

Cross-border
climate change
impacts and systemic
risks in Europe
and beyond



eurac
research

Center for Climate Change and Transformation

**Tessellated border-independent
exposure analysis for operational
climate and disaster risk preparedness
applications**

Chronicles from the DG-ECHO “TransAlp” project

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17.10.2023

A Concepts and Context

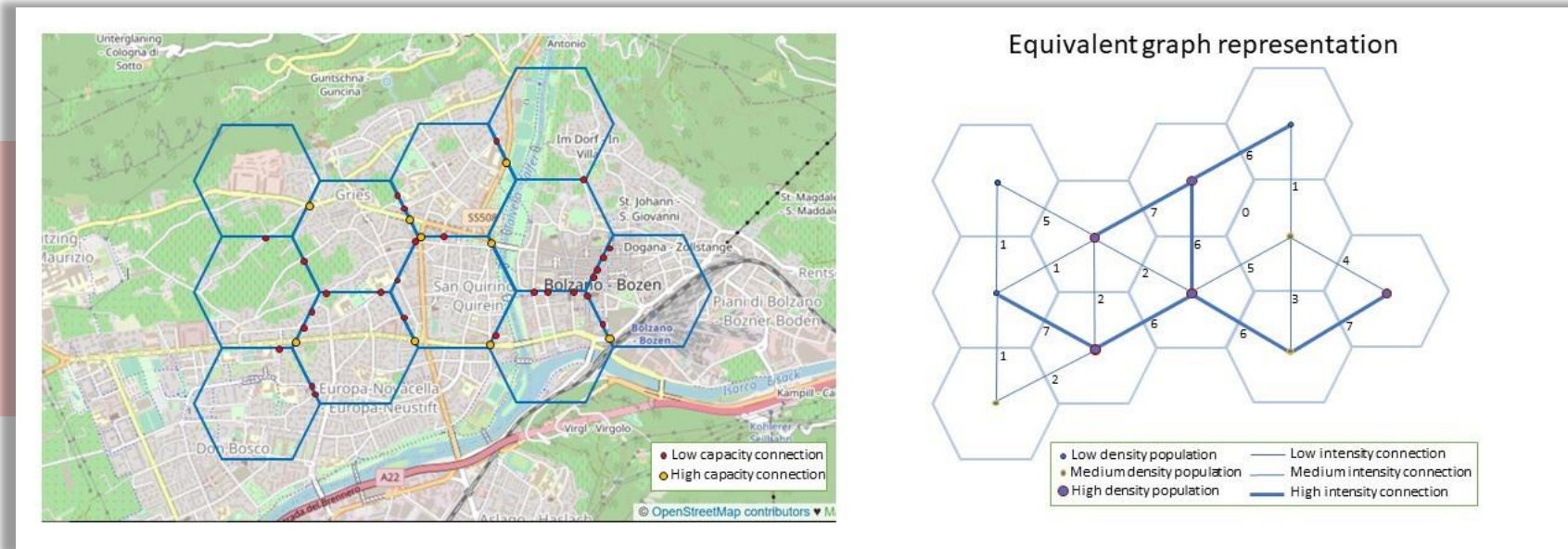
Q1 How to ease the life of DRR managers?

Available risk preparedness and prevention tools are increasingly lagging behind the growing threat of climate change, with multiple hazards often compounded causing cascaded and intertwined damages to society and the environment.

Q2 What about cross-border exposure data?

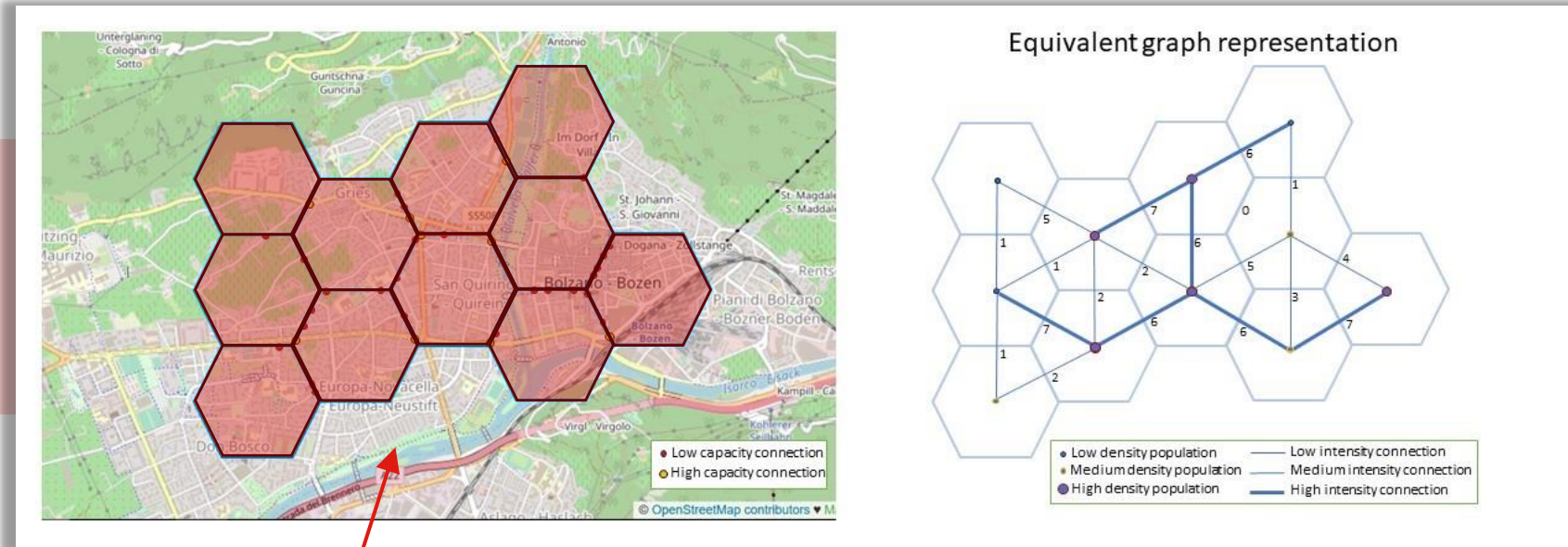
Transborder mountainous areas are especially vulnerable to such threats, given the susceptibility to natural hazards as well as remoteness of some settlements and the related importance of connectivity and accessibility.

Firstly, a simplified spatial support:



$$\begin{cases} T = \{l_i : i = 1, \dots, N\} \\ l_i \cap l_j = \emptyset, \forall i \neq j \\ \bigcup_{i=1}^N l_i = R \end{cases}$$

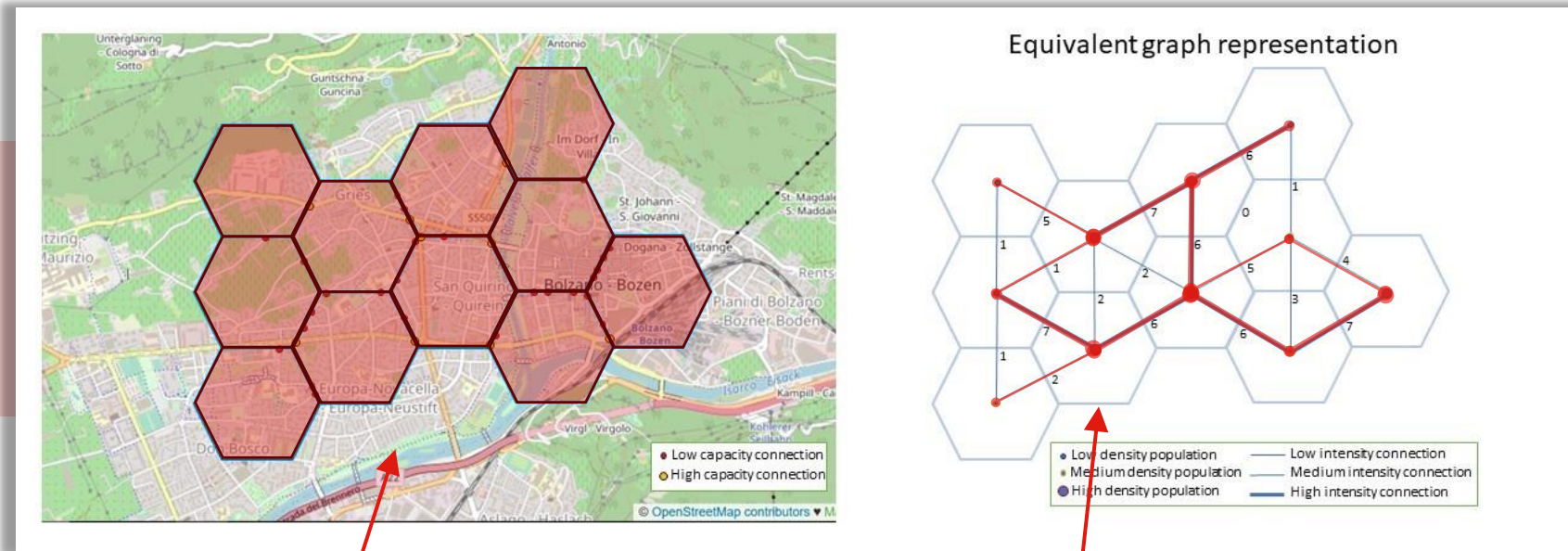
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HOMOGENEOUS PLANAR TESSELLATION

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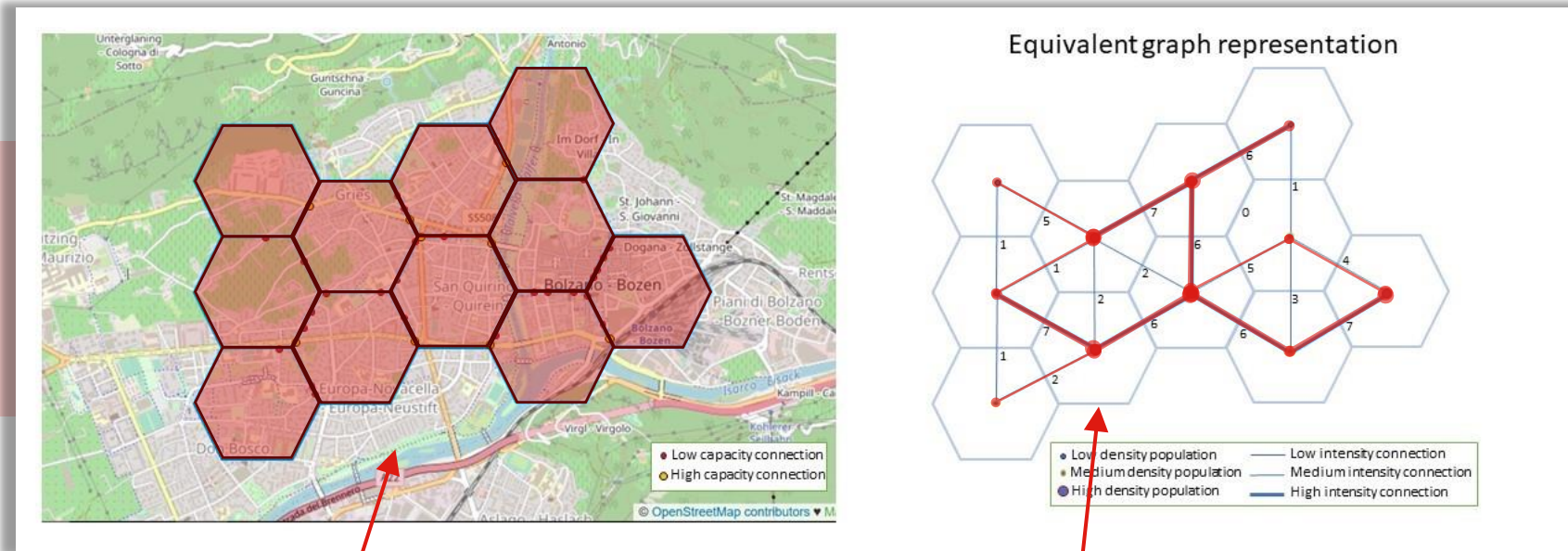


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DUAL-GRAPH REPRESENTATION

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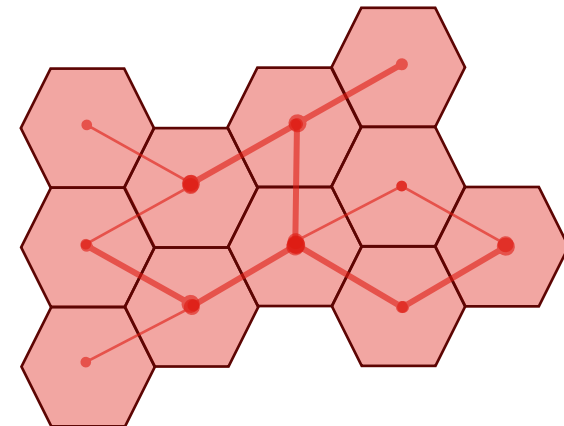
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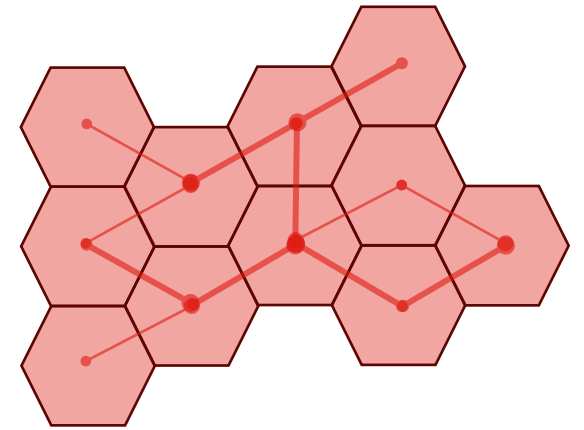
MULTIPLE RESOLUTION AGGREGATIONS ?

What is good:



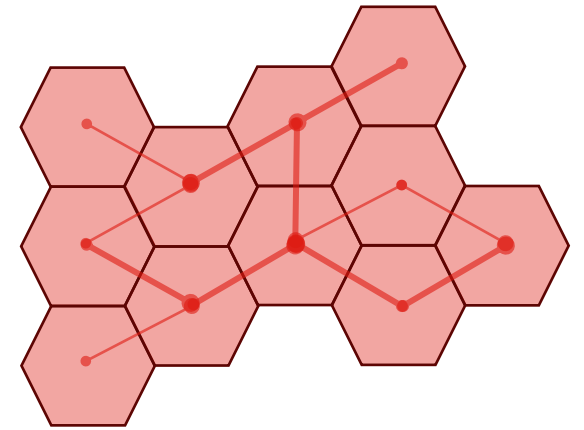
What is good:

- ✓ **Simplified** view on map for e.g. pre-operational identification of hotspot areas



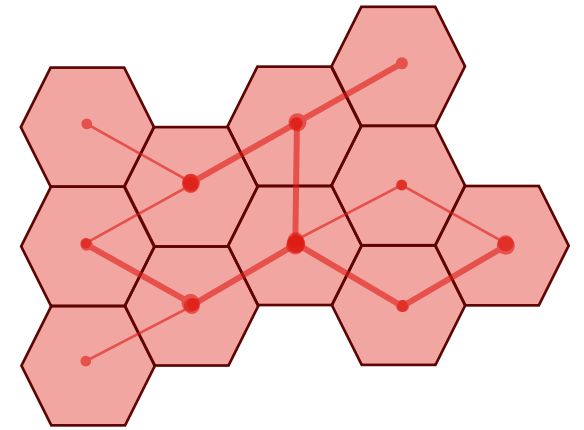
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- ✓ Tessellation can naturally provide an **anonymization** shield for sensible data → opens to potentially more availability of data



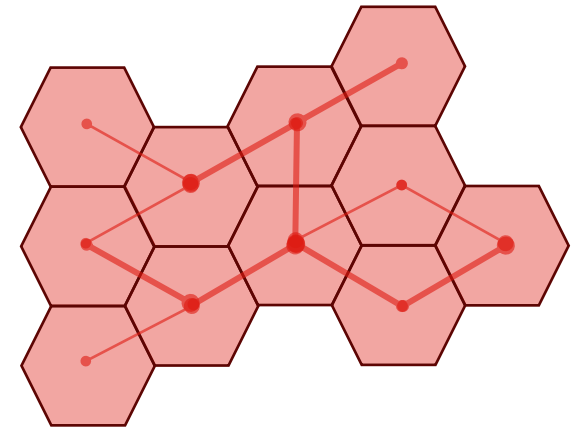
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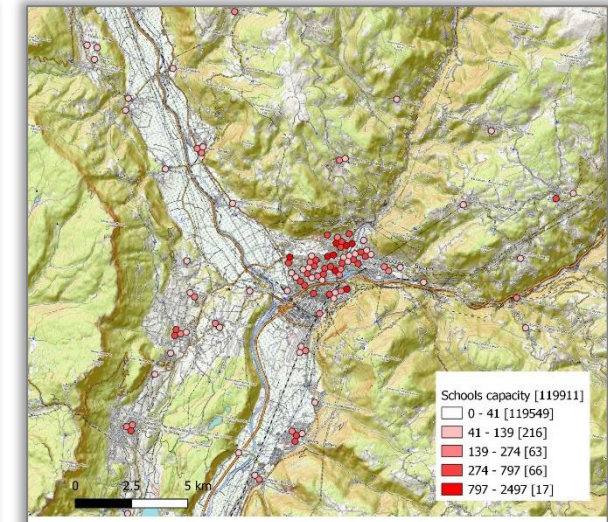
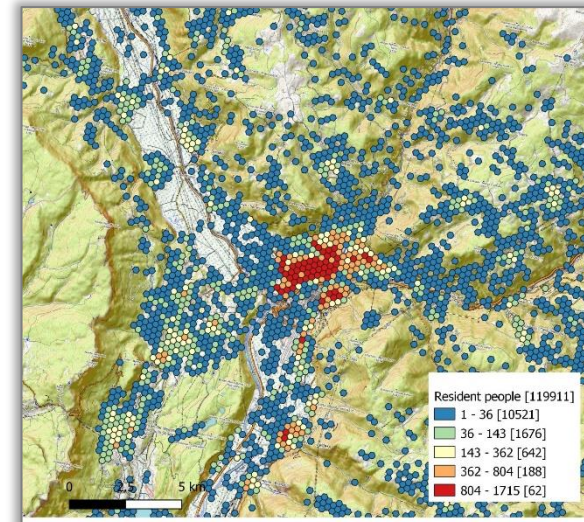
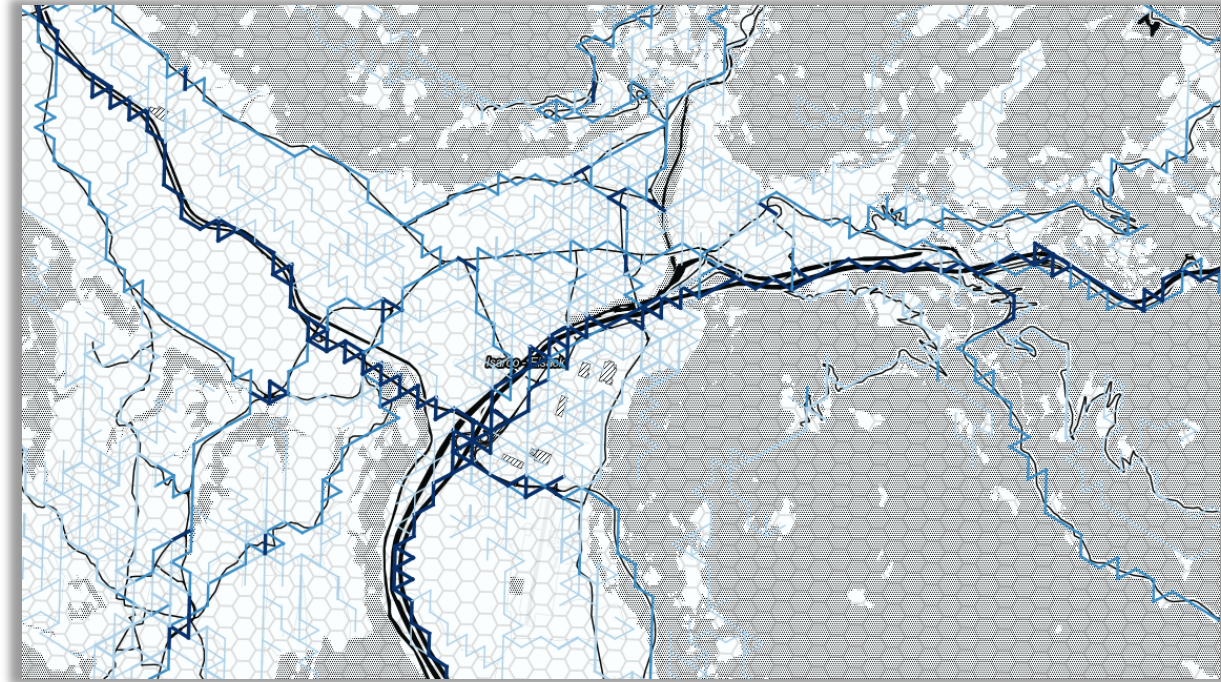


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- ✓ **Duality** cells/graph to represent both area- and flow/connection-oriented data

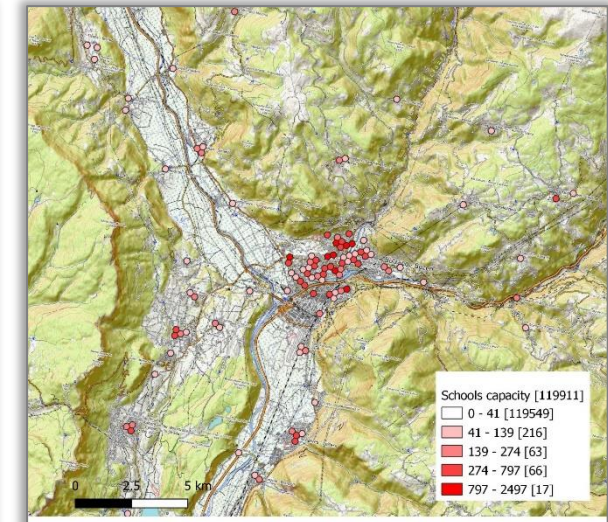
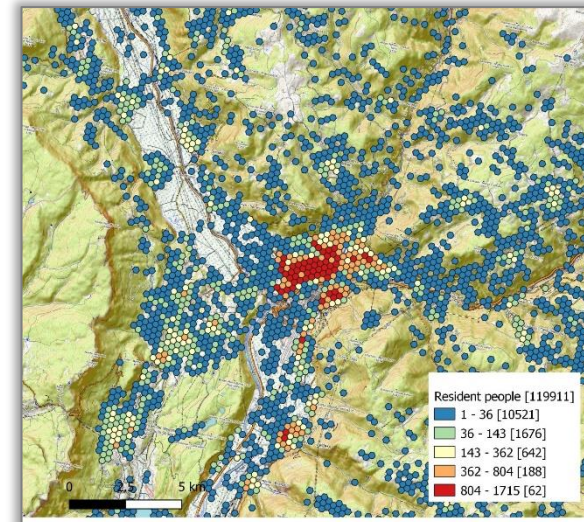
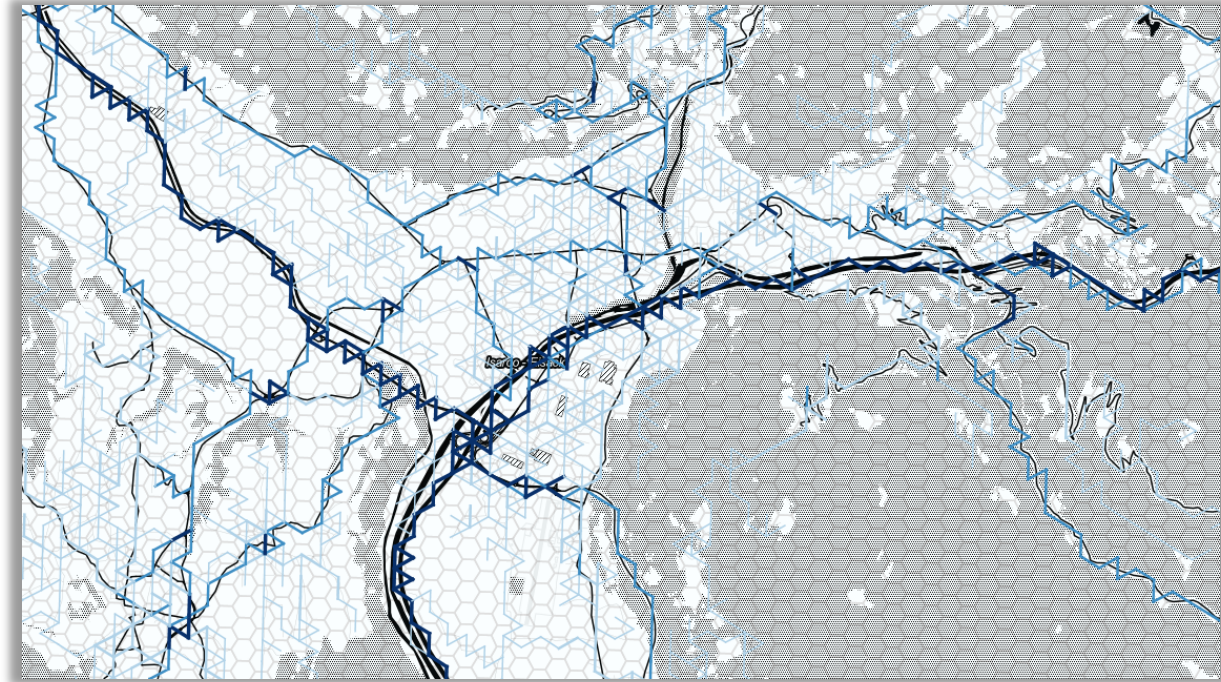


Border-independent data collection and assimilation



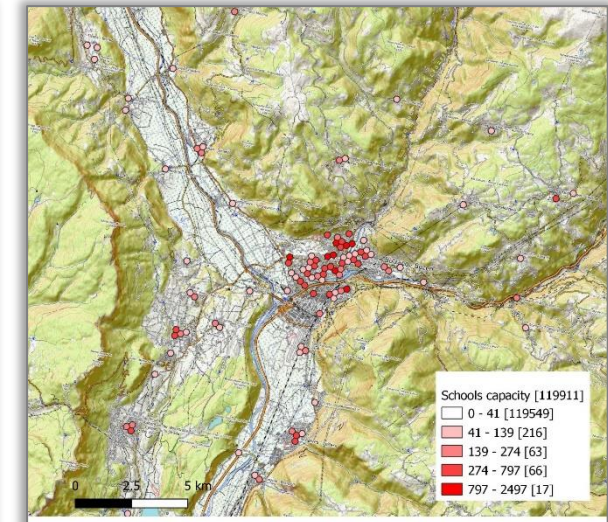
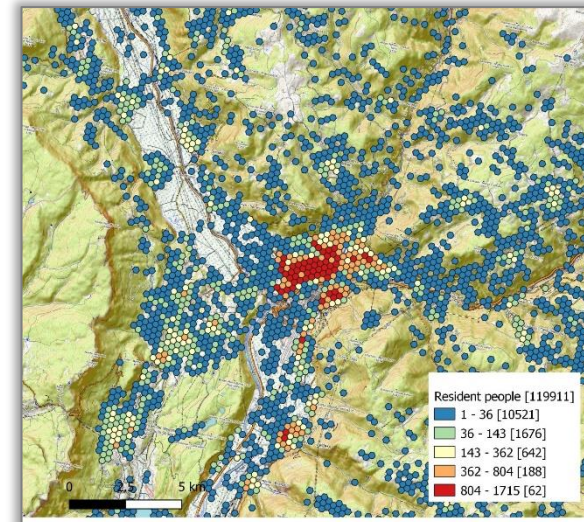
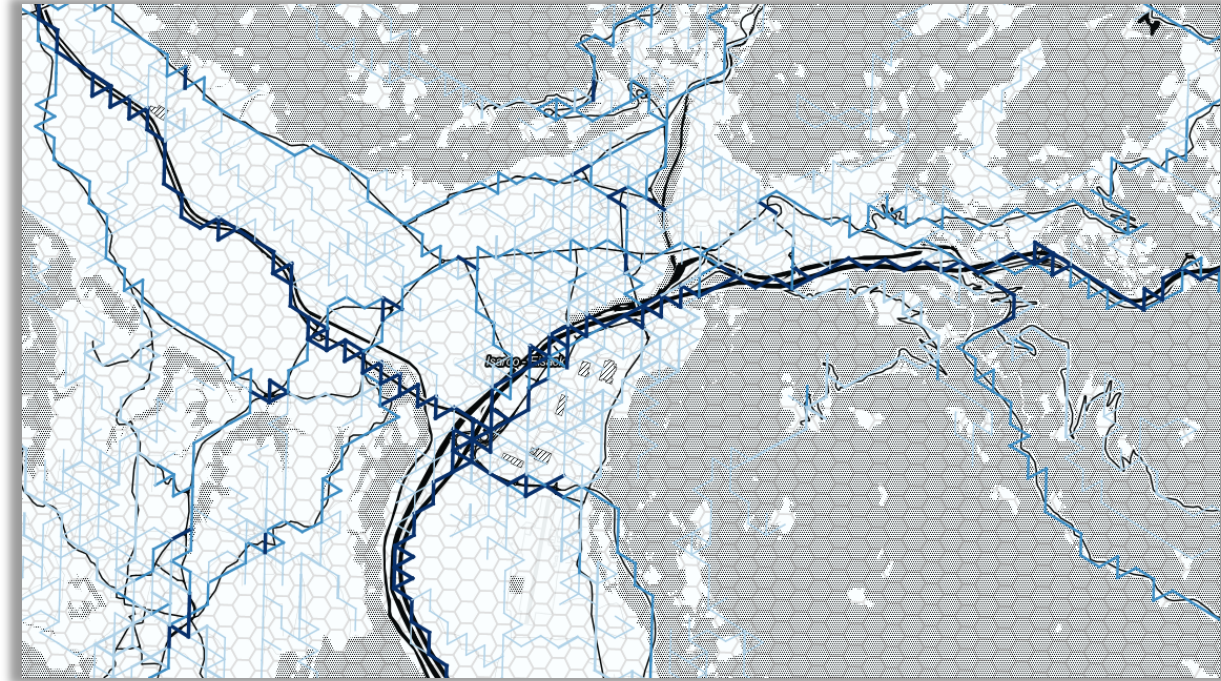
Border-independent data collection and assimilation

- **Define** a set of exposure assets to be included in the model



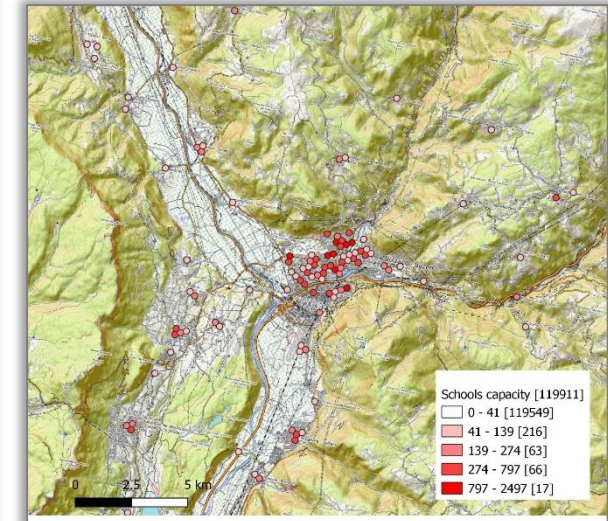
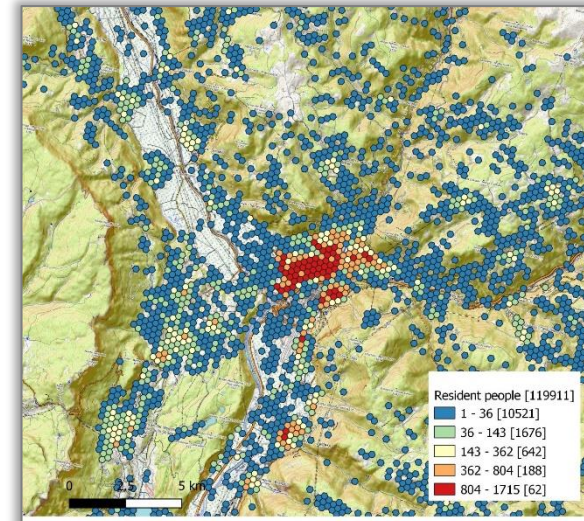
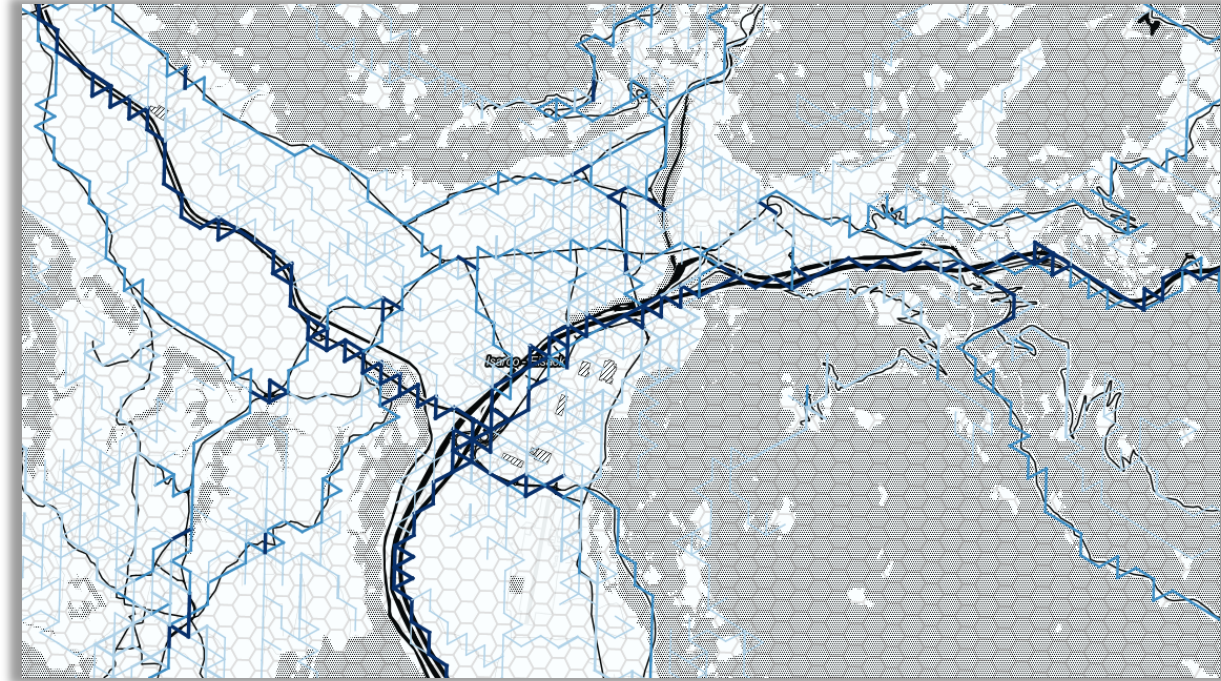
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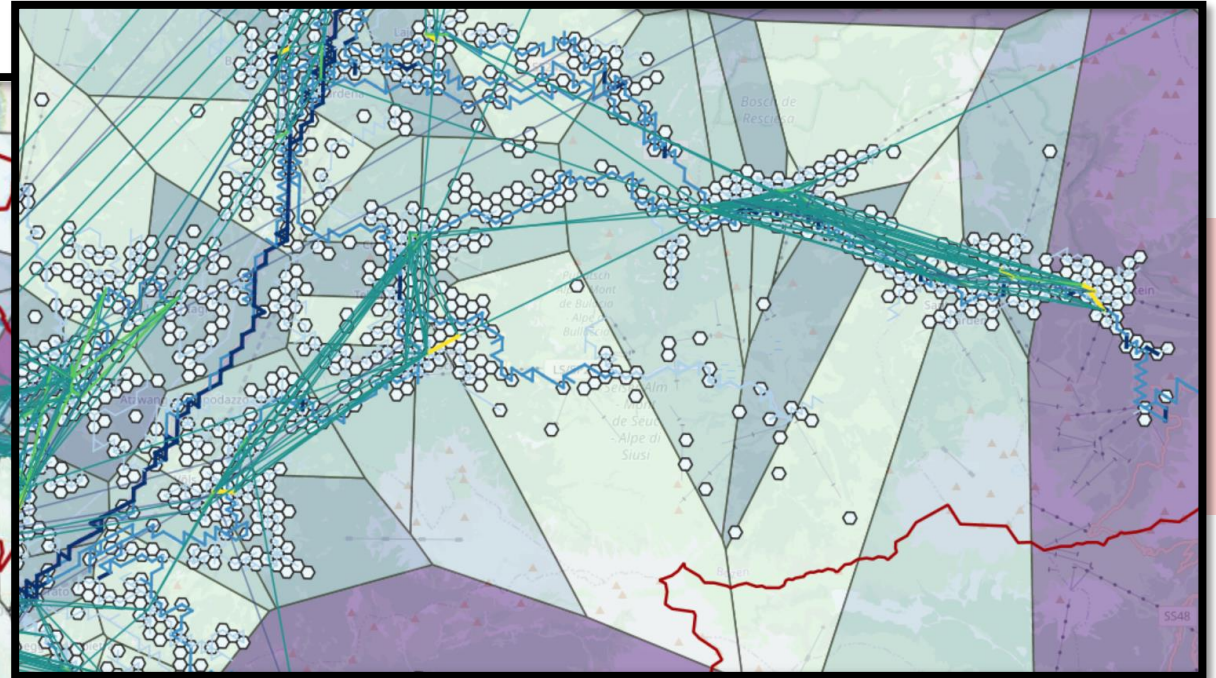
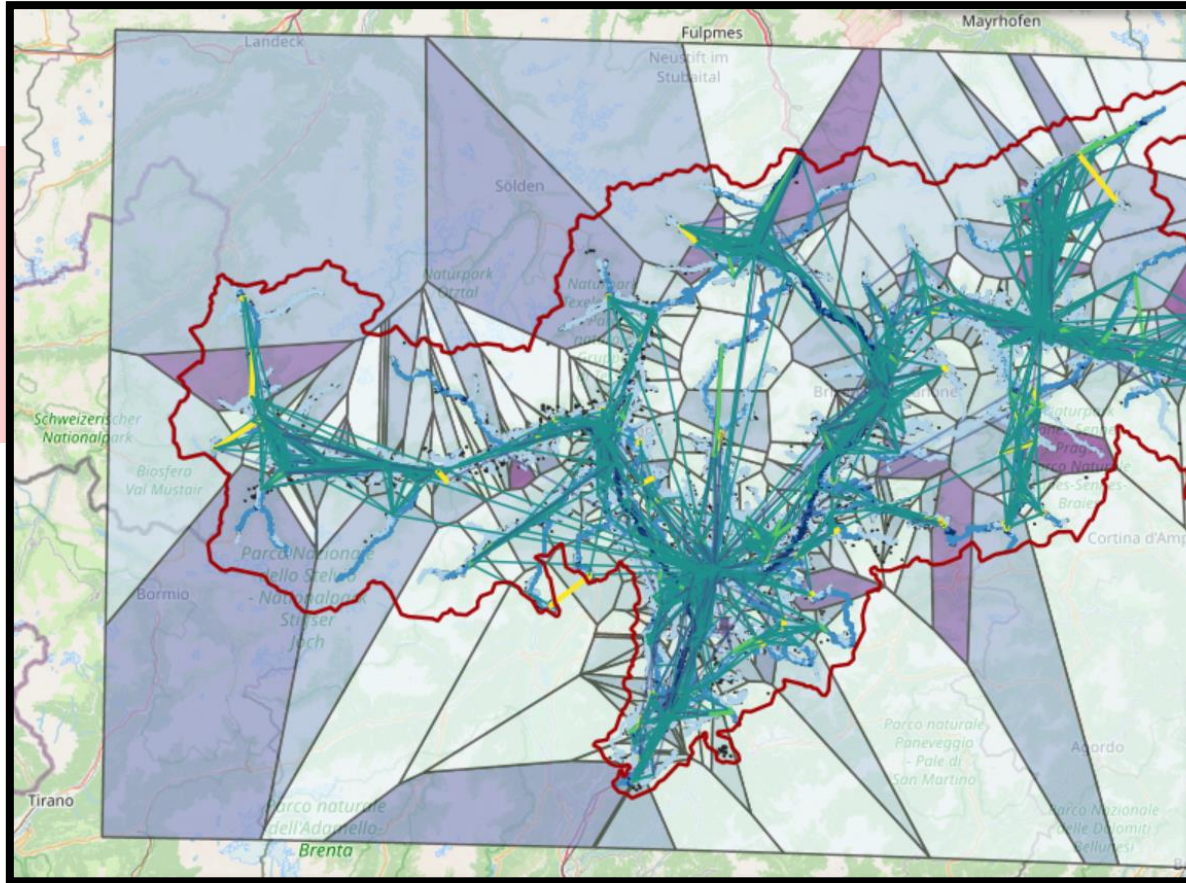
Border-independent data collection and assimilation

- **Define** a set of exposure assets to be included in the model
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- **Assimilate**/simplify all datasets to the topology



B Where is everybody?

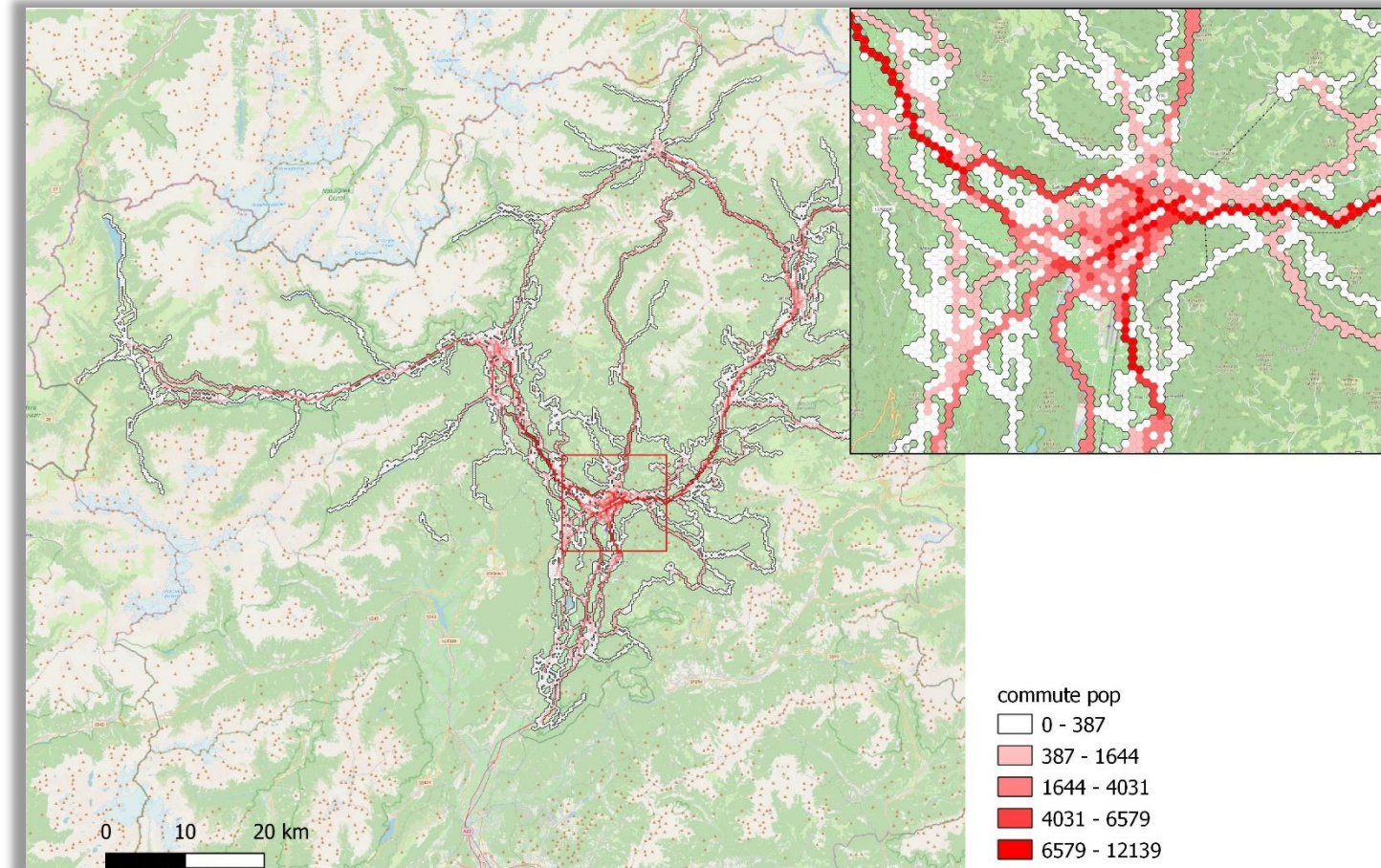
Modelling the population flow:



Commuters data from **Ufficio Osservazione Mercato del Lavoro** (South Tyrol, IT)



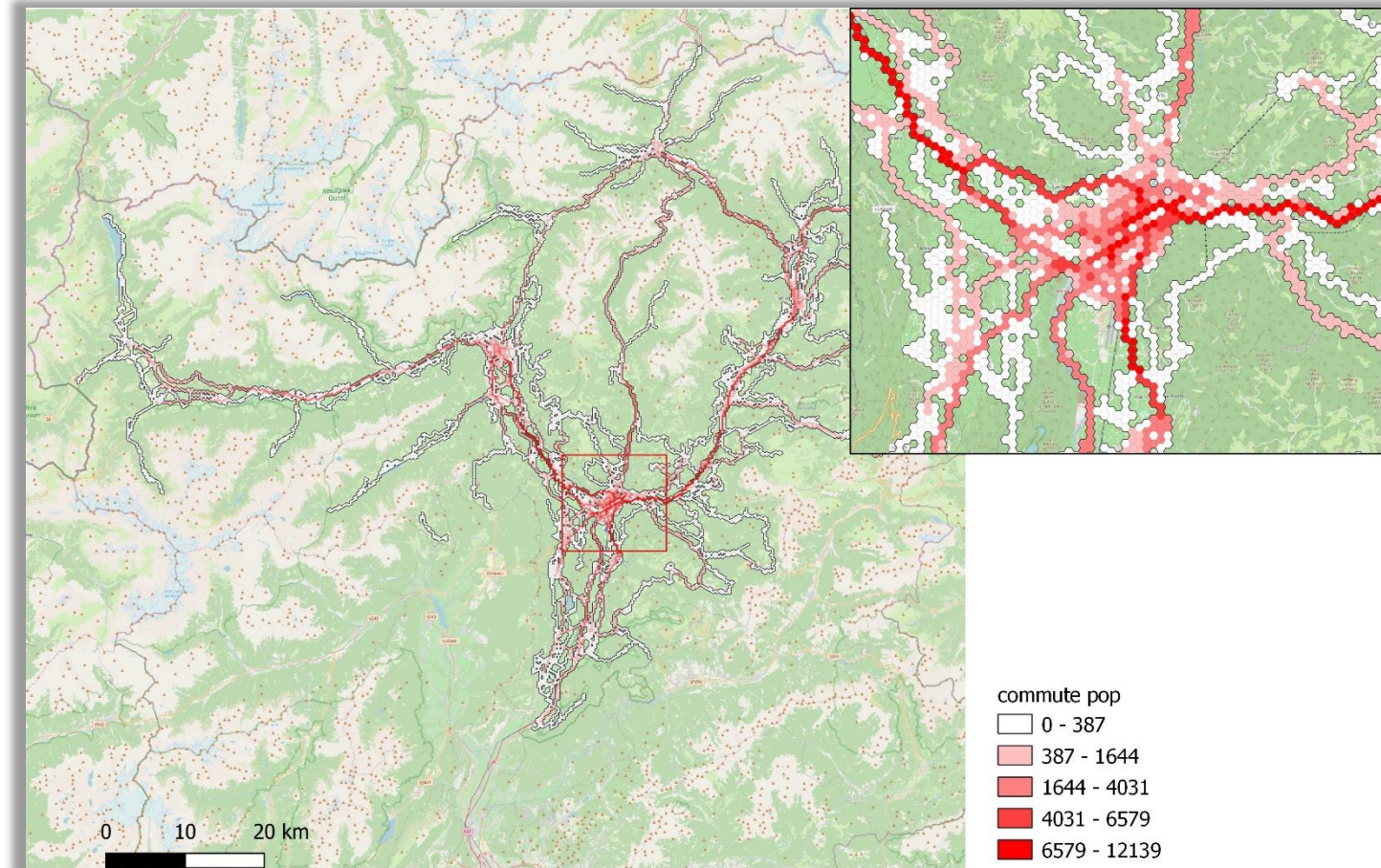
Need a flexible, border-independent solution



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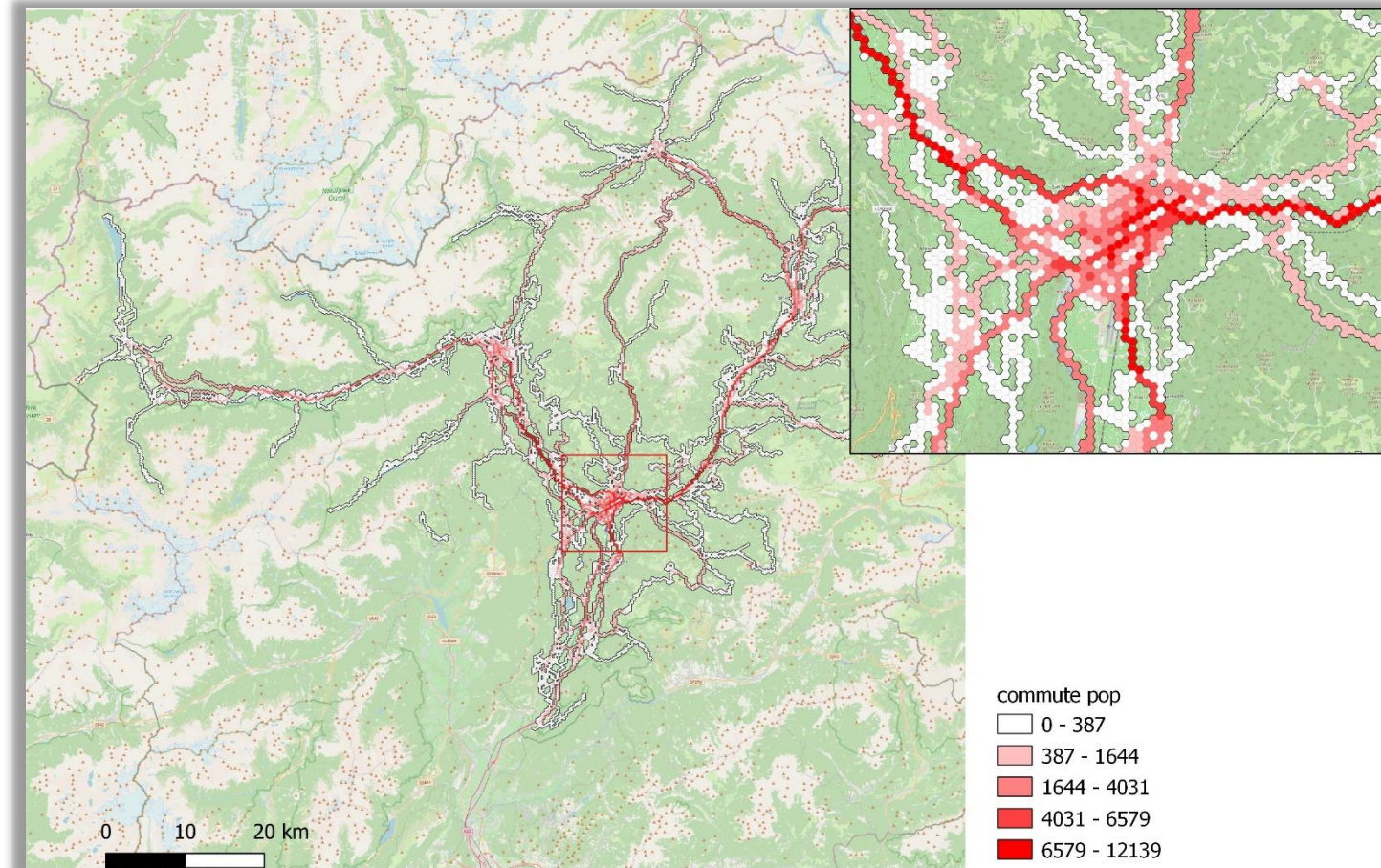
➤ Dynamic best-effort

From basic to refined behaviour
depending on data availability



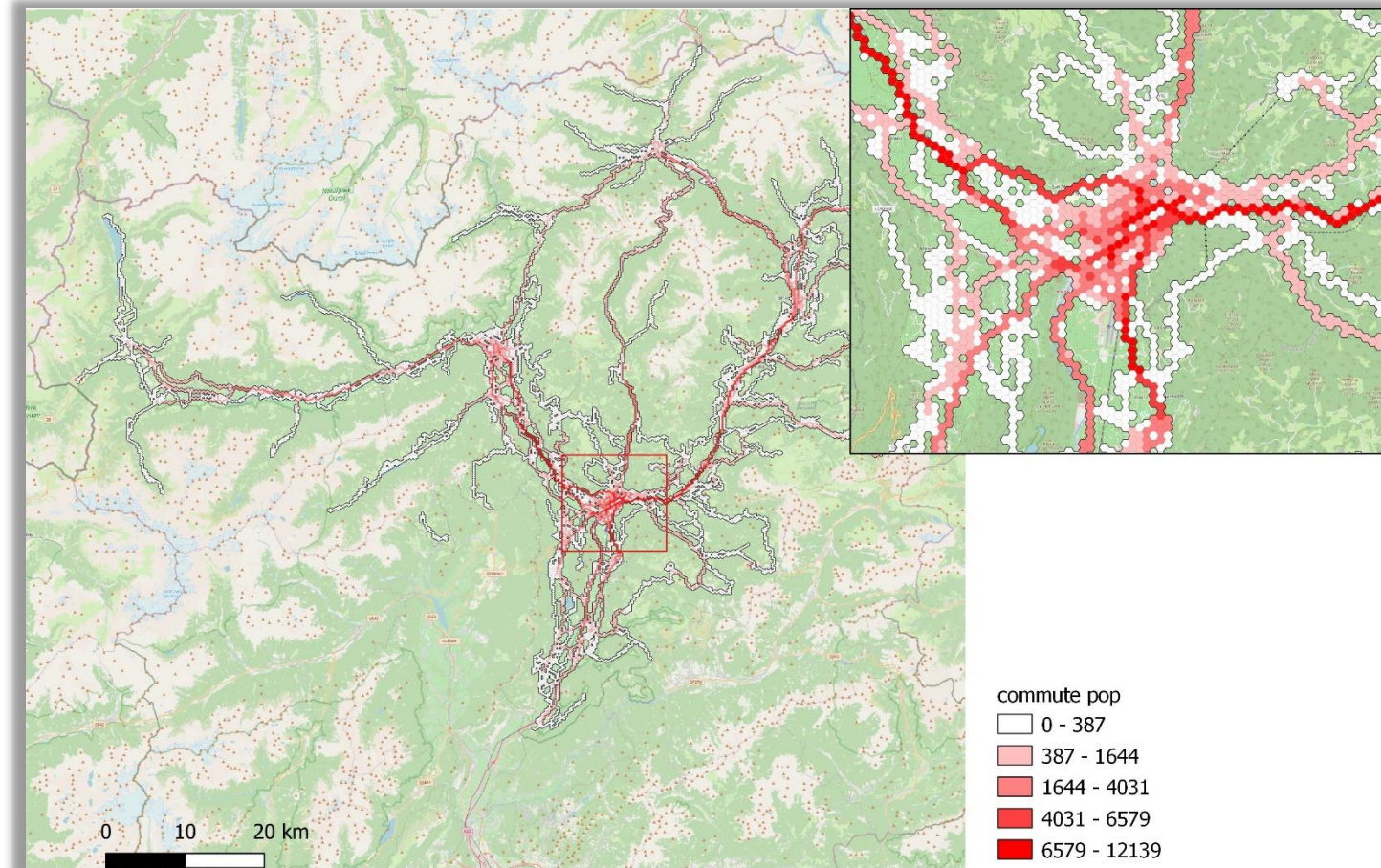
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- **Dynamic best-effort**
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- **Flexible training**
Possible data-driven model configuration on a country-base



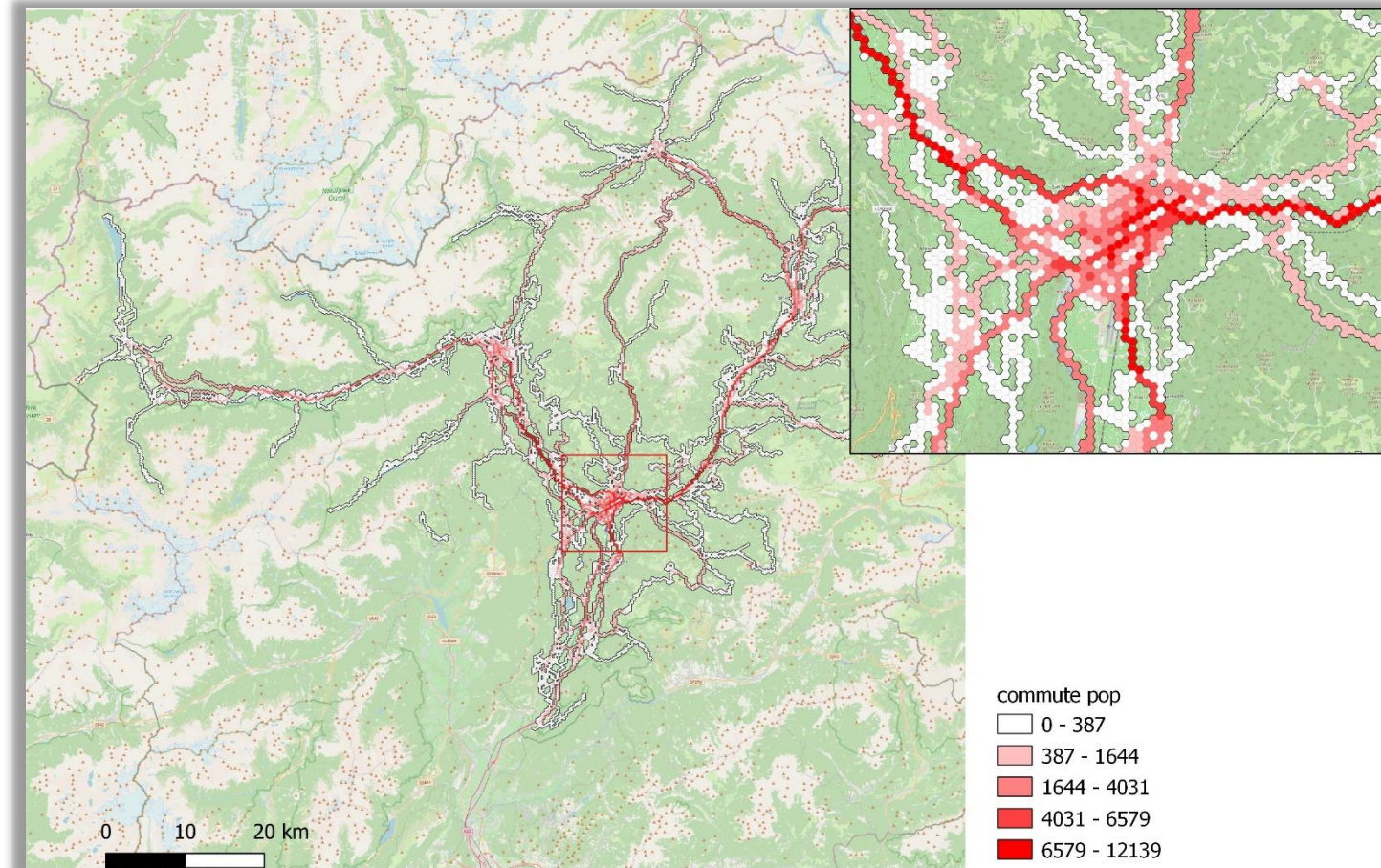
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- **Multi-scale**
Allow visual analysis at multiple scales (medium to small)



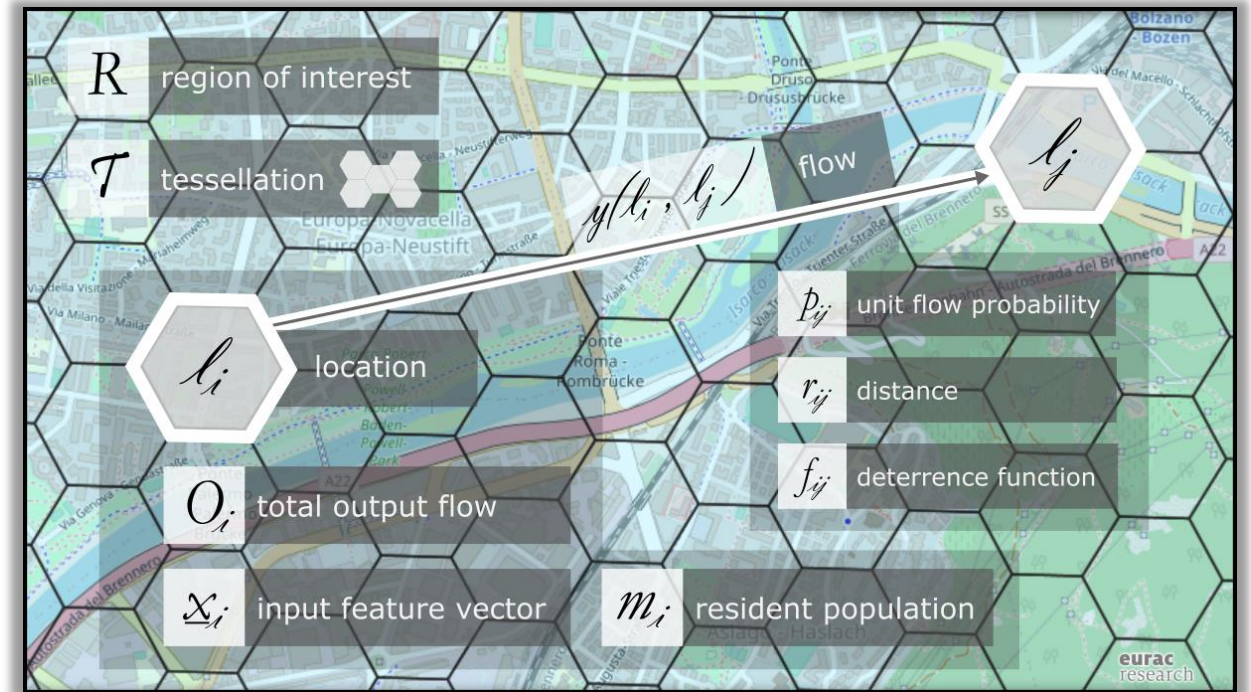
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- **Re-compute easily**
Pseudo real-time what-if scenarios visualizations



A gravity model ?

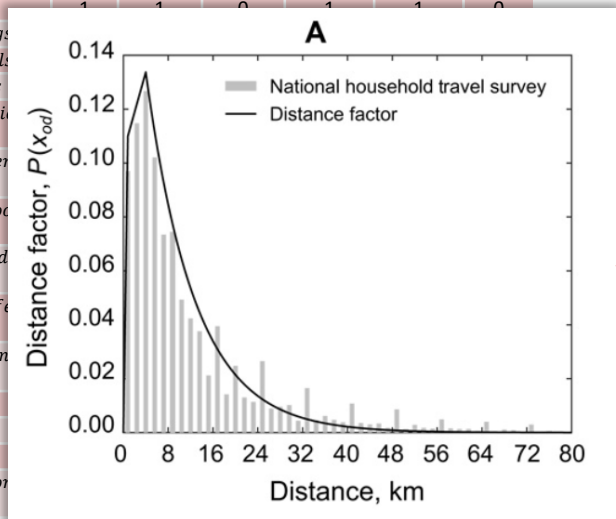
Asset / timeframe		Week days			Weekend and holidays			
		Morning	Afternoon	Night	Morning	Afternoon	Night	
w_u	Land Use	w_u^1 : urban	1/5	1/5	1/5	1/5	1/5	1/5
		w_u^2 : industrial	1/5	1/5	1/5	0	0	0
		w_u^3 : vegetated	1/5	1/5	0	1/5	1/5	0
		w_u^4 : crop/forest	0	0	0	1/5	1/5	0
w_n	Roads	w_n^5 : water	0	0	0	1/5	1/5	0
		w_n^1 : main	1/5	1/5	0	1/5	1/5	1/5
		w_n^2 : residential	1/5	1/5	1/5	1/5	1/5	1/5
w_t	Transport	w_t^3 : pedestrian	1/5	1/5	1/5	1/5	1/5	
		w_t^1 : stations	1	1	1	1	1	1
w_h	Health	w_t^2 : stops	1	1	0	1	1	0
		w_t^3 : parkings	1	1	1	1	1	1
		w_h^1 : hospitals	5	5	1	5	5	1
		w_h^2 : clinics	1	1	0	1	1	0
w_s	Education	w_h^3 : pharmacies	1	1	0	1	1	0
		w_h^4 : retirement	1	1	0	1	1	0
w_f	Food	w_s^1 : kita/schools	1	1	0	0	0	0
		w_s^2 : higher edu.	1	1	0	0	0	0
w_r	Retail	w_b^1 : bars/cafes	1	1	0	1	1	0
		w_b^2 : restaurants	0	1	1	0	1	1
w_a	Tourism	w_r^1 : malls	5	5	0	5	5	0
		w_r^2 : shops	1	1	0	1	1	0
w_a	Tourism	w_a^1 : hotels	1	1	1	1	1	1
		w_a^2 : attractions	1	1	1	1	1	1



$$\bar{y}(l_i, l_j) = O_i \cdot p_{ij} = O_i \cdot \frac{m_j^{\beta_1} (1 + A_j)^{\beta_2} f(r_{ij})}{\sum_k m_k^{\beta_1} (1 + A_k)^{\beta_2} f(r_{ik})}$$

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		w_u^3 : vegetated	1/5	1/5	0	1/5	1/5	0
		w_u^4 : crop/forest	0	0	0	1/5	1/5	0
w_n	Roads	w_n^5 : water	0	0	0	1/5	1/5	0
		w_n^1 : main	1/5	1/5	0	1/5	1/5	1/5
		w_n^2 : residential	1/5	1/5	1/5	1/5	1/5	1/5
w_t	Transport	w_n^3 : pedestrian	1/5	1/5	1/5	1/5	1/5	1/5
		w_t^1 : stations	1	1	1	1	1	1
		w_t^2 : stops	1	1	0	1	1	0
w_h	Health	w_t^3 : parking	1	1	0	1	1	0
		w_h^1 : hospitals	1	1	0	1	1	0
		w_h^2 : clinics	1	1	0	1	1	0
		w_h^3 : pharmacies	1	1	0	1	1	0
w_s	Education	w_h^4 : retirement	1	1	0	1	1	0
		w_s^1 : kindergarten/school	1	1	0	1	1	0
w_b	Food	w_s^2 : higher education	1	1	0	1	1	0
		w_b^1 : bars/cafes	1	1	0	1	1	0
w_r	Retail	w_b^2 : restaurants	1	1	0	1	1	0
		w_r^1 : malls	1	1	0	1	1	0
w_a	Tourism	w_r^2 : shops	1	1	0	1	1	0
		w_a^1 : hotels	1	1	0	1	1	0
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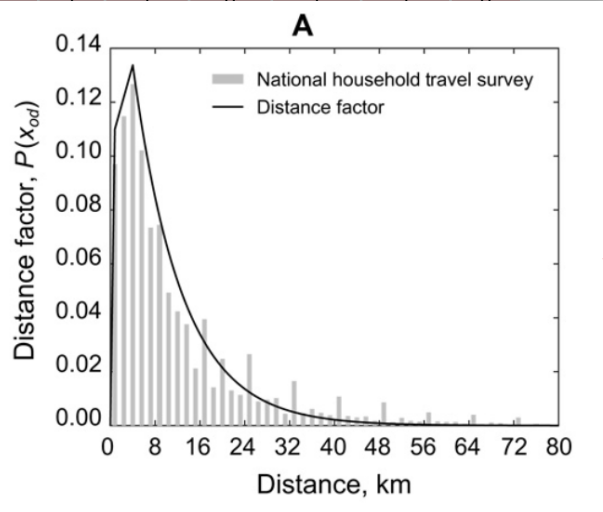
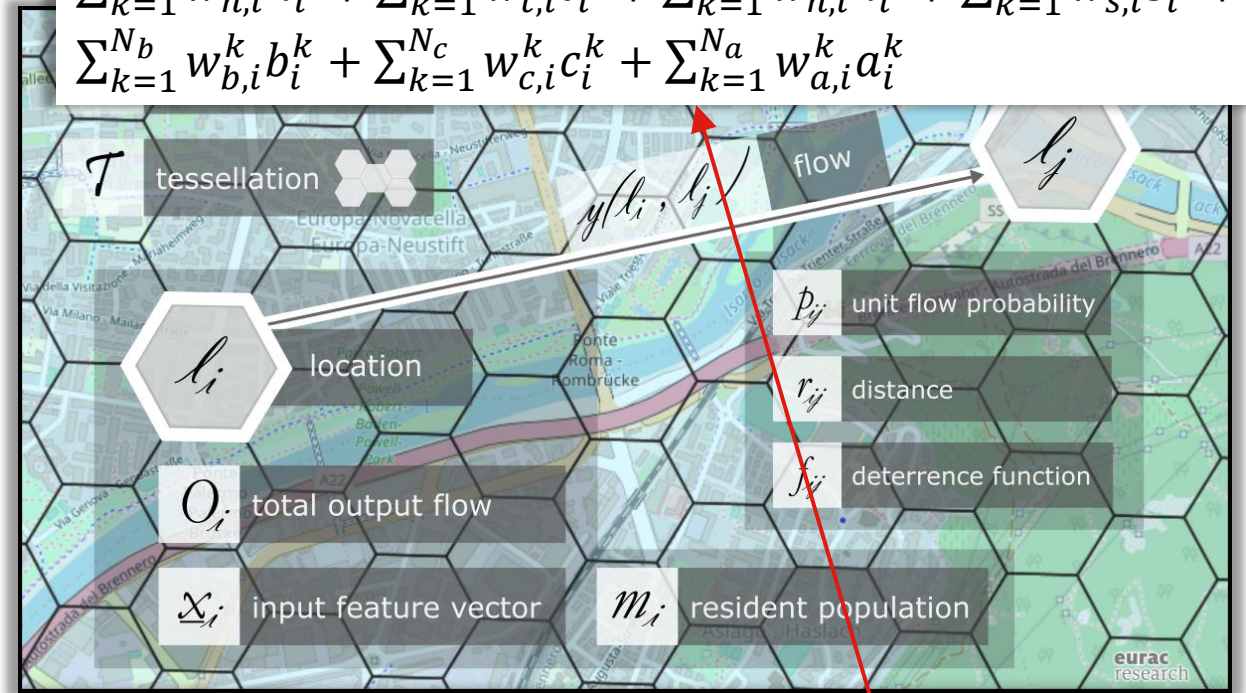
Ganin et al. (2017)
doi:10.1126/sciadv.1701079

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A gravity model ?

$$A_i = \underline{w}_i \cdot \underline{x}_i = \sum_{k=1}^N w_i^k x_i^k = \sum_{k=1}^{N_u} w_{u,i}^k u_i^k + \sum_{k=1}^{N_n} w_{n,i}^k n_i^k + \sum_{k=1}^{N_t} w_{t,i}^k t_i^k + \sum_{k=1}^{N_h} w_{h,i}^k h_i^k + \sum_{k=1}^{N_s} w_{s,i}^k s_i^k + \sum_{k=1}^{N_b} w_{b,i}^k b_i^k + \sum_{k=1}^{N_c} w_{c,i}^k c_i^k + \sum_{k=1}^{N_a} w_{a,i}^k a_i^k$$

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		w_u^4 : crop/forest	0	0	0	1/5	1/5	0
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\underline{w}_b	Food	w_b^2 : higher education						
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\underline{w}_c	Retail	w_b^2 : restaurants						
		w_c^1 : malls						
\underline{w}_a	Tourism	w_c^2 : shops						
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A Multicommodity Network Flow (MCNF) model?

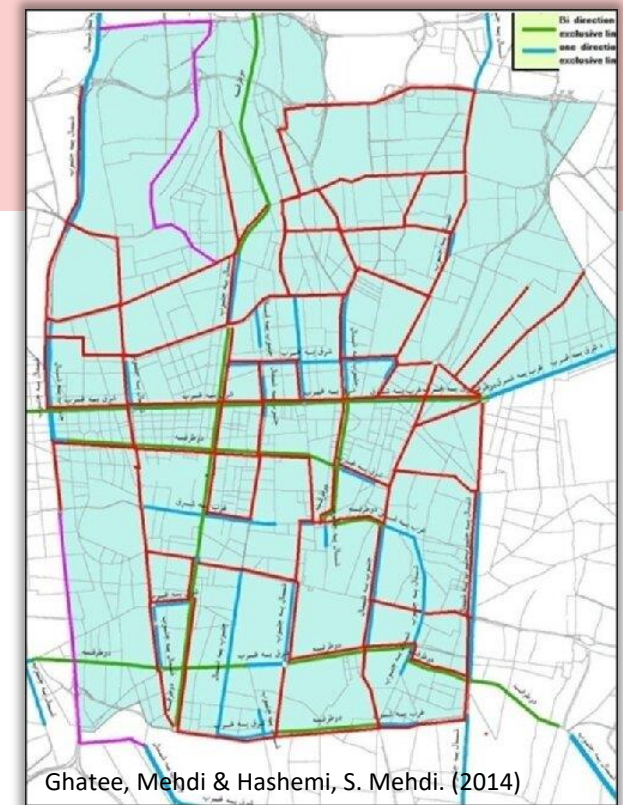
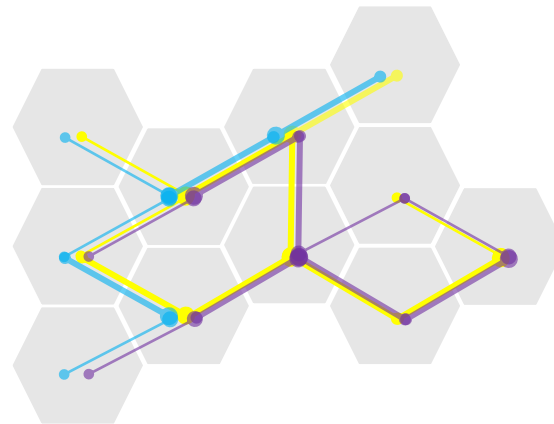
A Multicommodity Network Flow (MCNF) model?

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-  Daily commuters
-  Tourists
-  Trucks
-  External
-  ...



C Output of the *TransAlp* project

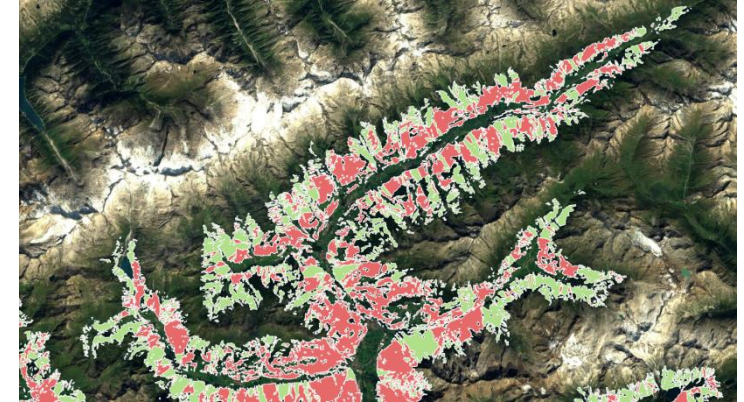
roads network



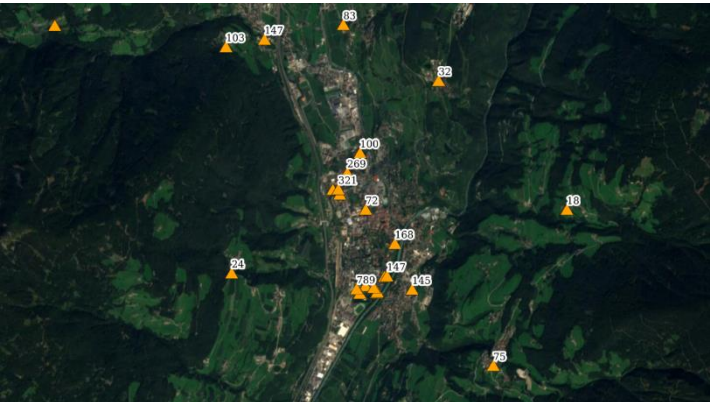
human settlements



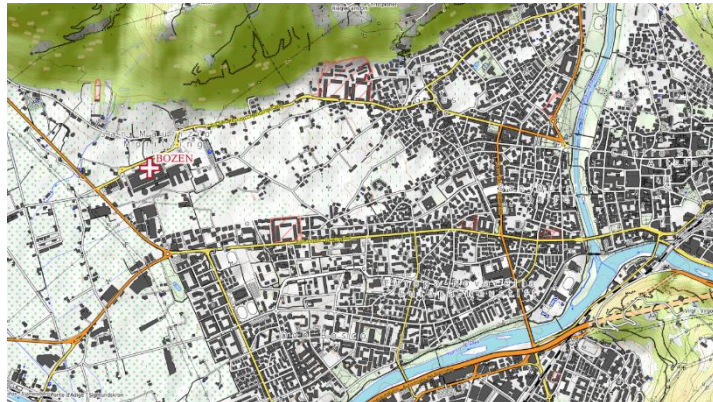
protection forest



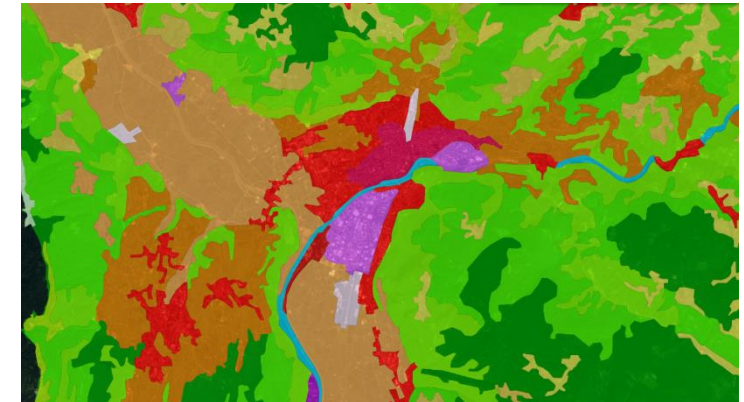
schools / kindergarten



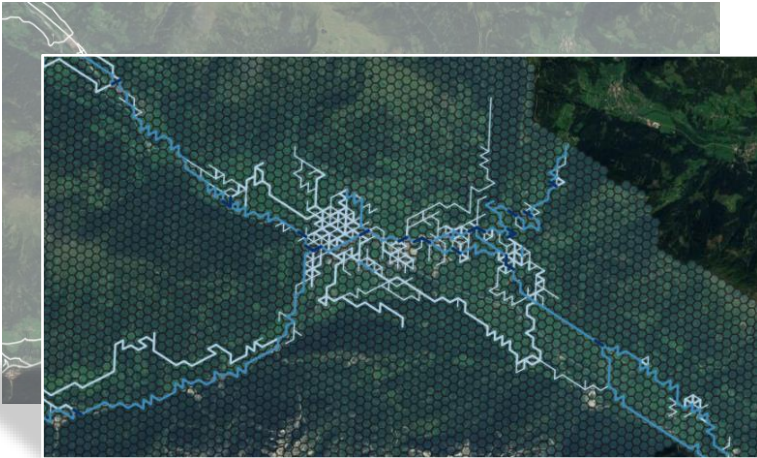
hospitals / daycare



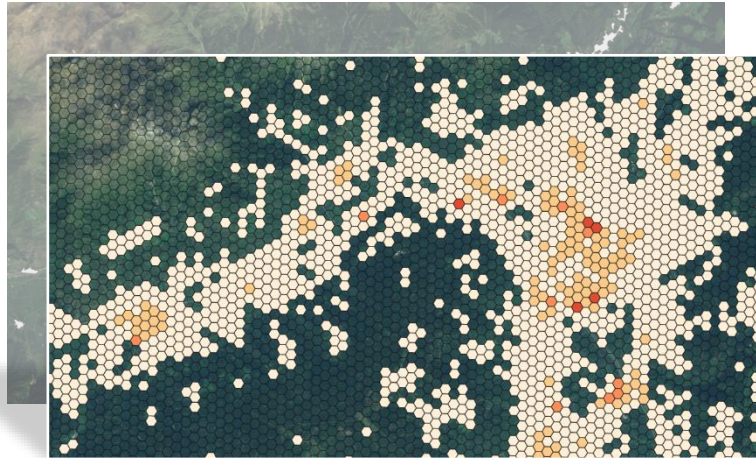
land cover



roads network



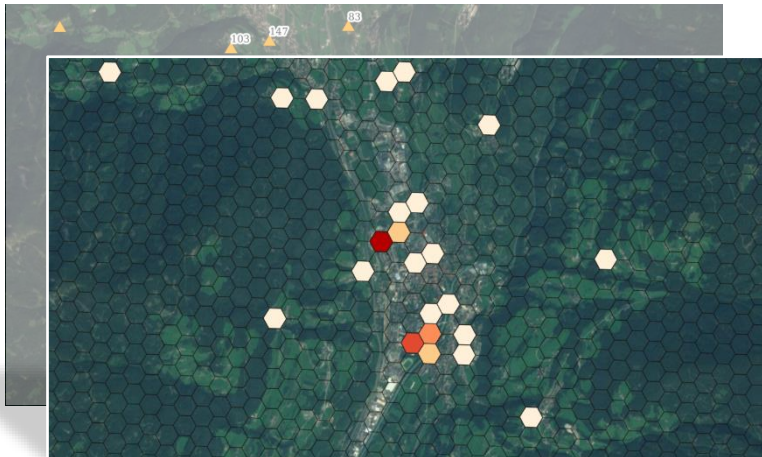
human settlements



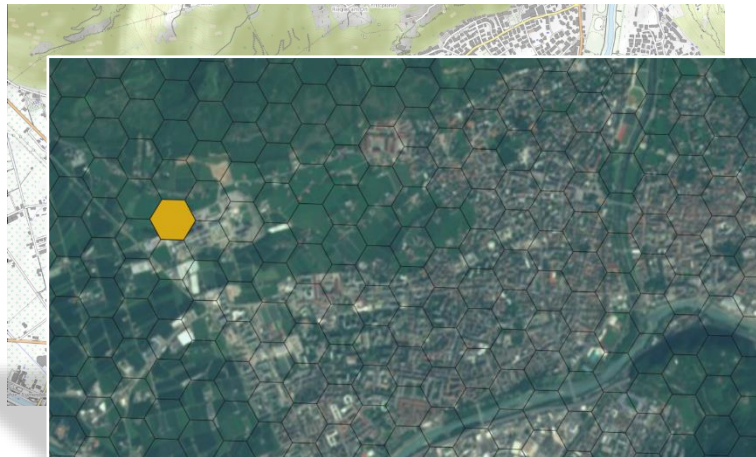
protection forest



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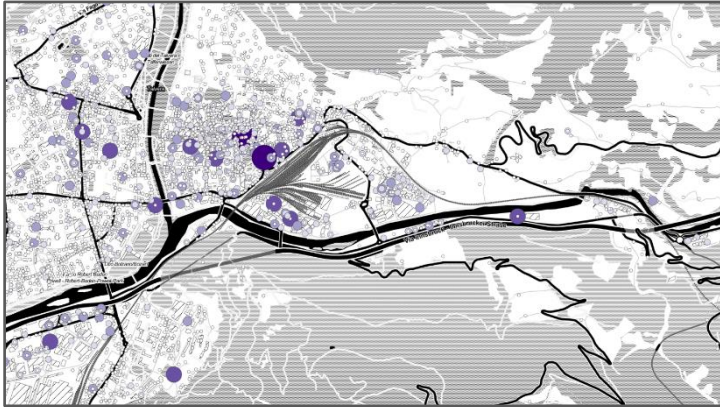
land cover



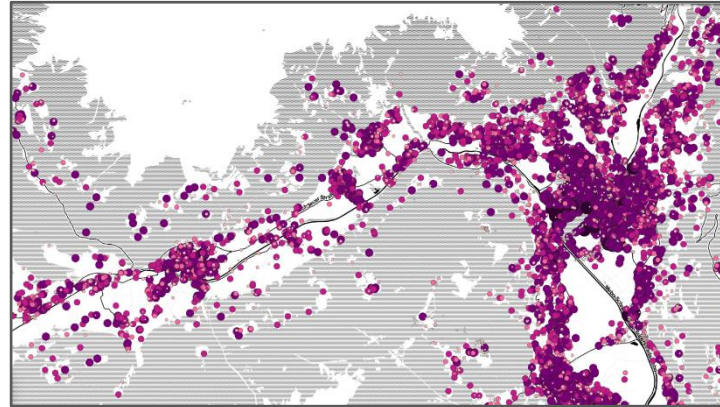


Predicting dynamic population flow

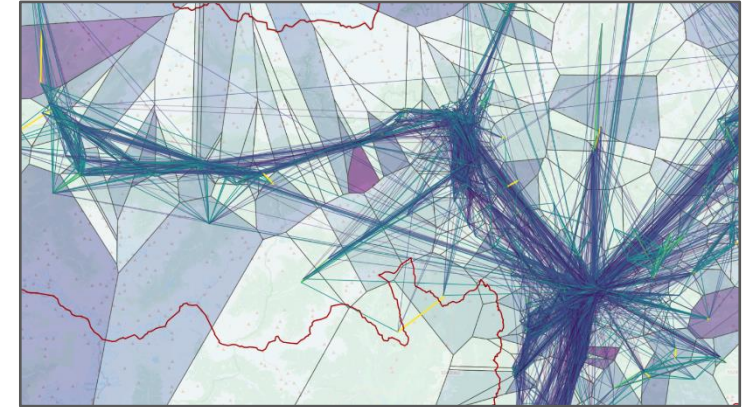
employees



residents



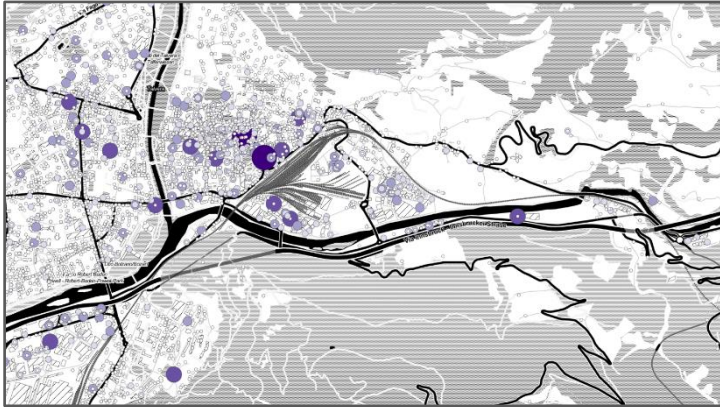
commuting trips



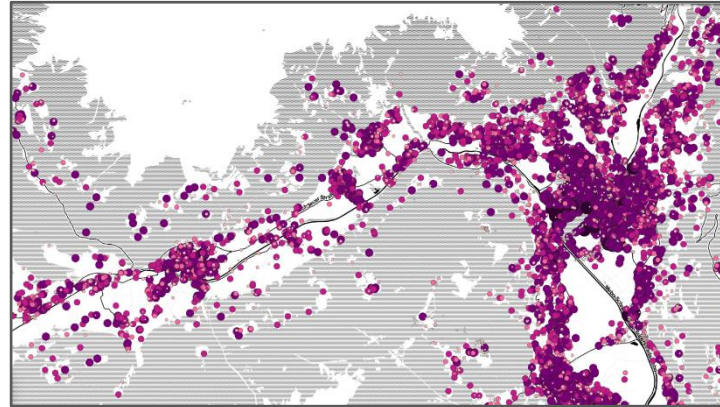


Predicting dynamic population flow

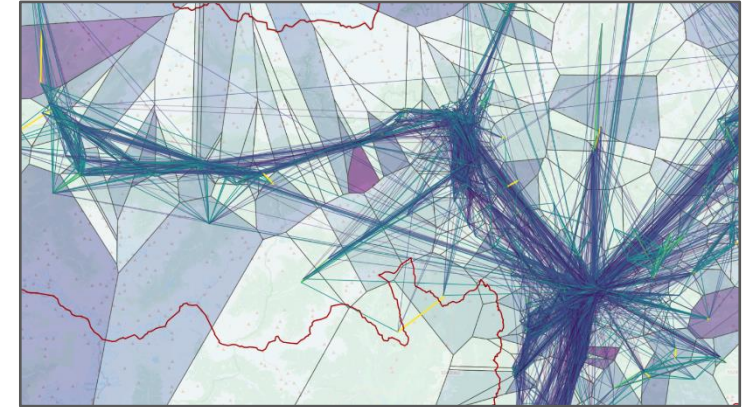
employees



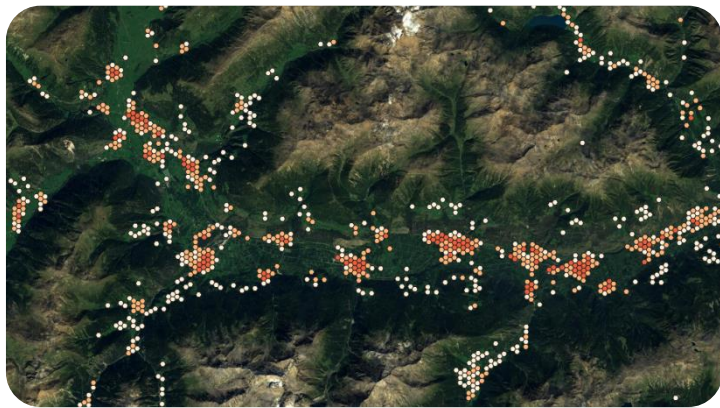
residents



commuting trips



daytime pop.



nighttime pop.



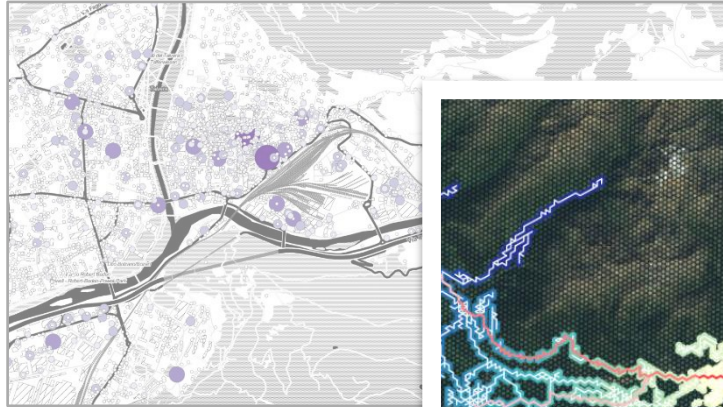
commuting pop.



Exposure

Predicting dynamic population flow

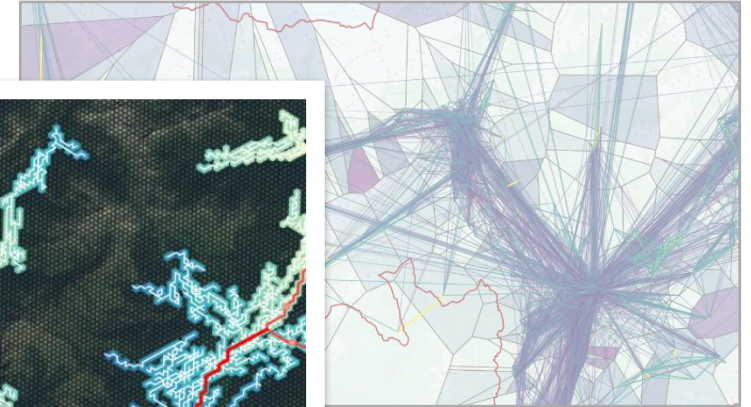
employees



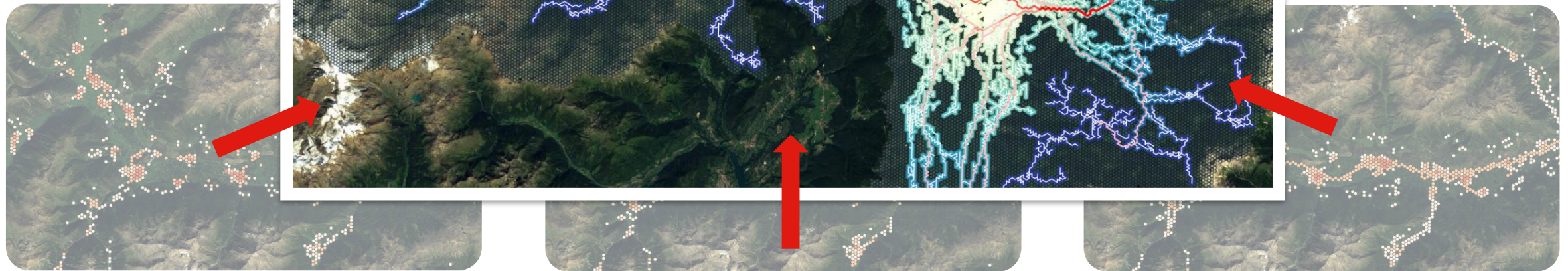
residents



commuting trips

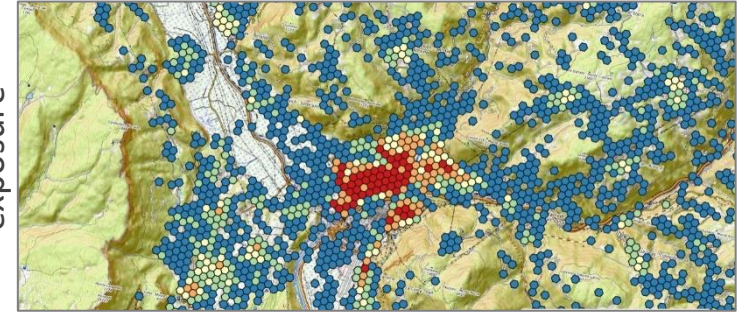
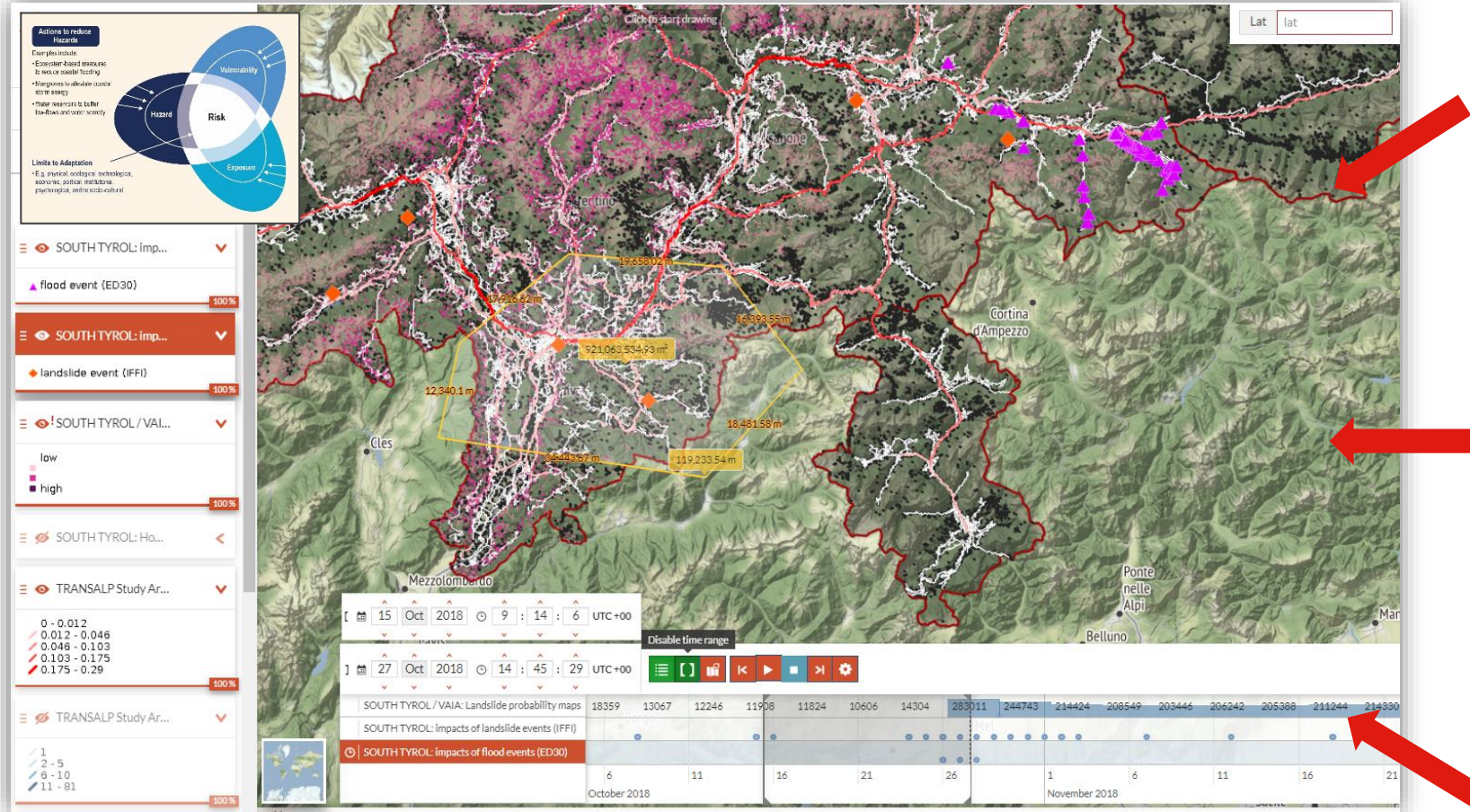


daytime pop.



Exposure

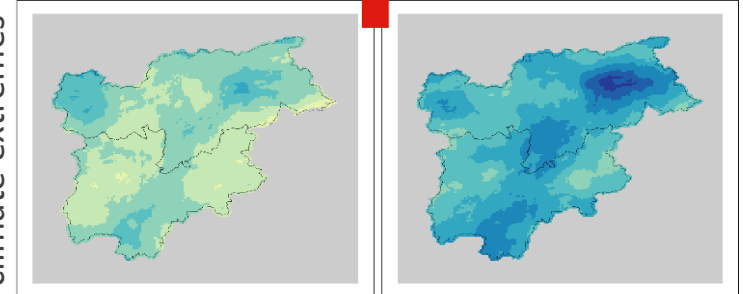
Putting it all together: towards an impact forecasting tool



exposure



hazards

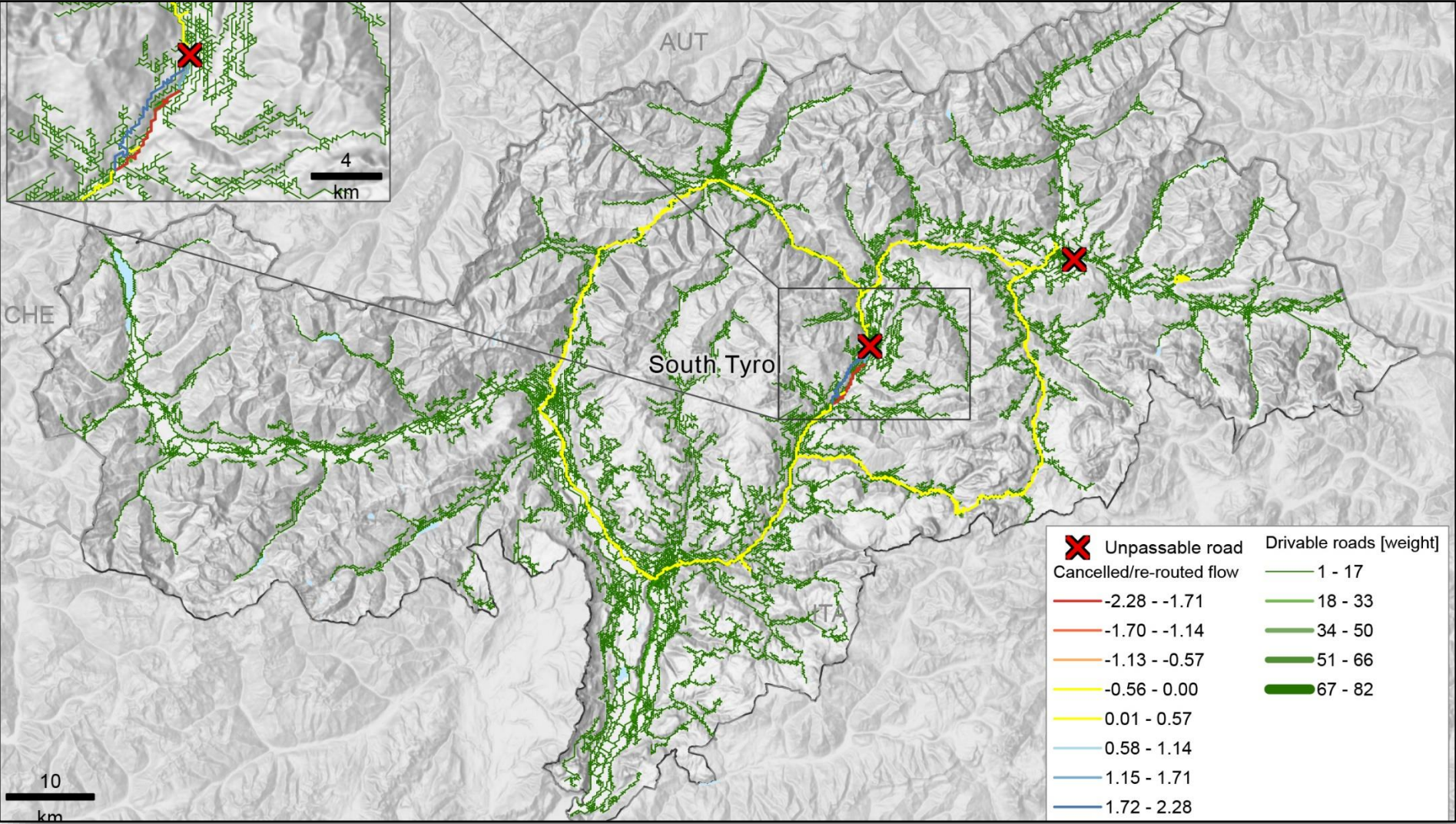


climate extremes

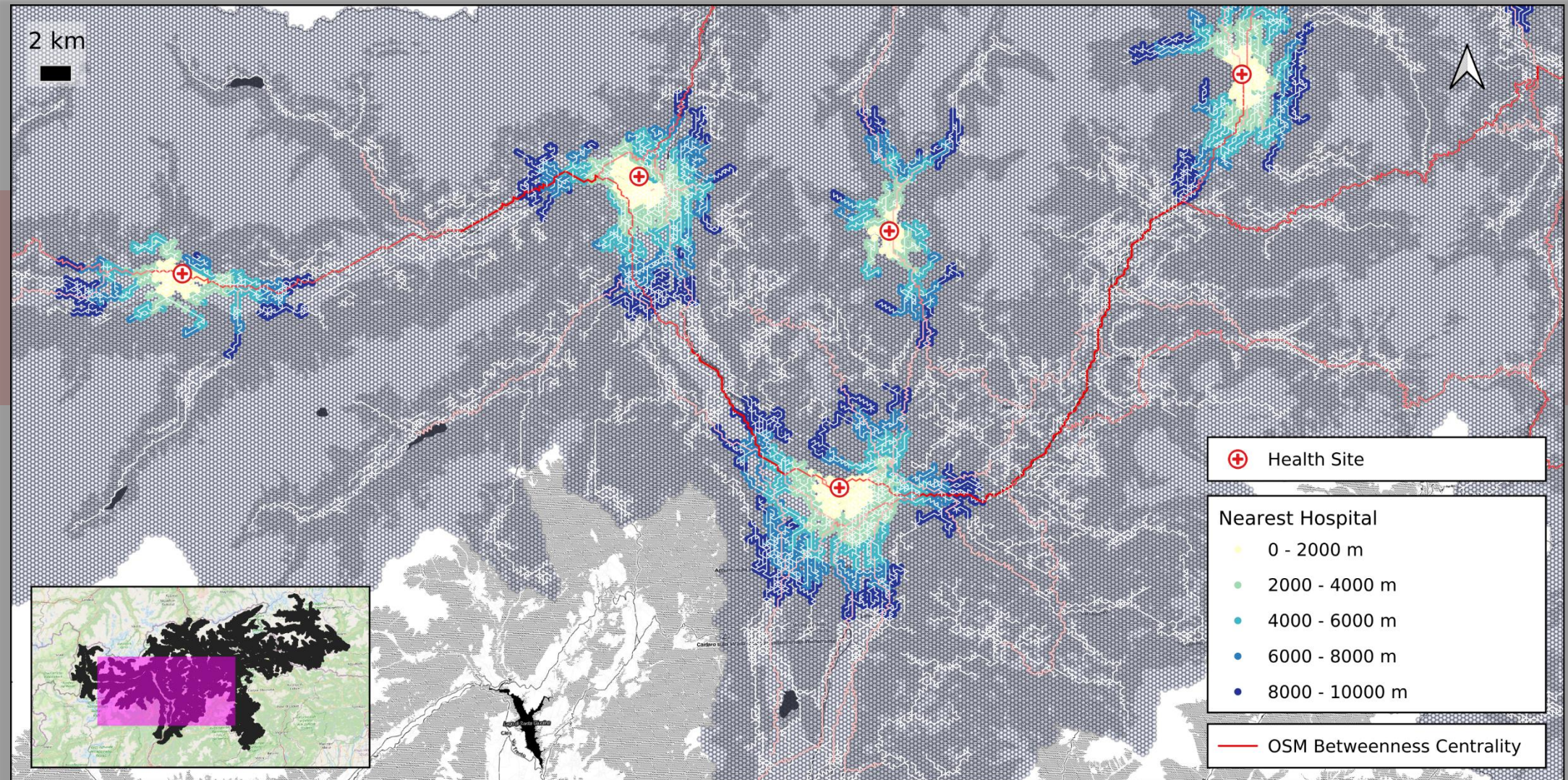
<https://maps.eurac.edu/maps/1274>

D Forward looking

Resilience and efficiency in transport networks



From exposure to vulnerability



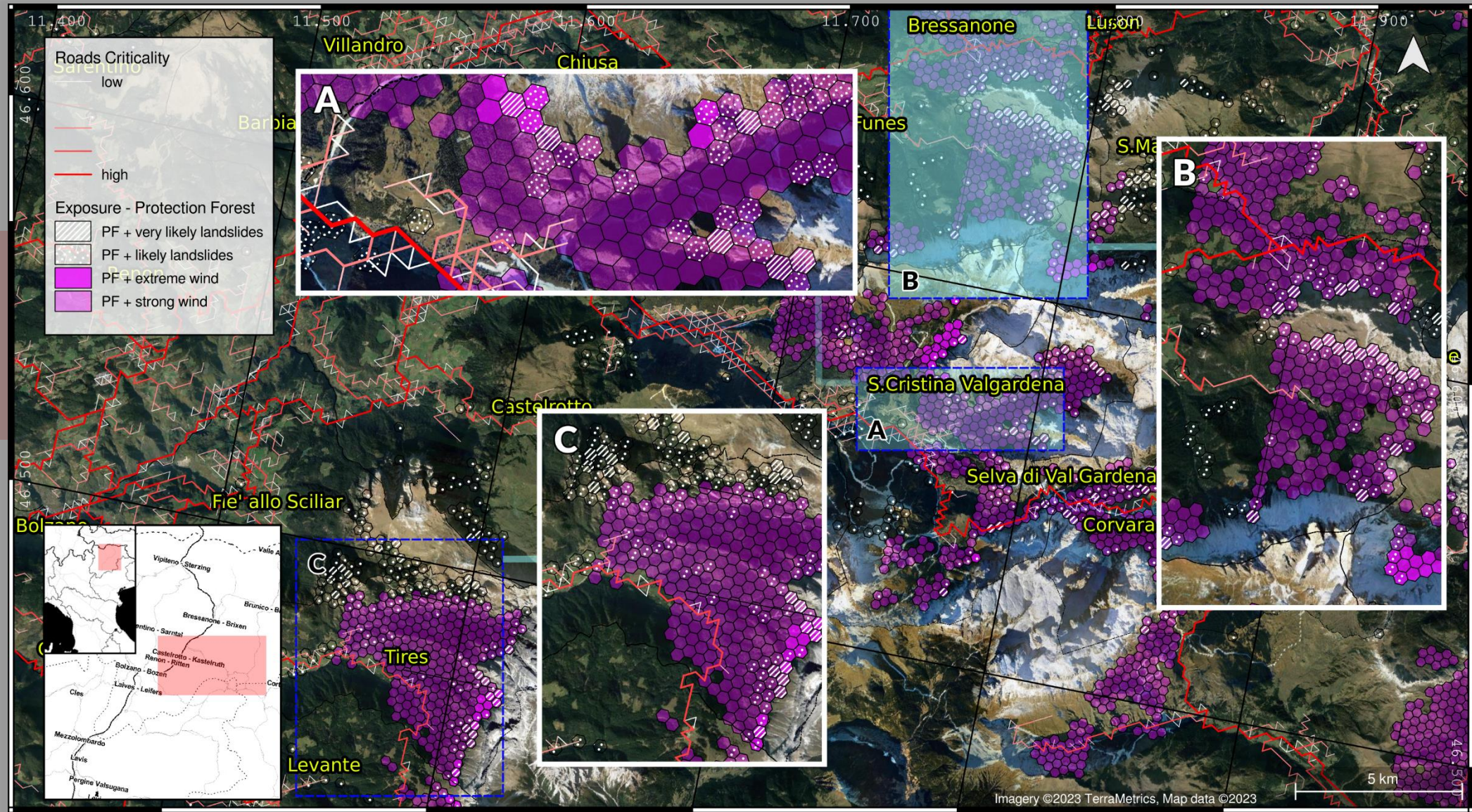
Large-scale hazard risk simulations



Large-scale hazard risk simulations



Multi-hazards risk nowcasting



Links

❑ The *TransAlp* Project

<https://project-transalp.eu/en/>

<https://www.linkedin.com/in/trans-alp-project-5b0437217/>

❑ WebGIS/Maps from *TransAlp*

https://maps.eurac.edu/maps/?group_group_profile_slug_in=trans-alp-project-public

❑ Pittore, M., Campalani, P., Renner, K. et al. “Border-independent multi-functional, multi-hazard exposure modelling in Alpine regions”. *Natural Hazards* (2023)

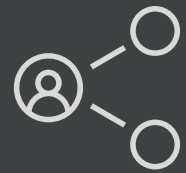

<https://doi.org/10.1007/s11069-023-06134-3>

eurac research

 <https://ror.org/01xt1w755>

Thank you!



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