm{FDF}}{T}$
τ_{yCCFDF}	Return period Complementary Cumulative Frequency Distribution Function	$\tau_{\mathrm{yCCFDF}} = \frac{1}{\mathrm{yCCFDF}}$

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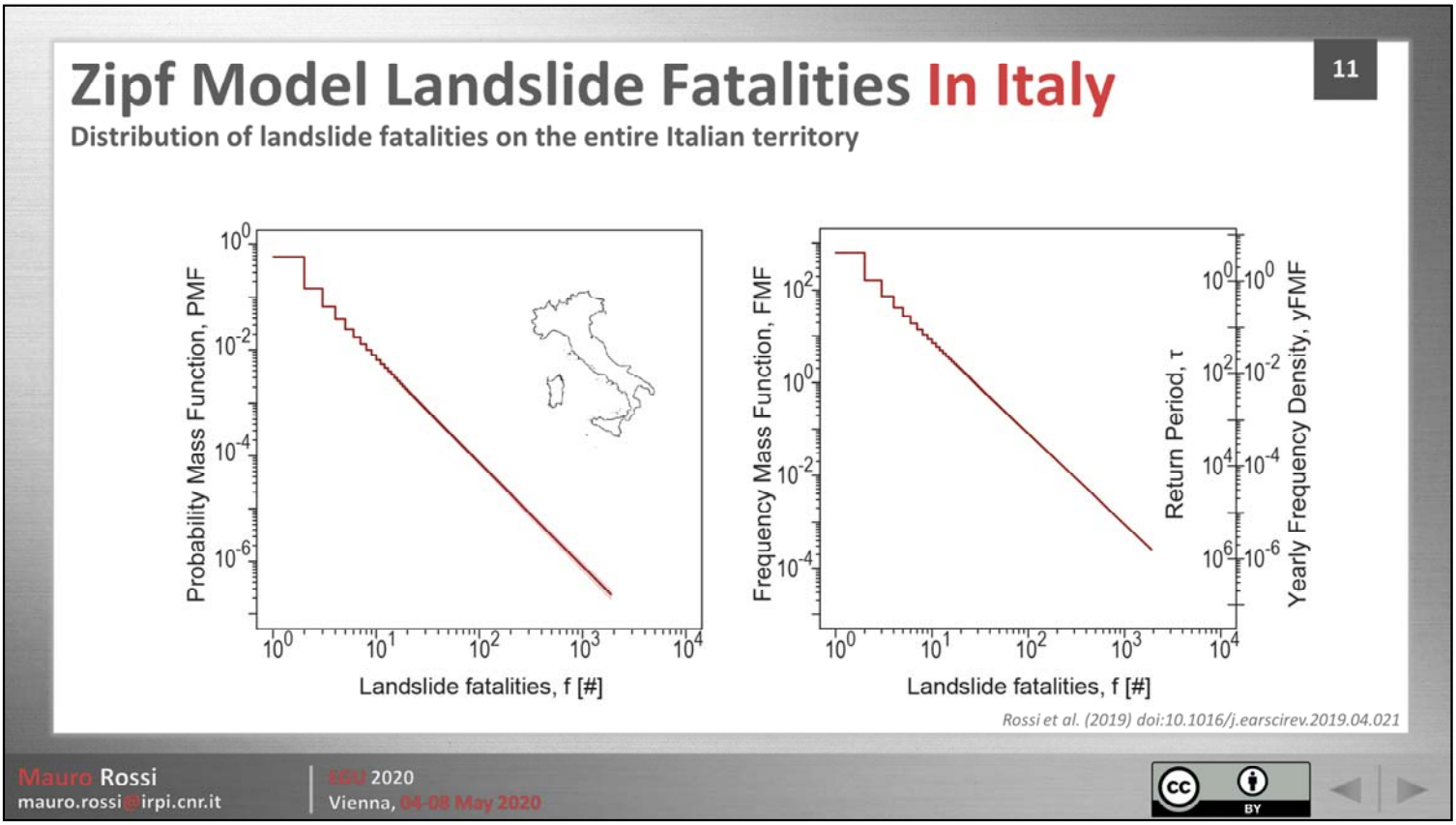
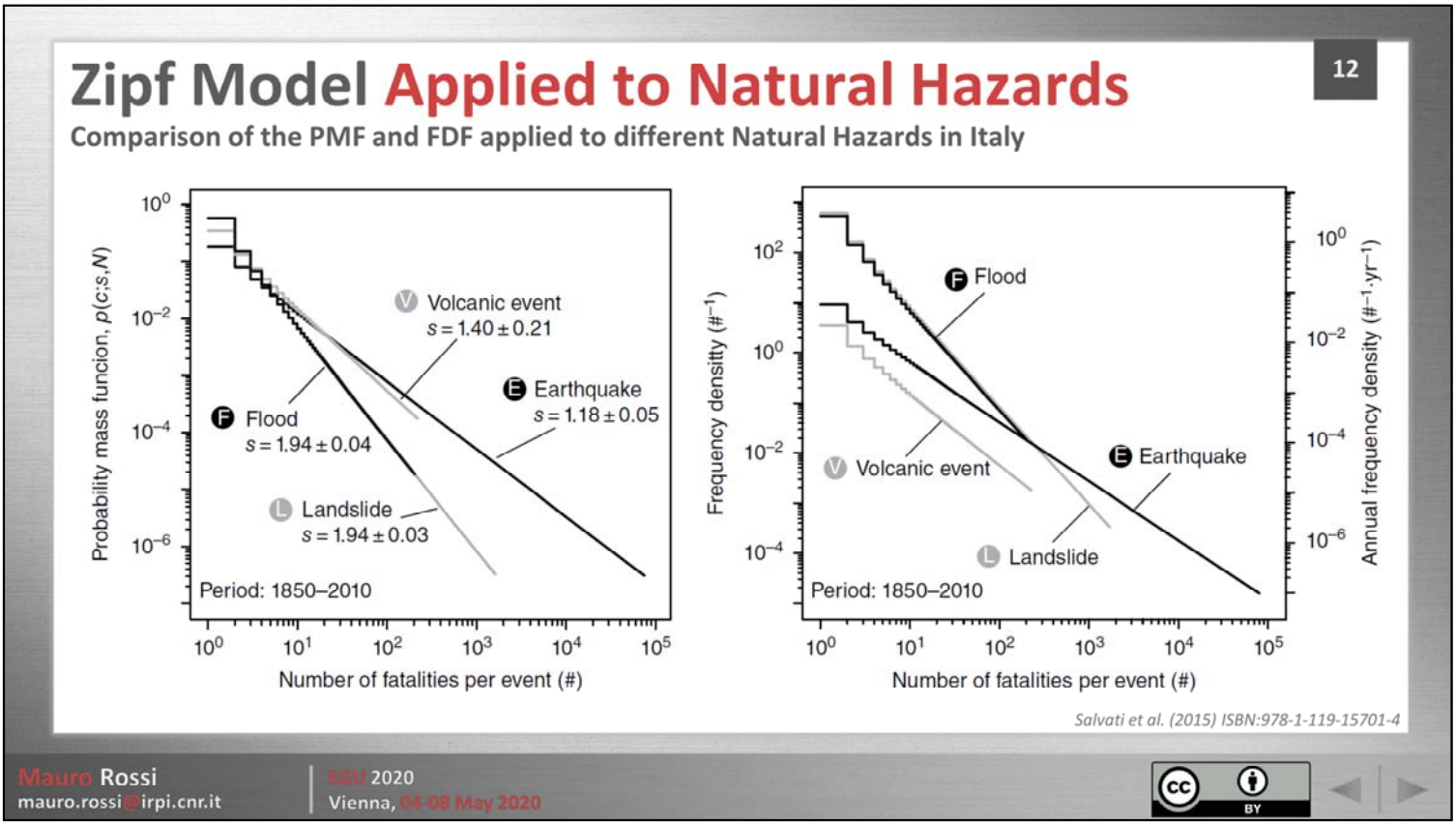
Different derivatives of the Zipf distribution model can be derived using the 3 model parameters, which can be used for societal landslide risk analysis

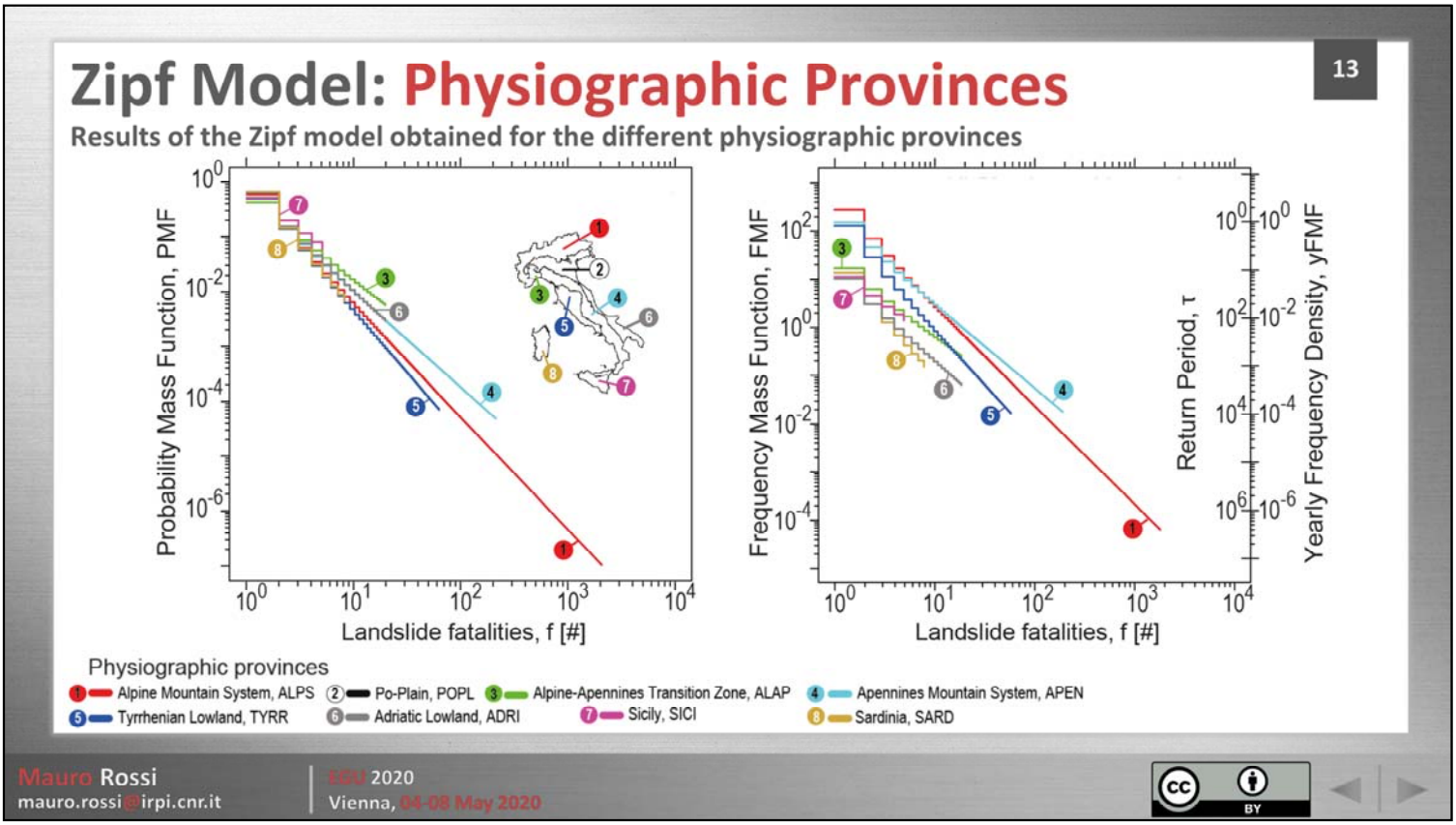


The first application of the Zipf distribution to model the landslide societal risk was done selecting all the fatal landslide events causing fatalities in the catalogue. Results shown in the figures are expressed in term of Probability Mass Function (the word mass here is a substitute of density and underline that we are dealing with a discrete variable) and in terms of Frequency Mass Function. On the right axis of the FMF plot, there are two additional secondary axes, the first is reporting the Yearly Frequency that can be calculated dividing FMF for the length of the period of the catalogue in years, and the second reporting the return period of FMF that is the reciprocal do the yearly FMF.



Similarly, we have it is also possible to derive the Zipf model for different natural hazards and compare their levels of societal risk. Here we show the modelled Probability mass function and the Frequency density of landslide events with similar densities for floods, earthquakes, and volcanoes. The societal risk posed by landslides and floods are nearly identical. These events are more frequent and less severe when compared to the earthquakes that are less frequent but often they produced large number of fatalities in Italy.

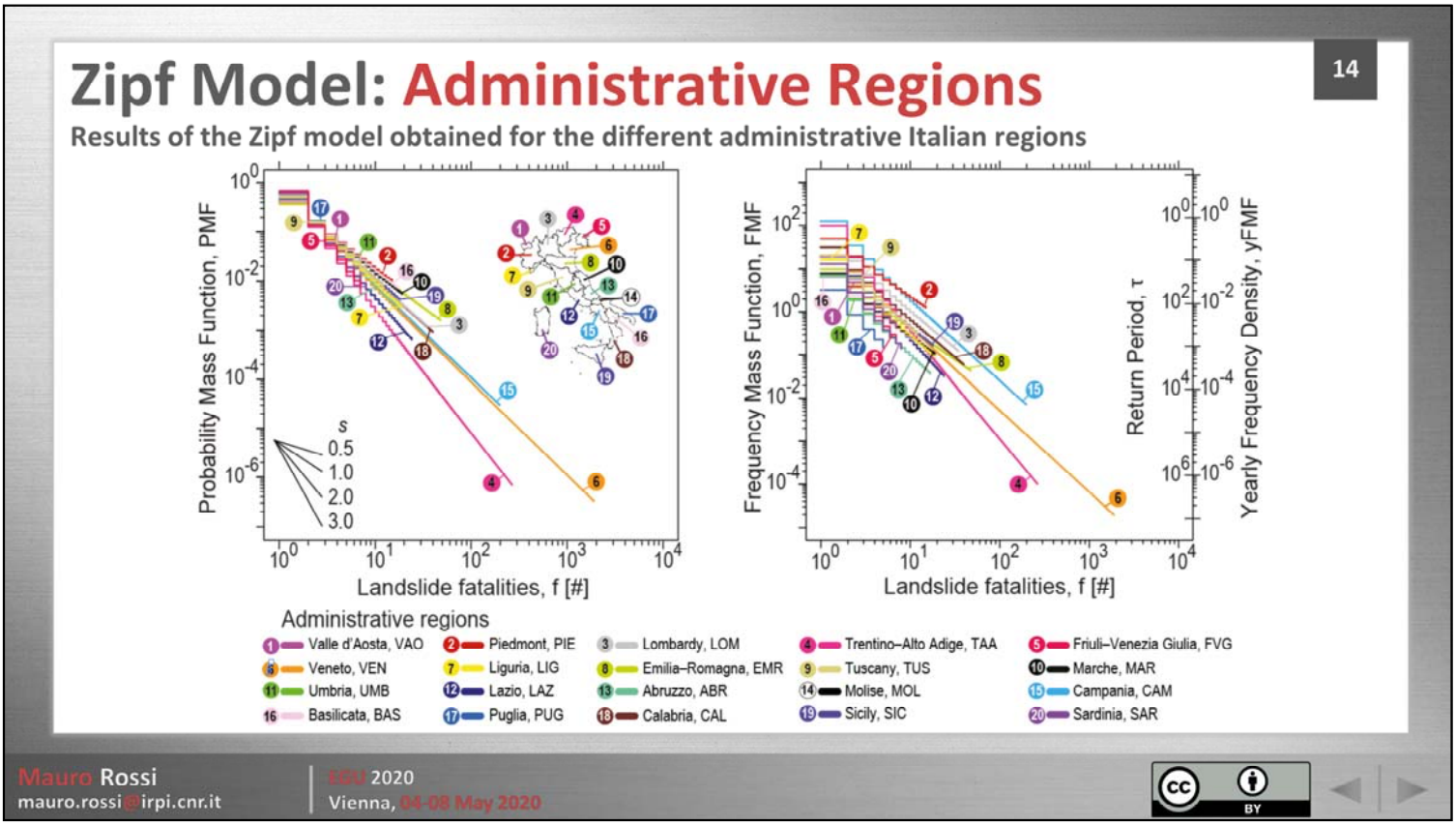
These comparison was possible because for Italy detailed catalogues of the fatalities due to geophysical hazards such as Earthquakes and Volcanic event are available, in addition to those developed by CNR IRPI for landslide and floods.



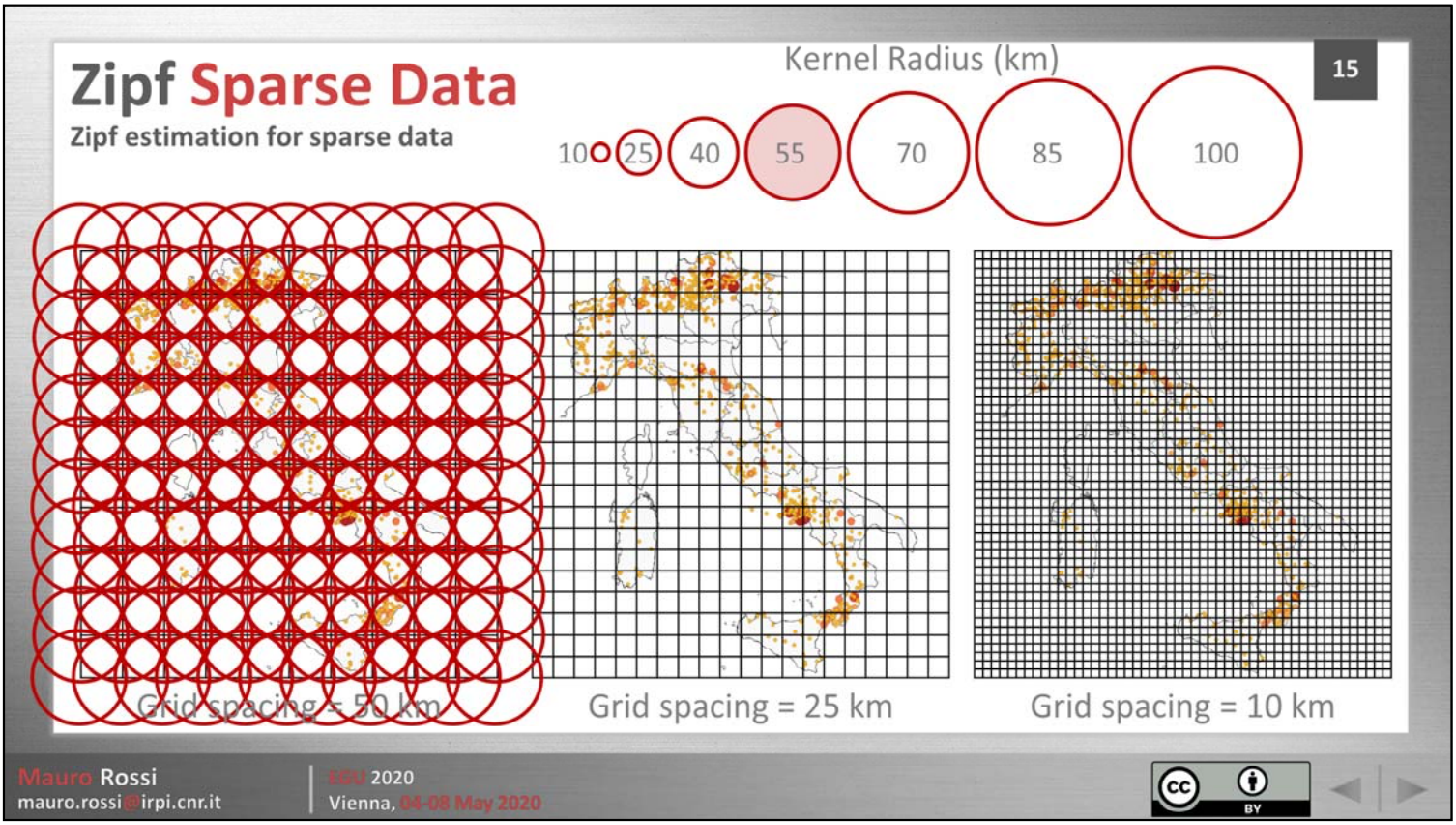
Then the questions was: how societal landslide risk varies across the territory? And how to answer these question having only sparse data?

Our first idea was to use some subdivision of the territory and evaluating the risk within each subdivision. In a preliminary attempt, we evaluate the risk within the different physiographic provinces of Italy. Such provinces are topographic subdivision of Italy proposed by Guzzetti and Reichenbach (1994) who classified the Italian landscape into eight provinces analyzing four derivatives of terrain elevation, and through the visual interpretation of morphometric, geological and structural maps.

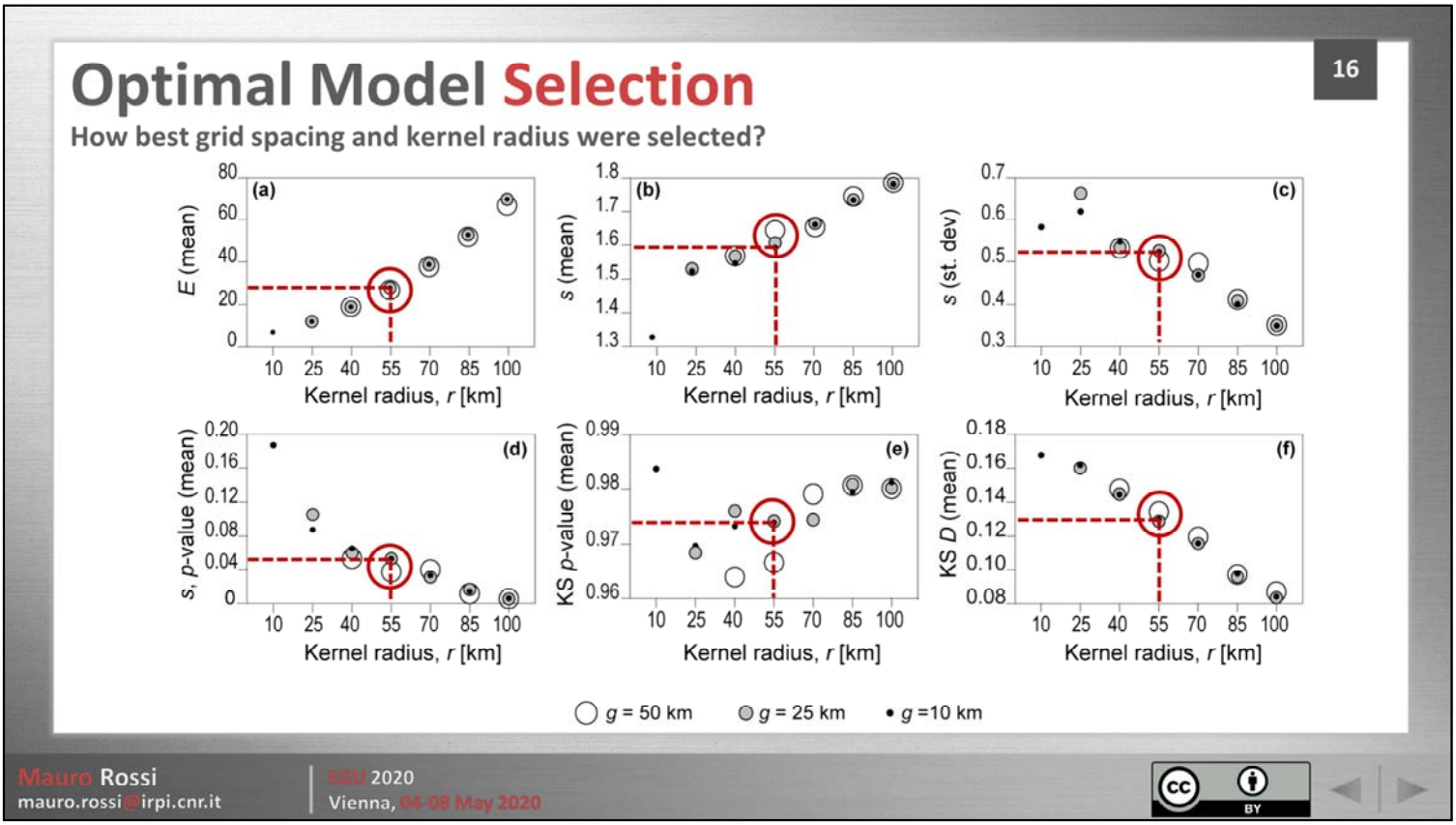
For very small magnitude landslides (f = 1), the PMF is lowest in the Alps–Apennines transition zone (3) followed by the Apennines mountain system (4), and it is highest in Sardinia (8) followed by the Tyrrhenian borderland (5). For large magnitude landslides (f ≥ 25), the PMF is largest in the Apennines mountain system (4) and lowest in the Tyrrhenian borderland (5) followed by the Alps mountain system. For very small magnitude landslides (f = 1) the FMF is largest in the Alps (1) followed by the Apennines (4), and lowest in the Adriatic borderland (6) followed by Sicily (7) and Sardinia (8), whereas for large magnitude landslides (f ≥ 25) the FMF is largest in the Apennines (4), followed by the Alps (1), and is lowest in the Alps–Apennines transition zone (3) and in the Tyrrhenian borderland (5). The range of the PMF and the FMF Zipf models is largest in the Alps (F = 1917, due to the Vajont rockslide) and it is smallest in Sicily (F = 5, E = 21) and in Sardinia (F = 8, E = 19).



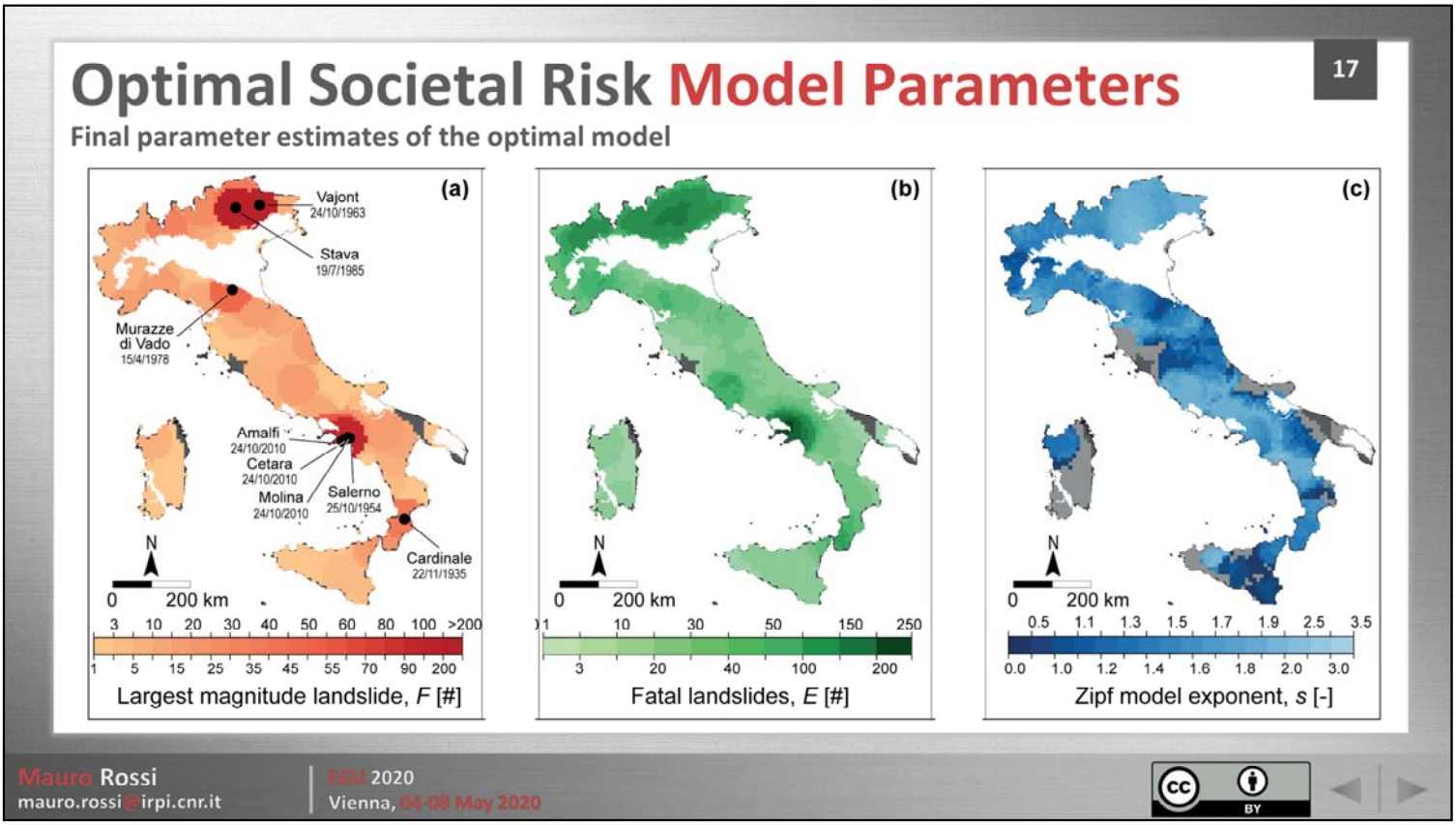
In a second attempt we consider instead the regional subdivision, which helped to have a more detailed information on the spatial variation of risk. Form this analysis we see that for very low magnitude landslides (f = 1) the PMF is largest in Trentino–Alto Adige (4) followed by Sicily (19), and is lowest in Emilia–Romagna (8) followed by Piemonte (2); whereas for large (f ≥ 25) and very large (f ≥ 50) magnitude landslides the PMF is largest in Emilia–Romagna (8) followed by Lombardy (3) and Calabria (18), and is lowest in Trentino–Alto Adige (4) with intermediate values in Campania (15) and Veneto (6) (Table 2). Examining the FMFs for the 20 Italian regions, one finds that for very low magnitude landslides the frequency of fatal landslides is largest in Campania (15) followed by Trentino–Alto Adige (4), and is smallest in Puglia (17), whereas for very large magnitude landslides the FMF is largest in Campania (15) followed by Lombardy (3), and is smallest in Trentino–Alto Adige (4). The magnitude range of the PMF and the FMF Zipf models is largest in Veneto (6, F = 1917, due to the Vajont rockslide) and is smallest in Puglia (17, F = 5, E = 5).



These risk figures, even if helpful for a preliminary comparison of the societal landslide risk in Italy, discretize the territory over polygon boundaries and fail to capture the internal and the cross border variability of the societal risk. To solve these problems we design a procedure to derive regularly spaced Zipf parameter estimations. For the purpose we used different grid spacings, namely 50, 25 and 10 km and a circular kernel with different radius (10, 25, 40, 55, 70, 85, 100 km radius) for the stepwise selection of the fatal landslide data. At each step the kernel is centered over a grid point and the data within the kernel are selected and the relative Zipf paramters estimated. Here I show just an example for the larger grid spacing for a kernel of 55 km radius.

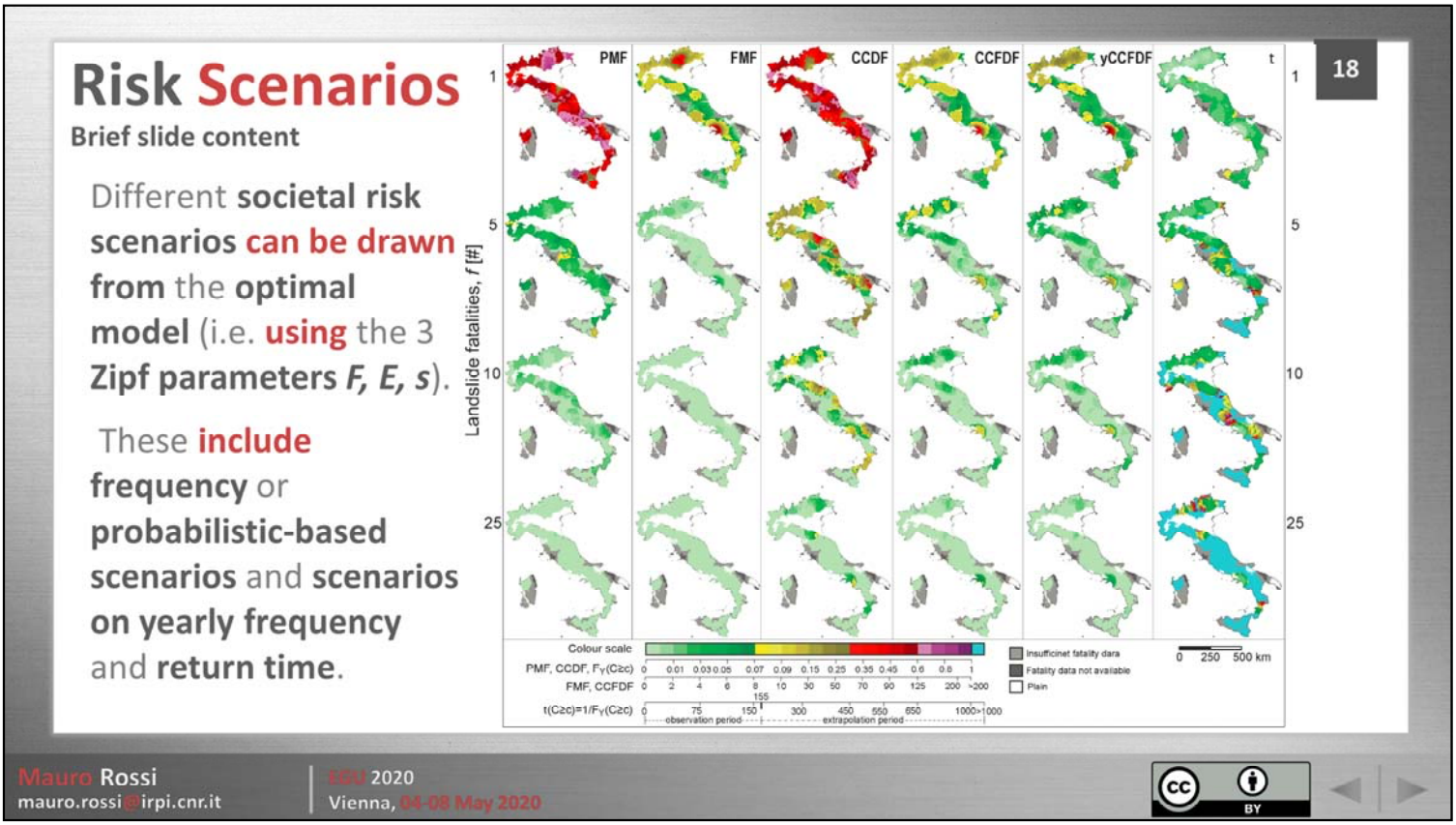


For each kernel and for each grid point of the different spacings, we estimated Zipf parameters, their significance and we execute the Kolmogorow Smirnow tests to evaluate the appropriateness of using Zipf model for that particular kernel selection. These plot for each couple of grid spacing and kernel radius show the averages and in some cases the standard deviations of the parameters estimated by the procedure. Parameters varies largely with the kernel radius and less with grid spacing. Considering the expected optimal behavior of each parameter we chose a grid spacing = 10 km and a kernel radius = 55 km as the “optimal” parameters used to construct our spatially distributed predictive model of societal landslide risk in Italy. The selection provides a high spatial resolution of the prediction (grid cells of 100 km2) without losing model performance. Further, using a sampling kernel area of about 9503 km2 (r = 55 km), in each grid cell the single predictive models were determined with an average of 30 fatal landslides. This guarantees that the scaling exponent of the Zipf distribution model is robust, and its variability remains limited (on average σs < 0.5).



Using the optimal combination of grid spacing and kernel radius we were able to calculate the three main Zipf model parameters for each grid point resulting in a regularly spaced estimation of the societal risk over Italy.

The three different colour scales rank the model parameter form the less risky value (lighter colors) to the more risky values (darker colors). Indeed as a first approximation darker colors mean higher level of societal risk.



The model outcomes allow for designing scenarios of societal landslide risk in Italy. From left to right, maps show the Probability Mass Function (PMF, Eq. (B1)), the Frequency Mass Function (FMF, Eq. (B3)), the Complementary Cumulative Distribution Function (CCDF, Eq. (B2)), the Complementary Cumulative Frequency Distribution Function (CCFDF, Eq. (B4)), the yearly Complementary Cumulative Distribution Function (yCCFDF, Eq. (B5)), and the projected return period (τyCCFDF, Eq. (B6)).

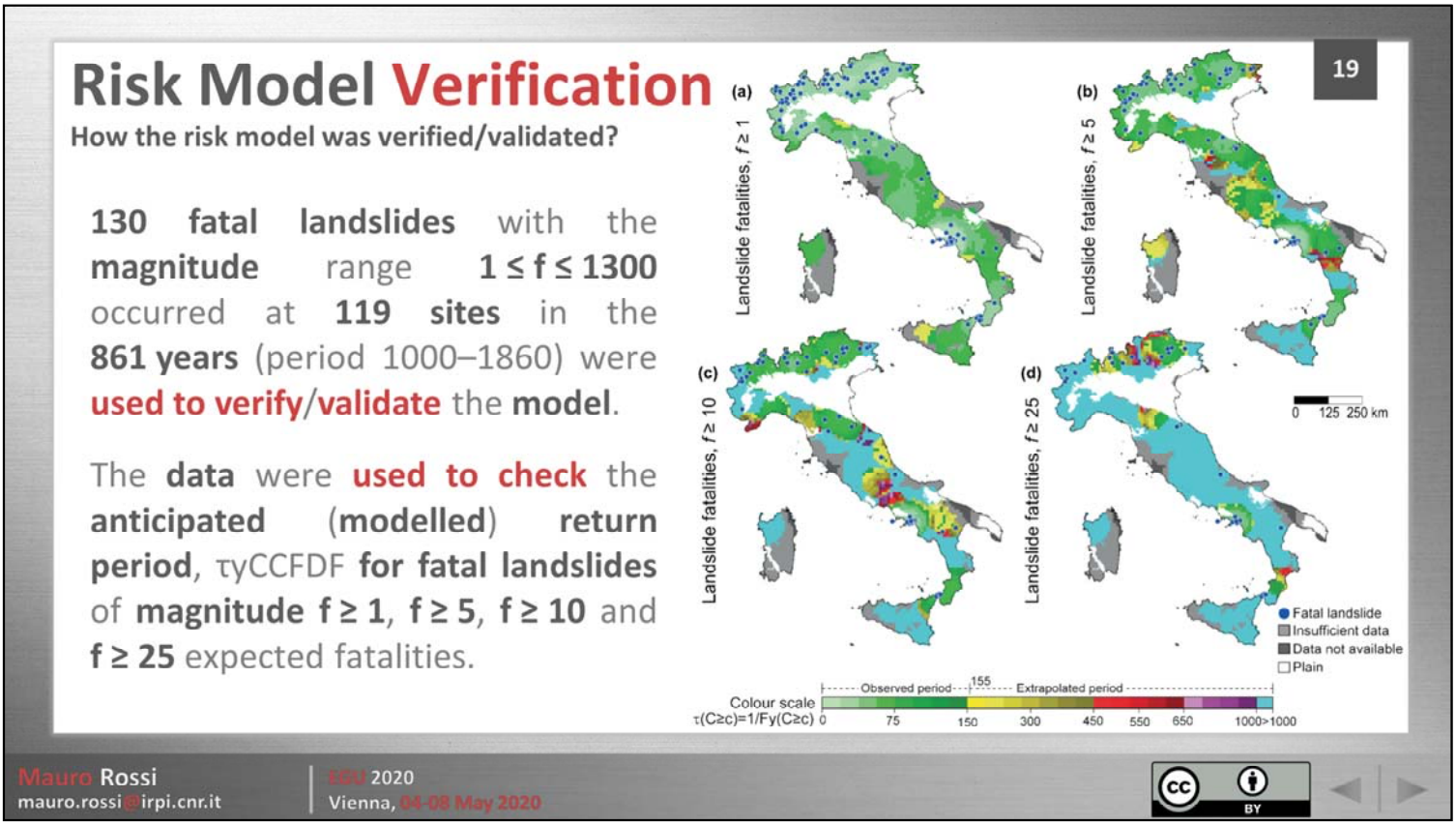
The PMF and the FMF of the fatal landslides are largest for the very low magnitude landslides (f = 1) and they reduce rapidly with the increase of the landslide magnitude. This was expected, as in the historical record the proportion of large magnitude landslides with many or very many fatalities is significantly smaller than the proportion of low magnitude landslides with one or a few fatalities. For very low magnitude landslides the PMF ≥ 0.30 in most of Italy, and PMF ≥ 0.50 in most of NE Italy, in large parts of the Apennines range and the Tyrrhenian borderland, and in NW Sicily.

The FMF is very large (FMF > 80) in the coastal area of Campania, in southern Italy, and subordinately (FMF > 50) in the NE Italian Alps. Most of the Alps, large parts of the Alps–Apennines transition zone, limited parts of the NW Apennines, the area encompassing Rome and its surroundings, the southern part of Calabria and an area in NE Sicily have FMF > 8. We take these as evidences of the fact that single landslide fatalities can be expected in most

of the mountain areas and in large parts of the hills of Italy. For medium landslide magnitudes (f = 10), the picture is somewhat different with most of Italy exhibiting PMF ≤ 0.03, and FMF ≤ 1. The pattern is even more evident for the large magnitude landslides (f = 25), for which all of Italy has PMF ≤ 0.01 and FMF ≤ 1.0. This is evidence that very large magnitude fatal landslides are rare in Italy, but they can be expected in significant parts of the mountains and the hills of Italy.

The maps showing the geographical distribution of the Complementary Cumulative Distribution Function (CCDF), also known as the "survival" or "risk" function, provide a more diverse picture of societal landslide risk in Italy. For very low magnitude landslides, most of the Italian territory, and particularly the hills and the mountains, have CCDF ≥0.30, indicating that the probability of experiencing f ≥ 1 landslide fatalities is large almost everywhere in Italy. For large (f ≥ 10) and very large (f ≥ 25) magnitude landslides, the probability is large (CCDF ≥0.1) or very large (CCDF ≥0.2) in SE Emilia–Romagna, and in places in Campania, Basilicata and southern Calabria (Fig. 9).

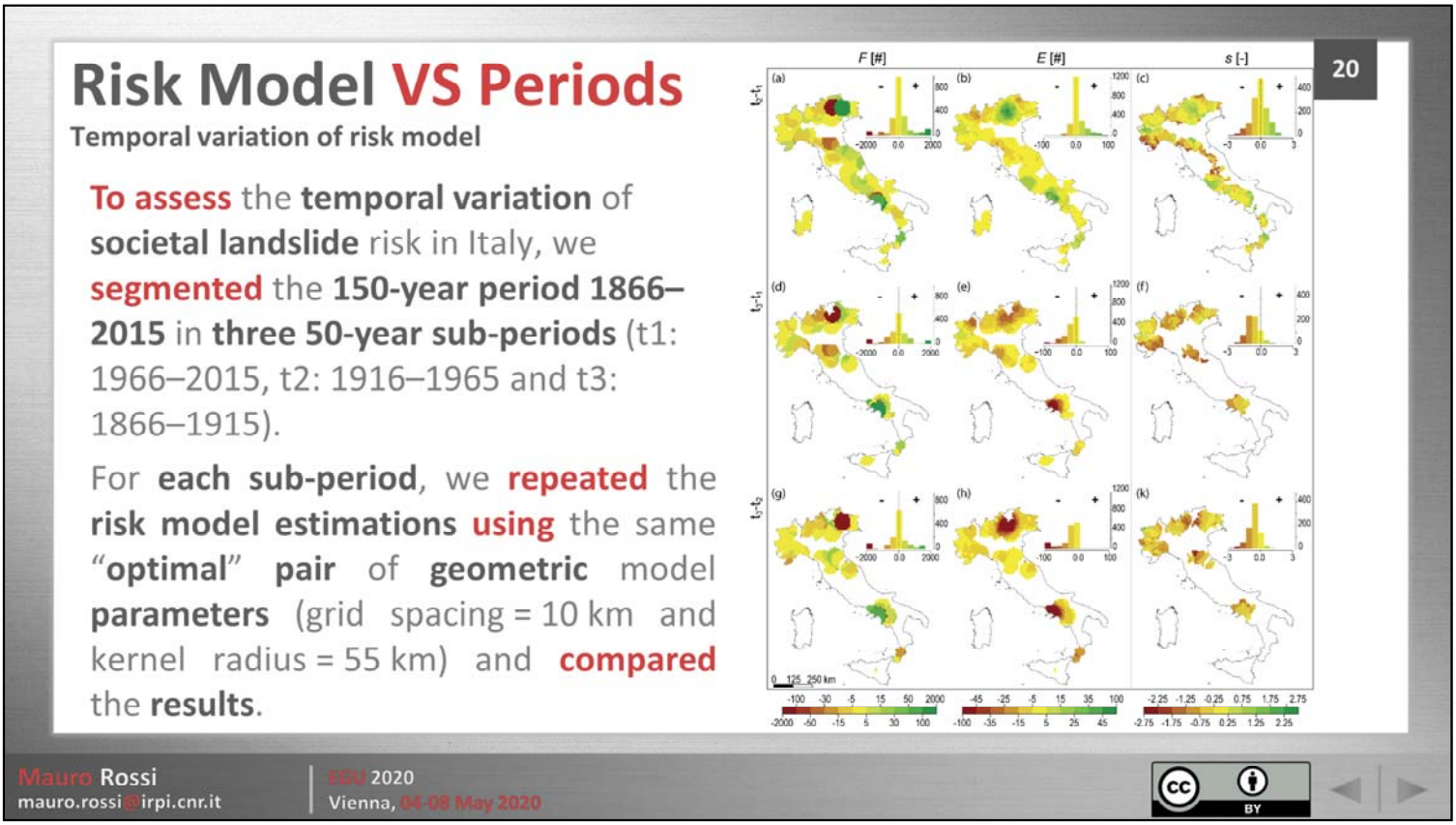
The yCCFDF was obtained dividing the CCFDF by the length of the observation period, T = 155 years (t0 in Table 1), and therefore it shows a scaled version of the CCFDF. For very low magnitude landslides the annual frequency is large (yCCFDF ≥0.3) in Campania, and is yCCFDF ≥0.02 in small parts of the Alps. For medium magnitude landslides (f = 10), the annual frequency is large (yCCFDF ≥0.08) in Campania, and is yCCFDF ≥0.25 in large parts of the Alps, in parts of the Emilia–Romagna region, and in southern Calabria. For large magnitude landslides (f = 25) the annual frequency is large (yCCDFF ≥0.04) in Campania, and is yCCFDF ≥0.02 in limited parts of the NE Alps and of the Emilia–Romagna region. Similarly, the return period – the reciprocal of yCCFDF i.e., τyCCFDF = 1/yCCFDF – also shows a scaled version of the CCDF and the yCCFDF. For the lowest magnitude landslides (f = 1) the return period is short (τ < 30 years) in most of the Alps, in the Alps–Apennines transition zone, in large parts of the Apennines range, of the Tyrrhenian and the Adriatic borderlands, and in NE Sicily. For large magnitude landslides (f ≥ 25), most of the hills and mountains of Italy exhibit a very large return period (τyCCFDF >1000 years, light blue colour), whereas parts of the central and the eastern Alps, of the Emilia–Romagna, Campania and Calabria regions have τyCCFDF ≥150 years. In these areas societal landslide risk should be considered high or very high.



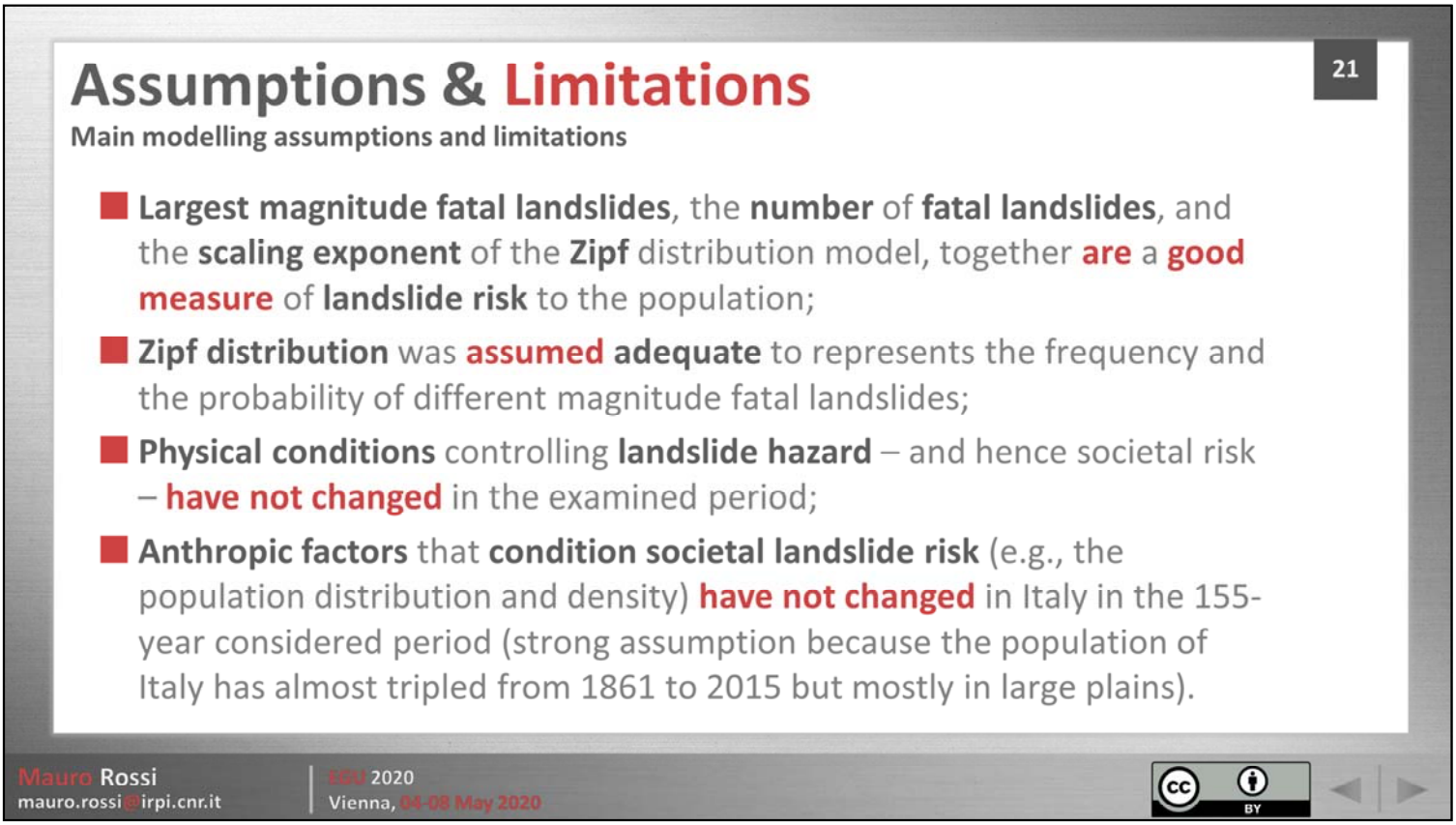
We validated the societal landslide risk model using information on 130 fatal landslides in the magnitude range 1 ≤ f ≤ 1300 occurred at 119 sites in the 861 years, t4 period 1000–1860. With this independent information, we checked the anticipated (modelled) return period, τyCCFDF for fatal landslides of magnitude f ≥ 1, f ≥ 5, f ≥ 10 and f ≥ 25 expected fatalities. The four maps portray the geographical distribution of the expected return periods for the four considered landslide magnitude scenarios, together with the location of the fatal landslides (blue dots) with f ≥ 1 (E = 137 fatal landslides), f ≥ 5 (E = 74), f ≥ 10 (E = 58) and f ≥ 25 (E = 37) fatalities occurred in the t4 validation period 1000–1860.

Regardless of their magnitude (i.e., for f ≥ 1), the majority of the fatal landslides have occurred where the return period was anticipated to be small, τyCCFDF ≤30 years. This is confirmed by the empirical Cumulative Density Function (eCDF) for f ≥ 1 (Fig. 10e) that increases very rapidly with the return period, reaching the maximum value for τyCCFDF = 78 years. The CDF shows that 50% of the landslides with f ≥ 1 have occurred in areas where τyCCFDF ≤6 years, and 90% of the landslides with f ≥ 1 have occurred where τyCCFDF ≤14 years. Similarly, 50% (90%) of the landslides with f ≥ 5 have occurred where τyCCFDF ≤21 (87) years. The figures indicate that in the t4 validation period the 67 (48.9%) reported very small and small magnitude landslides (f ≤ 5) have occurred at a lower occurrence frequency i.e., with a higher return period than what was anticipated by the scenario (Fig. 9). We explain this result with the known incompleteness of the landslide record,

particularly for the old and very old periods and for landslides with one or a few fatalities (Guzzetti et al., 2005b). For the large and very large magnitude landslides ($f \geq 25$), examination of Fig. 10d reveals that 25 landslides (67.8%) occurred where $\tau_{yCCFDF} \leq 600$ years, and 12 landslides where $\tau_{yCCFDF} \geq 1000$ years i.e., where the return period was anticipated to be very low.



To assess the temporal variation of societal landslide risk in Italy, we segmented the 150-year period 1866–2015 in three 50-year sub-periods i.e., t1, 1966–2015, t2, 1916–1965 and t3, 1866–1915 (Table 1), which collectively cover a very large part (96.8%) of the t0 period 1861–2015. For each sub-period, we repeated the analysis performed before on the t0 period – described in Section 5.1 – using the same "optimal" pair of geometric model parameters (g = 10 km and r = 55 km), and we then compared the geographical distributions of the model variables {Fk, Ek, sk} obtained for the three sub-periods. Inspection of the results, summarized in the figure, reveals a general similarity of the societal landslide risk models obtained for the recent, t1 (1966–2015) and the intermediate, t2 (1916–1965) sub-periods, which both differ notably from the model obtained for the old, t3 (1866–1915) sub-period. We maintain that the differences depend chiefly on the different completeness of the landside record for the three sub-periods, which also affected the proportion of the Italian territory for which the risk models could be prepared.

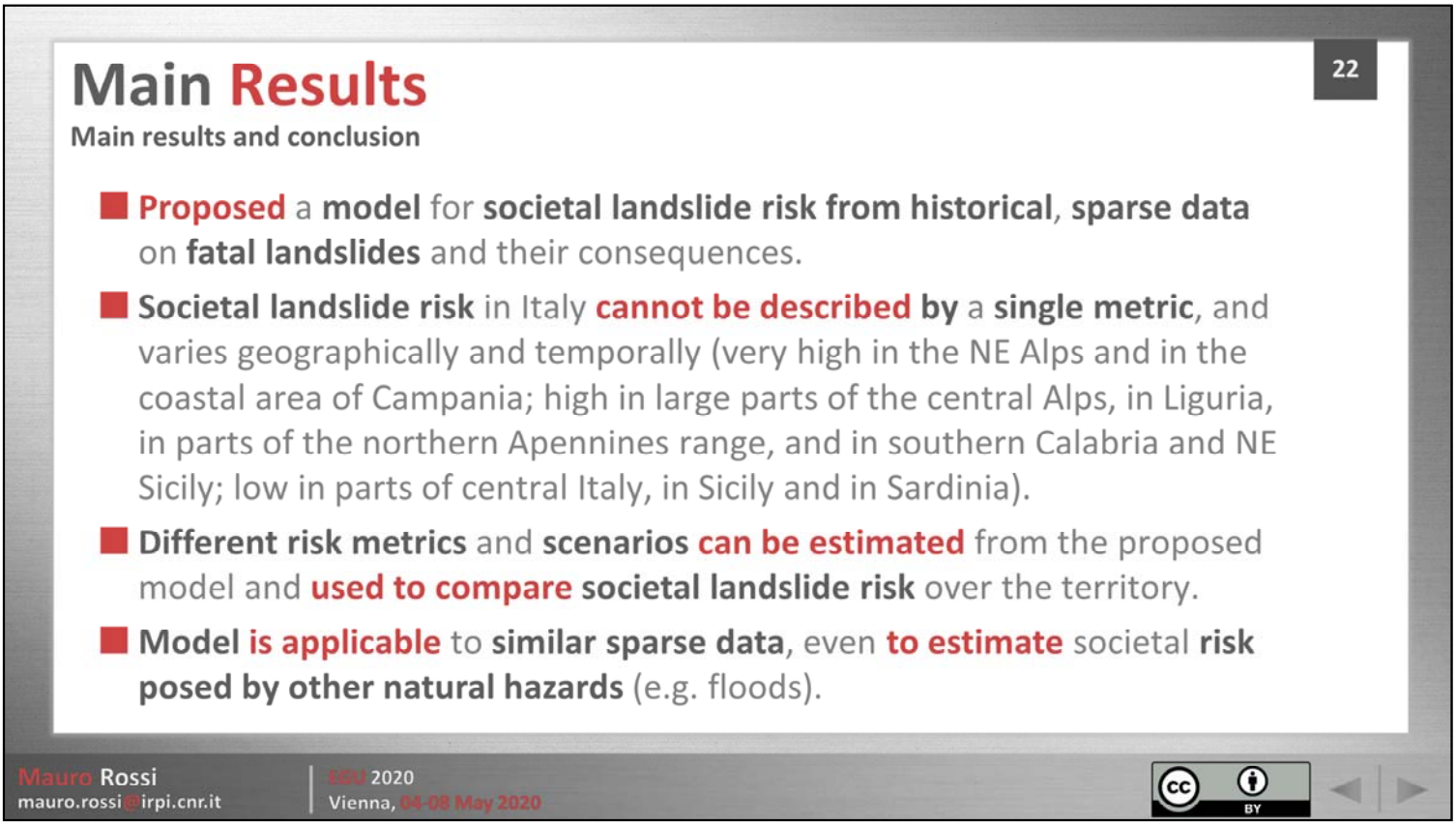


Largest magnitude fatal landslides, the number of fatal landslides, and the scaling exponent of the Zipf distribution model, together are a good measure of landslide risk to the population;

Zipf distribution was assumed adequate to represents the frequency and the probability of different magnitude fatal landslides;

Physical conditions controlling landslide hazard – and hence societal risk – have not changed in the examined period;

Anthropic factors that condition societal landslide risk (e.g., the population distribution and density) have not changed in Italy in the 155-year considered period (strong assumption because the population of Italy has almost tripled from 1861 to 2015 but mostly in large plains).



Proposed a model for societal landslide risk from historical, sparse data on fatal landslides and their consequences.

Societal landslide risk in Italy cannot be described by a single metric, and varies geographically and temporally (very high in the NE Alps and in the coastal area of Campania; high in large parts of the central Alps, in Liguria, in parts of the northern Apennines range, and in southern Calabria and NE Sicily; low in parts of central Italy, in Sicily and in Sardinia).

Different risk metrics and scenarios can be estimated from the proposed model and used to compare societal landslide risk over the territory.

Model is applicable to similar sparse data, even to estimate societal risk posed by other natural hazards (e.g. floods).

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A predictive model of societal landslide risk in Italy

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