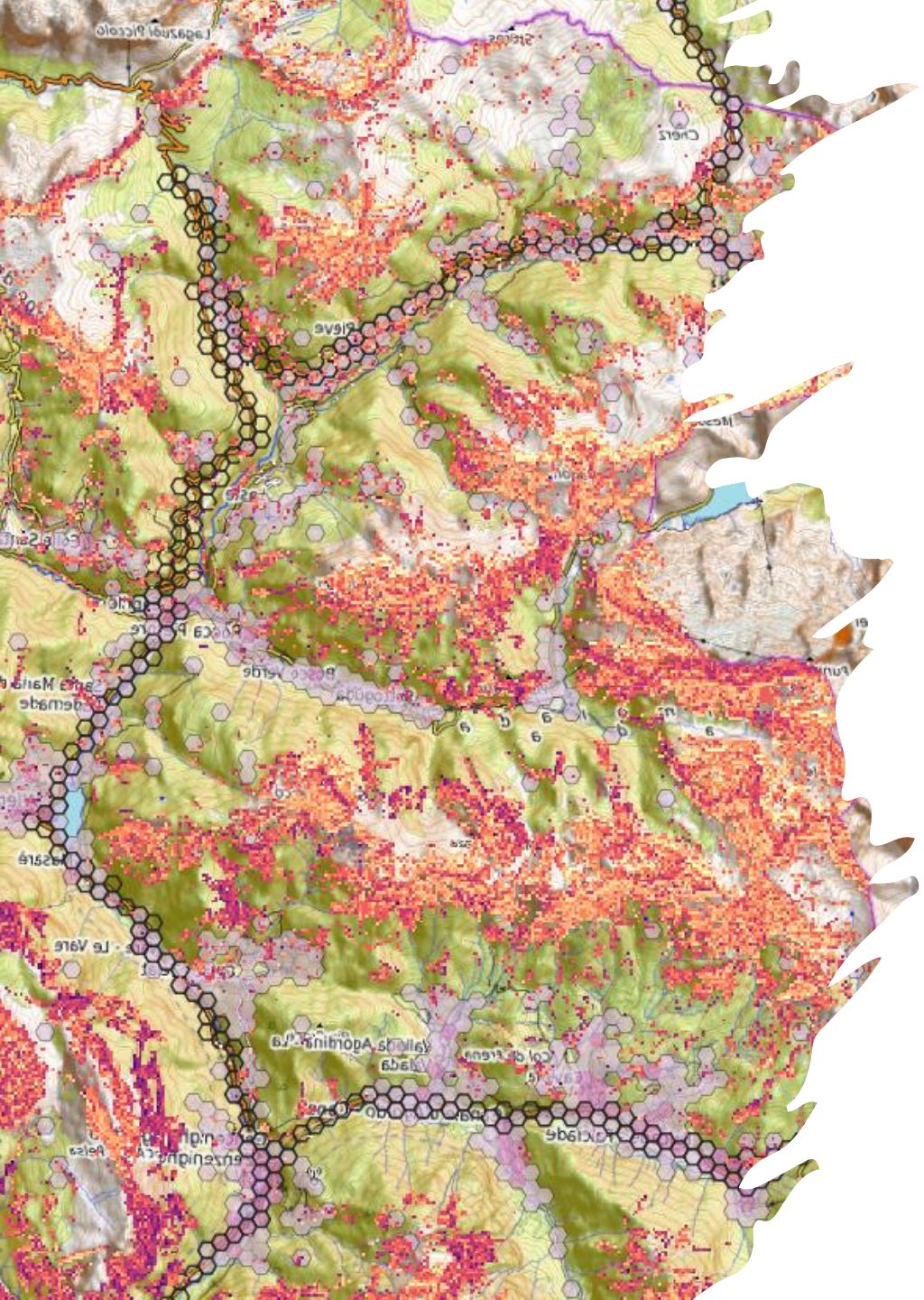


eurac research

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

Piero Campalani, Kathrin Renner, Massimiliano Pittore

0000-0002-1032-9825 0000-0001-7757-799X 0000-0003-4940-3444

17.10.2023

A Concepts and Context

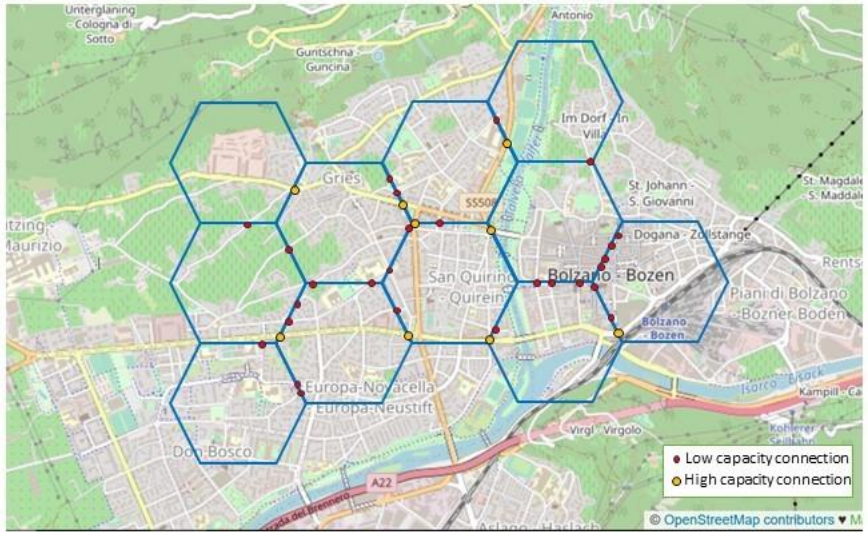
Q1 How to ease the life of DRR managers?

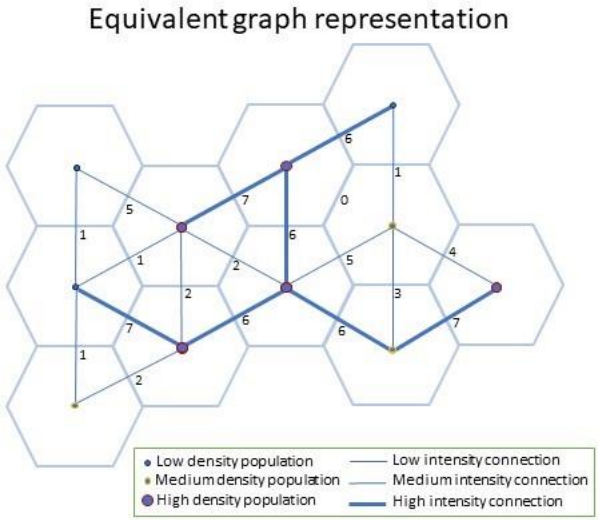
Available risk preparedness and prevention tools are increasingly lagging behind the growing threat of climate change, with multiple hazards often compounded causing cascaded and intertwined damages to society and the environment.

Q2 What about cross-border **exposure** data?

Transborder mountainous areas are <u>especially vulnerable</u> 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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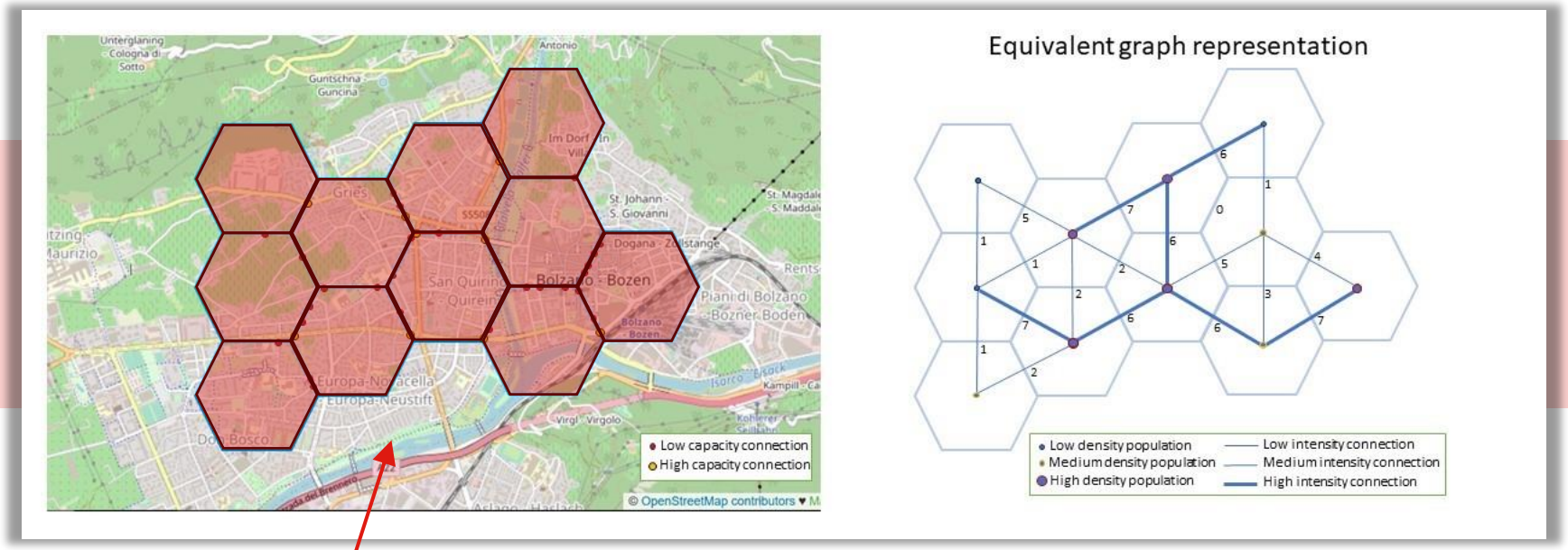

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HOMOGENEOUS PLANAR TESSELLATION

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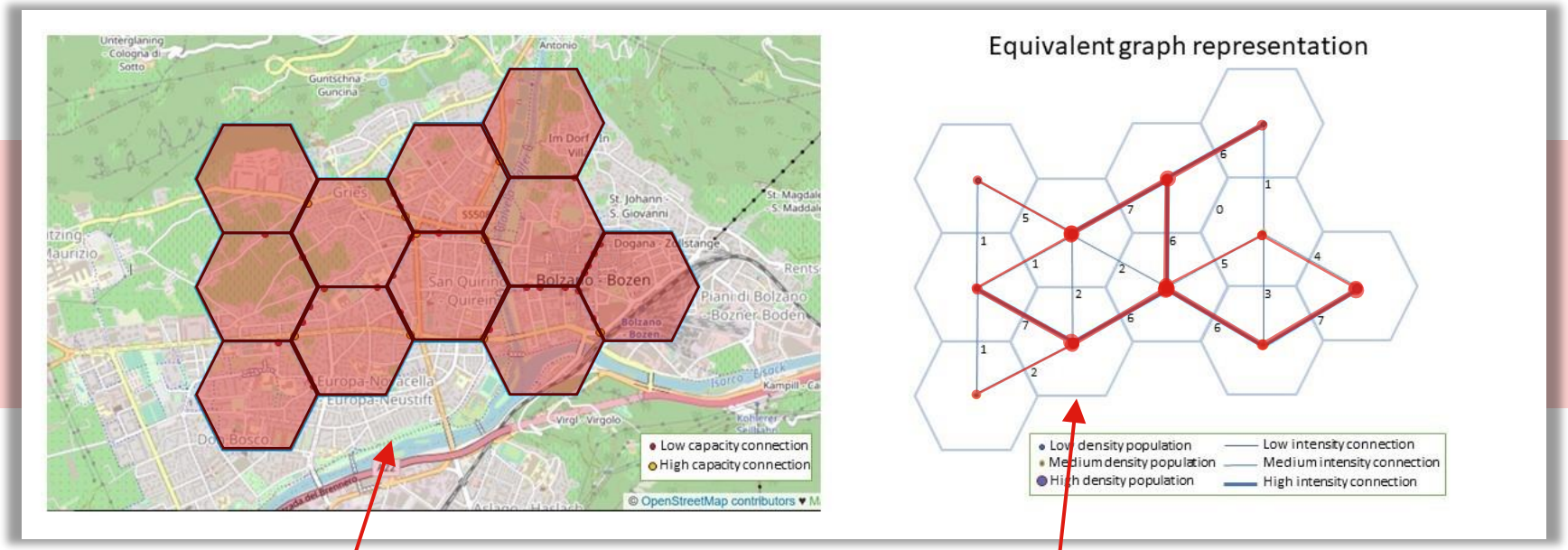

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DUAL-GRAPH REPRESENTATION

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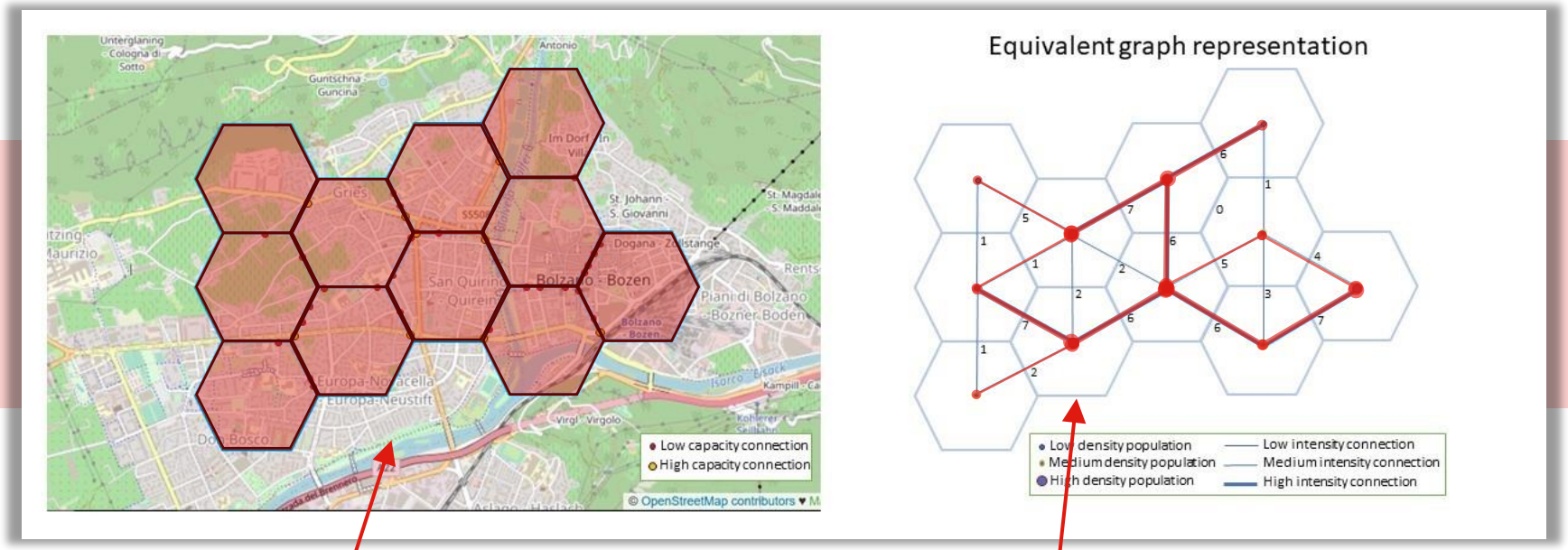

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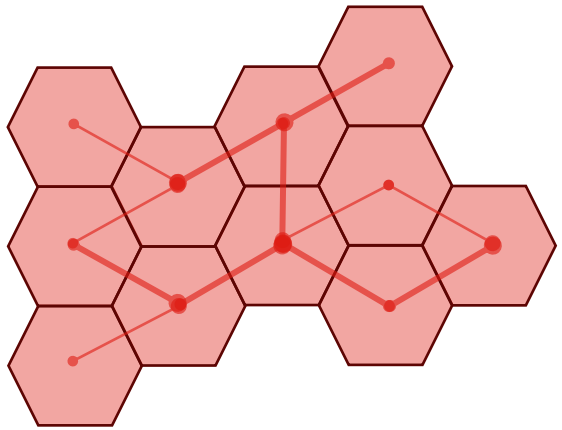
HOMOGENEOUS PLANAR TESSELLATION

DUAL-GRAPH REPRESENTATION

MULTIPLE RESOLUTION AGGREGATIONS ?

What is good:



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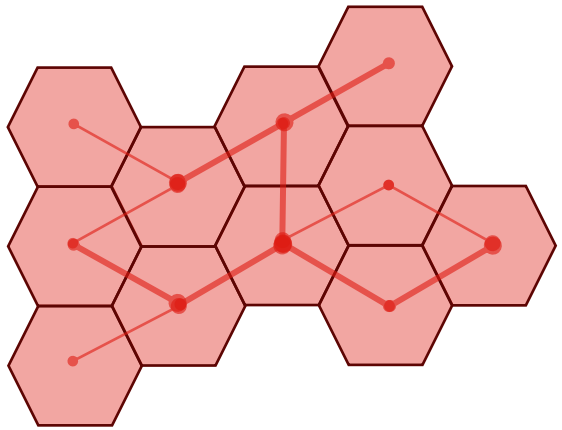
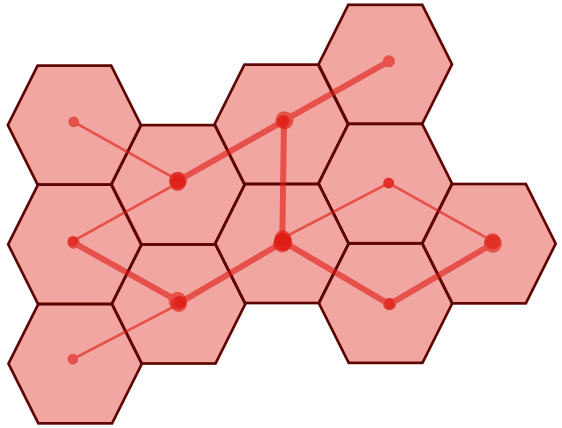


- ✓ **Simplified** view on map for e.g. pre-operational identification of hotspot areas

What is good:



- ✓ **Simplified** view on map for e.g. pre-operational identification of hotspot areas
- ✓ Tessellation can naturally provide an **anonymization** shield for sensible data → opens to potentially more availability of data

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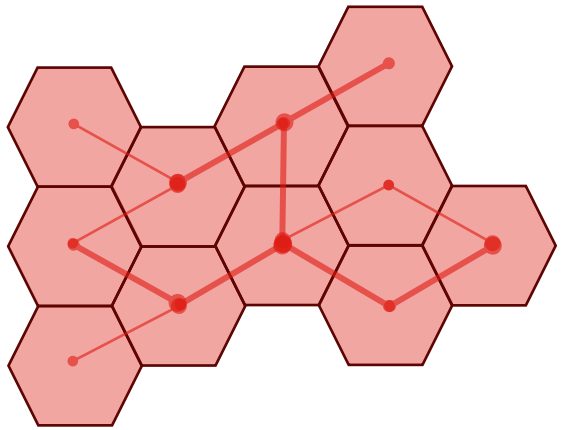

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- ✓ Hexagons reduce **sampling bias**, and improve spatial representativeness and topological expressivity

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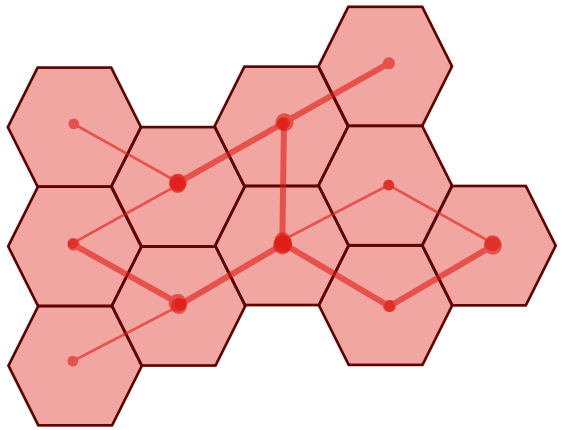
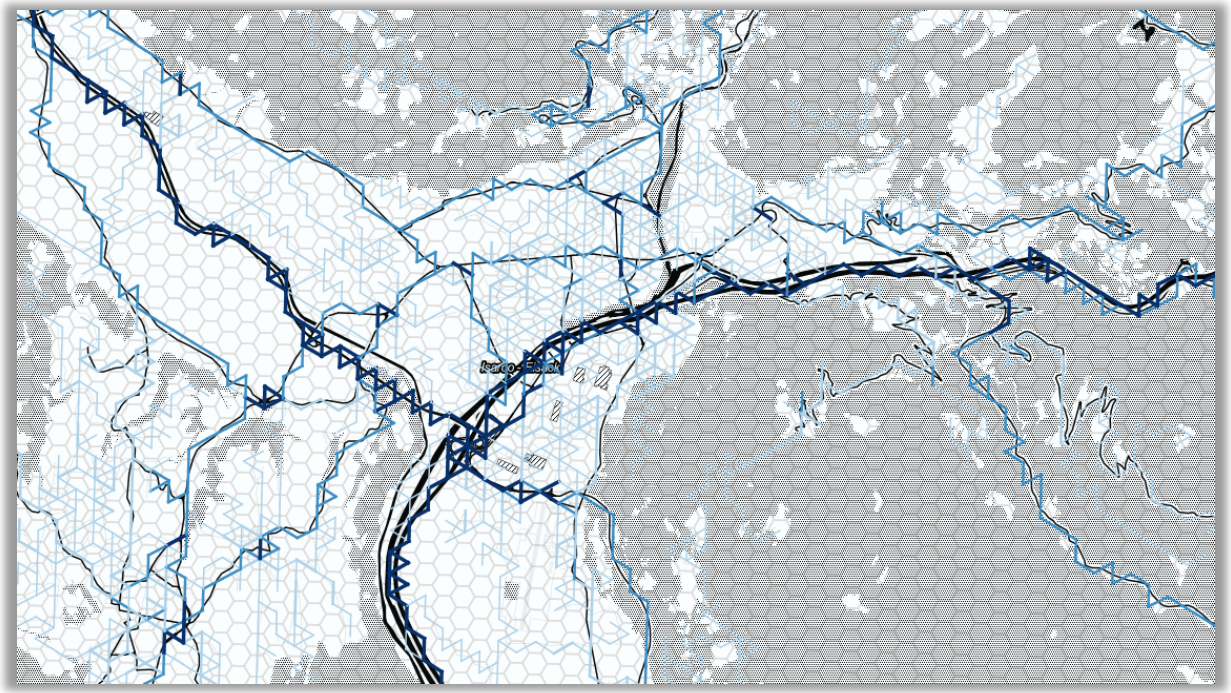
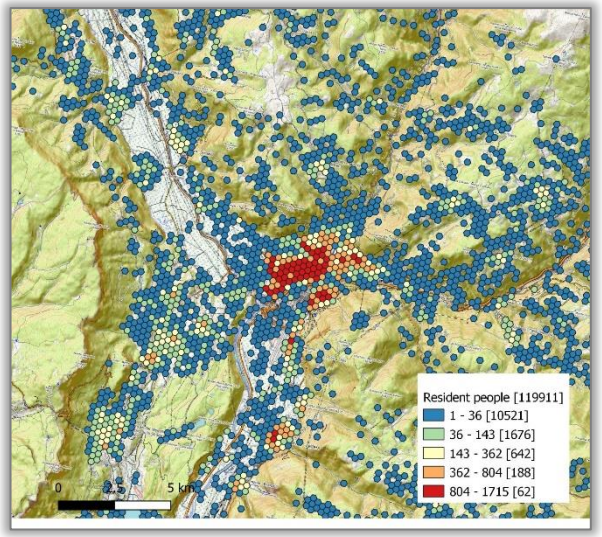
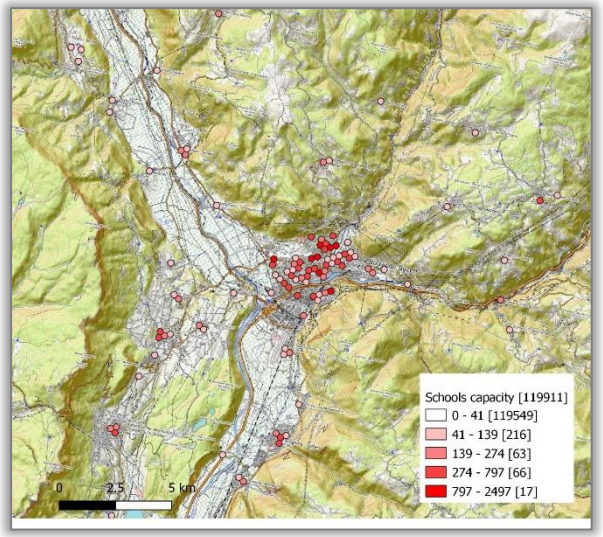


- ✓ **Simplified** view on map for e.g. pre-operational identification of hotspot areas
- ✓ Tessellation can naturally provide an **anonymization** shield for sensible data → opens to potentially more availability of data
- ✓ Hexagons reduce **sampling bias**, and improve spatial representativeness and topological expressivity
- ✓ **Duality** cells/graph to represent both area- and flow/connection-oriented data

Border-independent data collection and assimilation

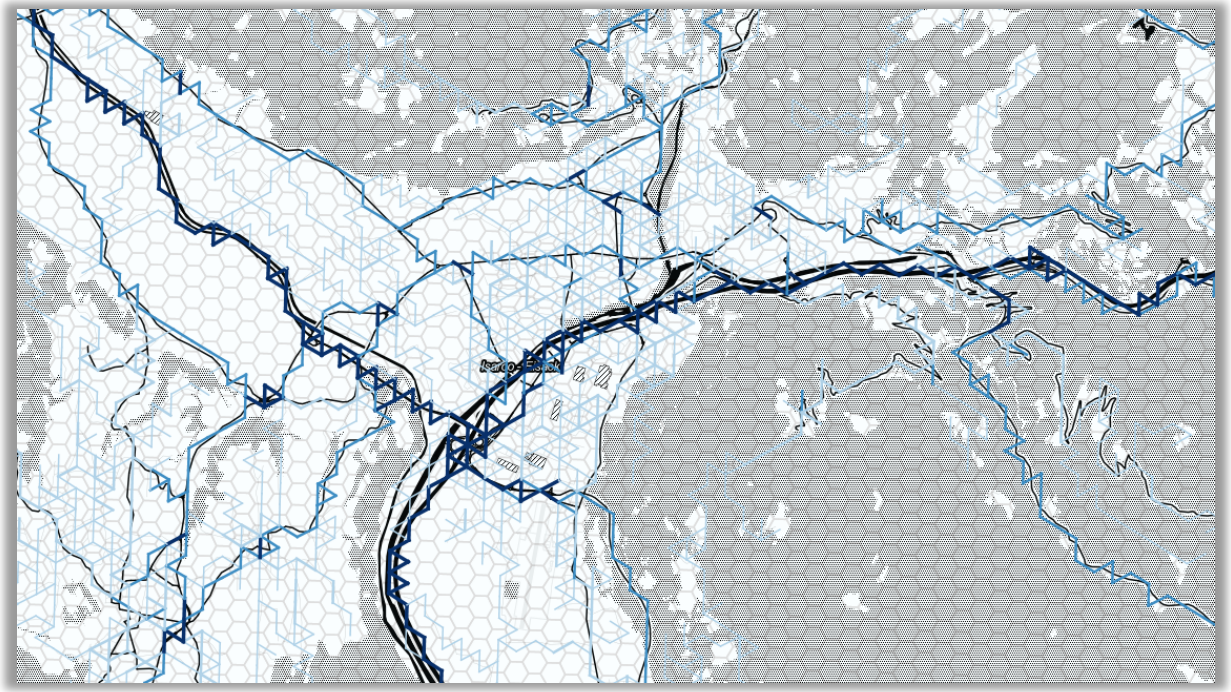


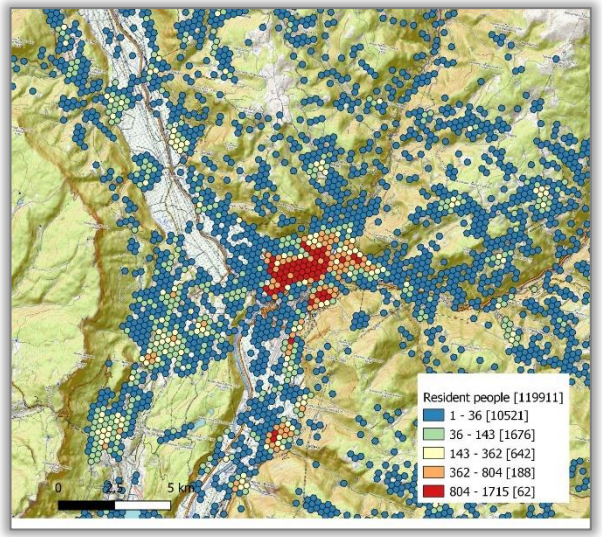


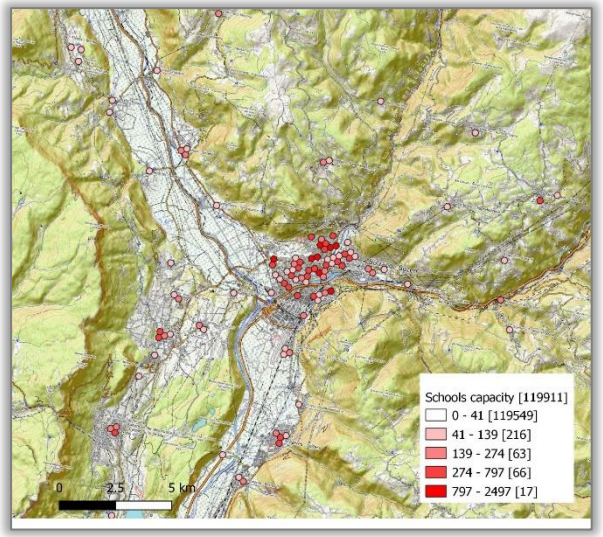


Border-independent data collection and assimilation

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







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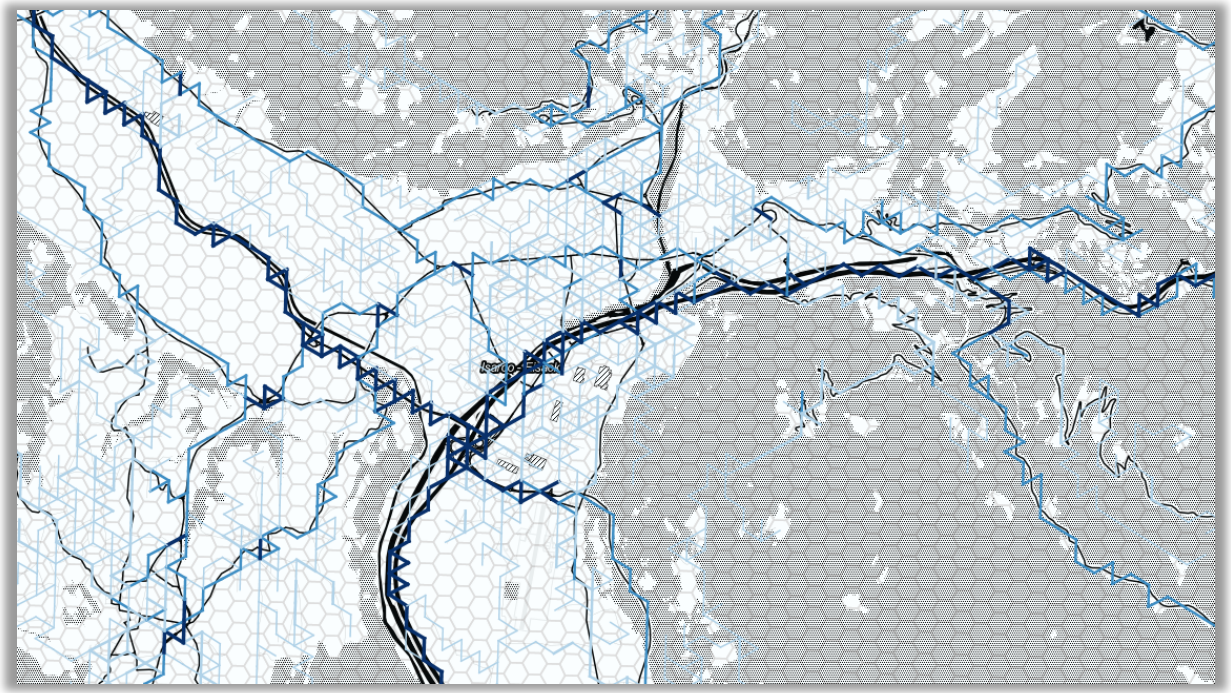
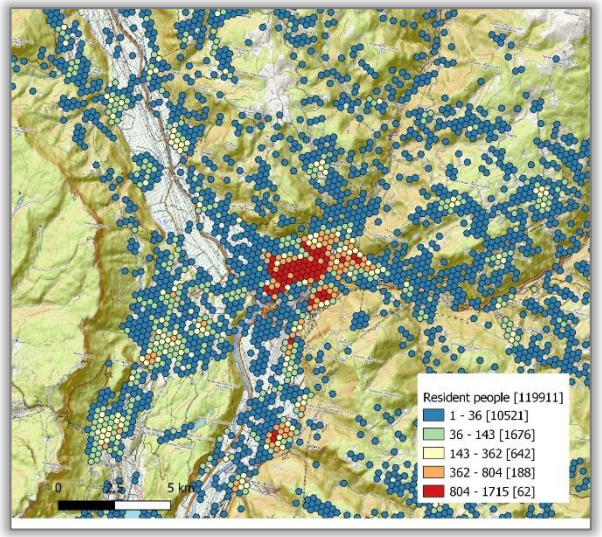
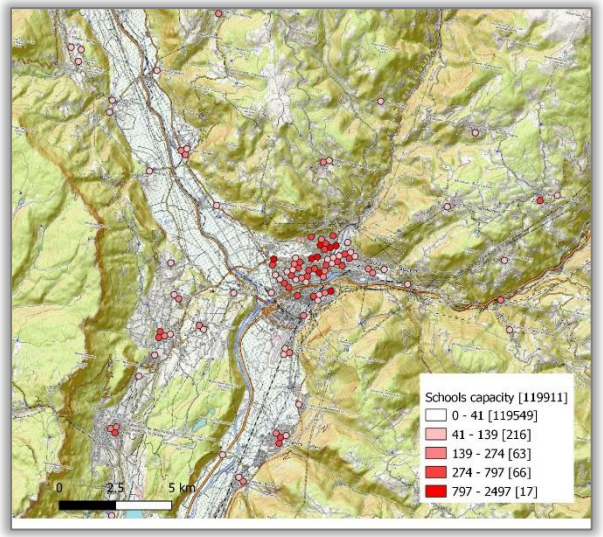
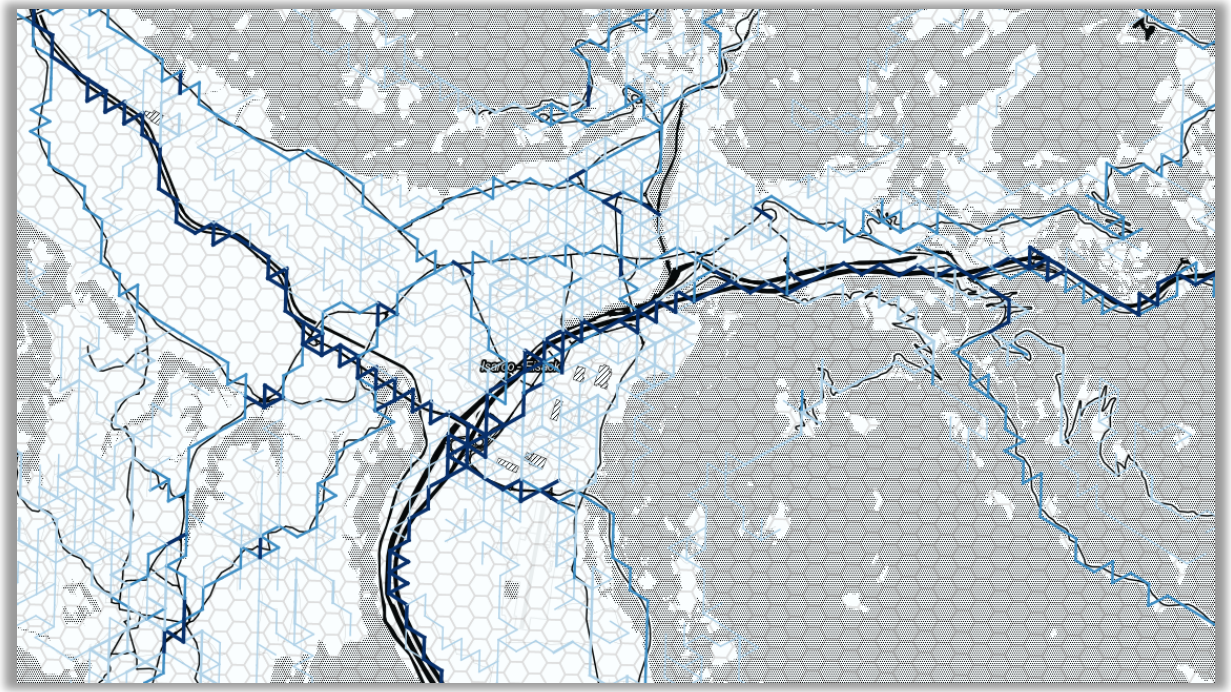


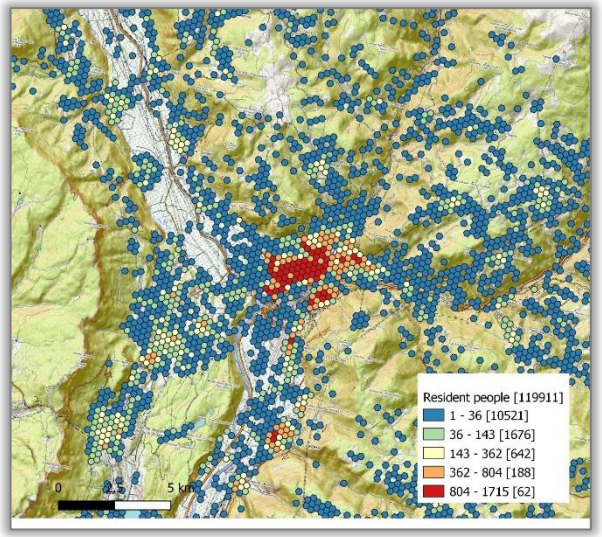


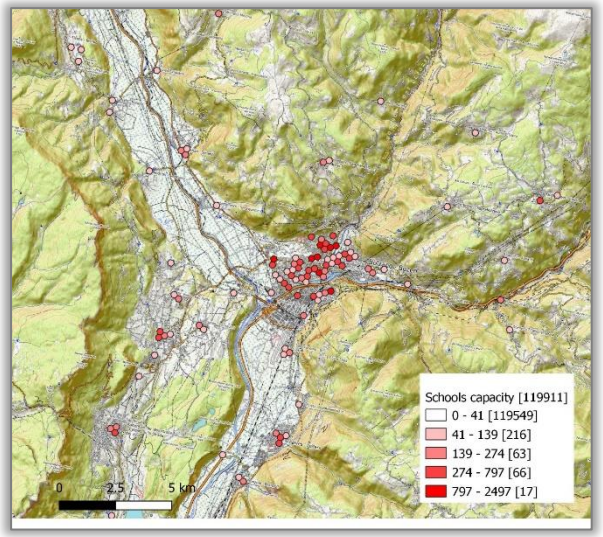


Border-independent data collection and assimilation

- **Define** a set of exposure assets to be included in the model
- **Harmonize** cross-border heterogeneities when necessary (scale, type of measurement, unit of measure)
- **Assimilate**/simplify all datasets to the topology

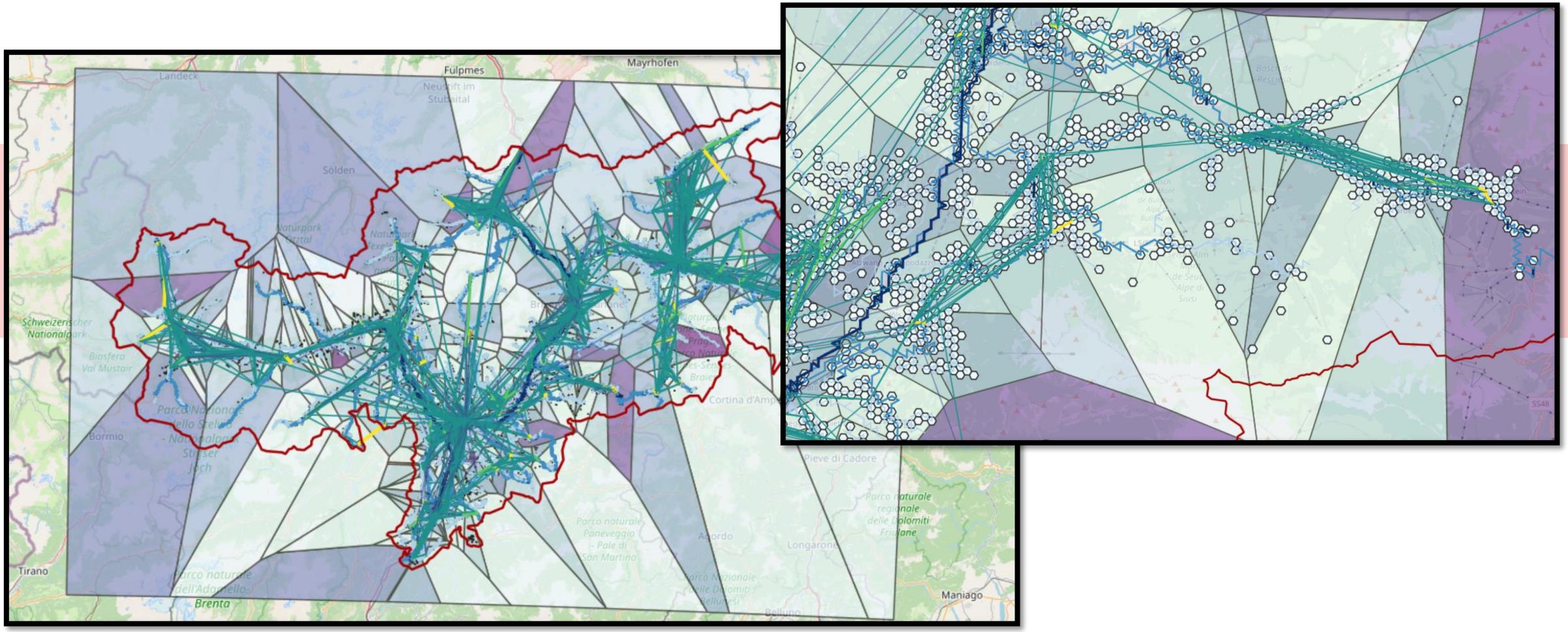






B Where is everybody?

Modelling the population flow:



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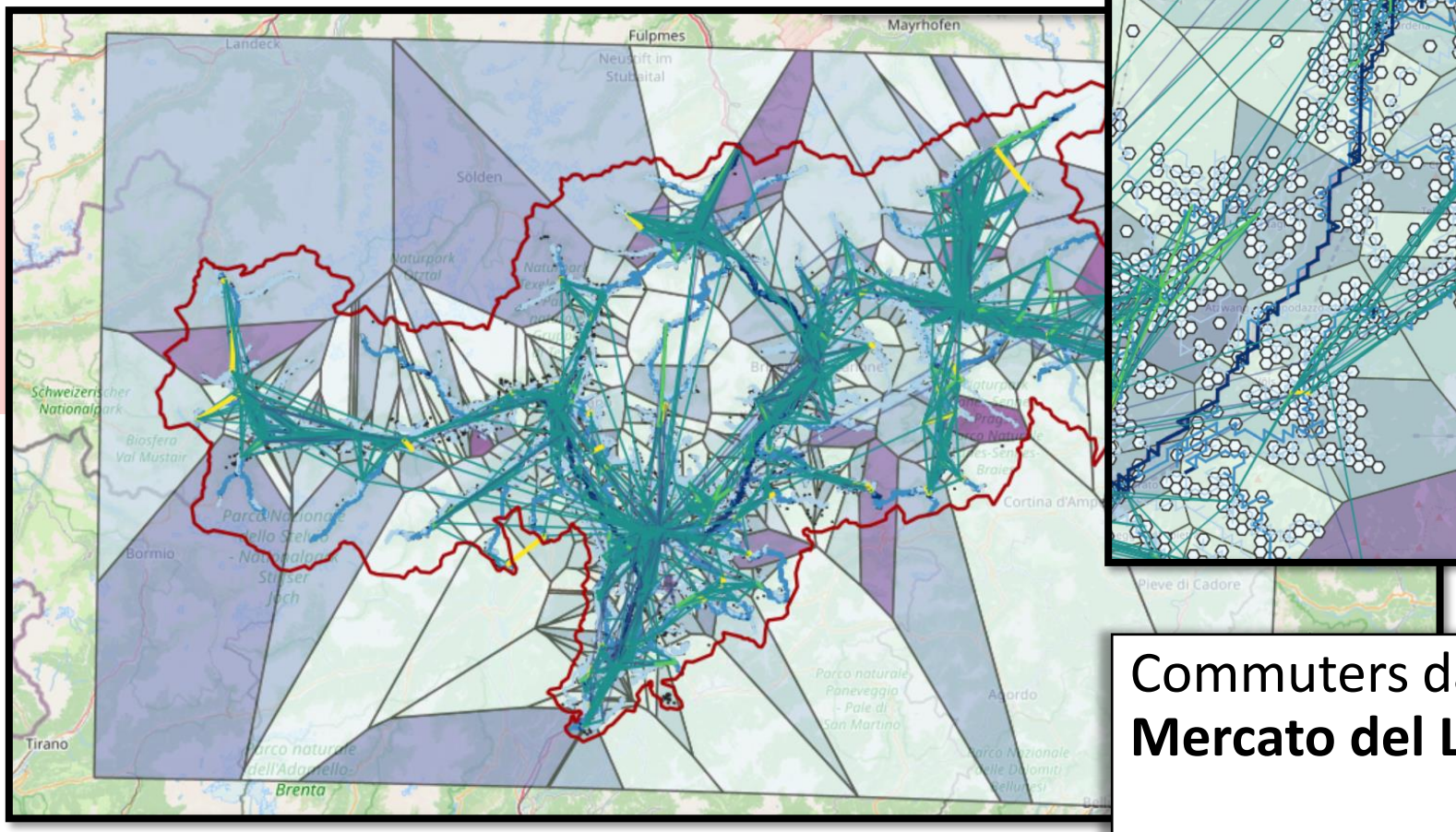
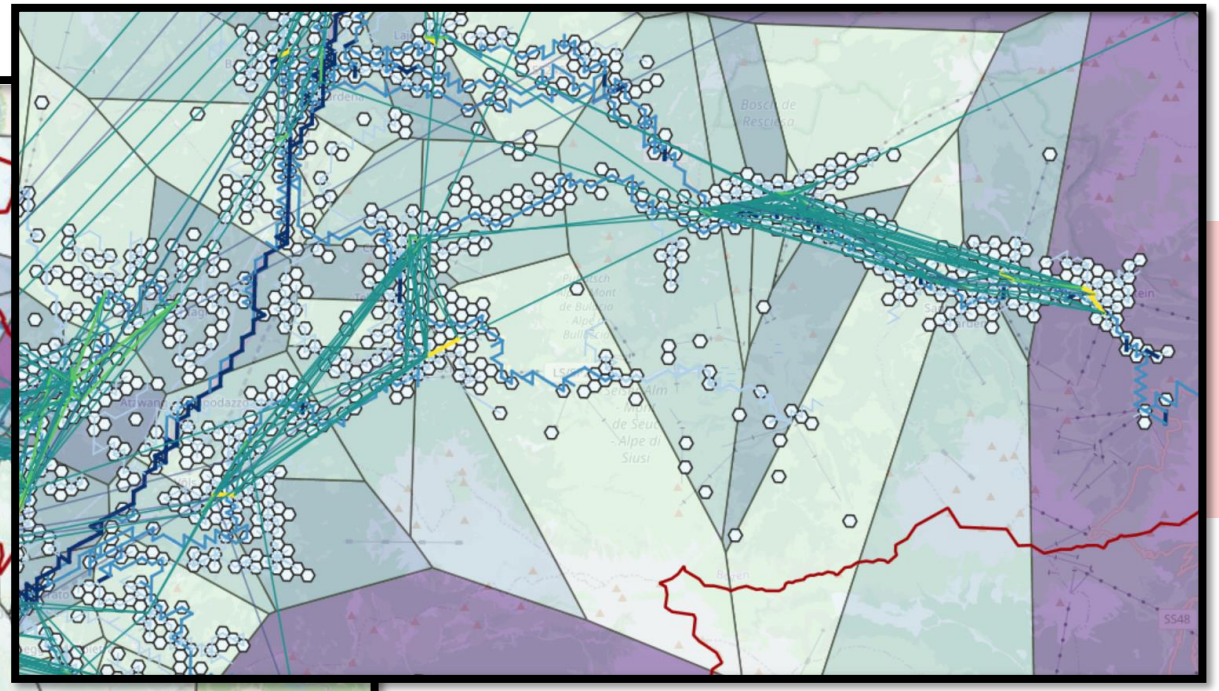
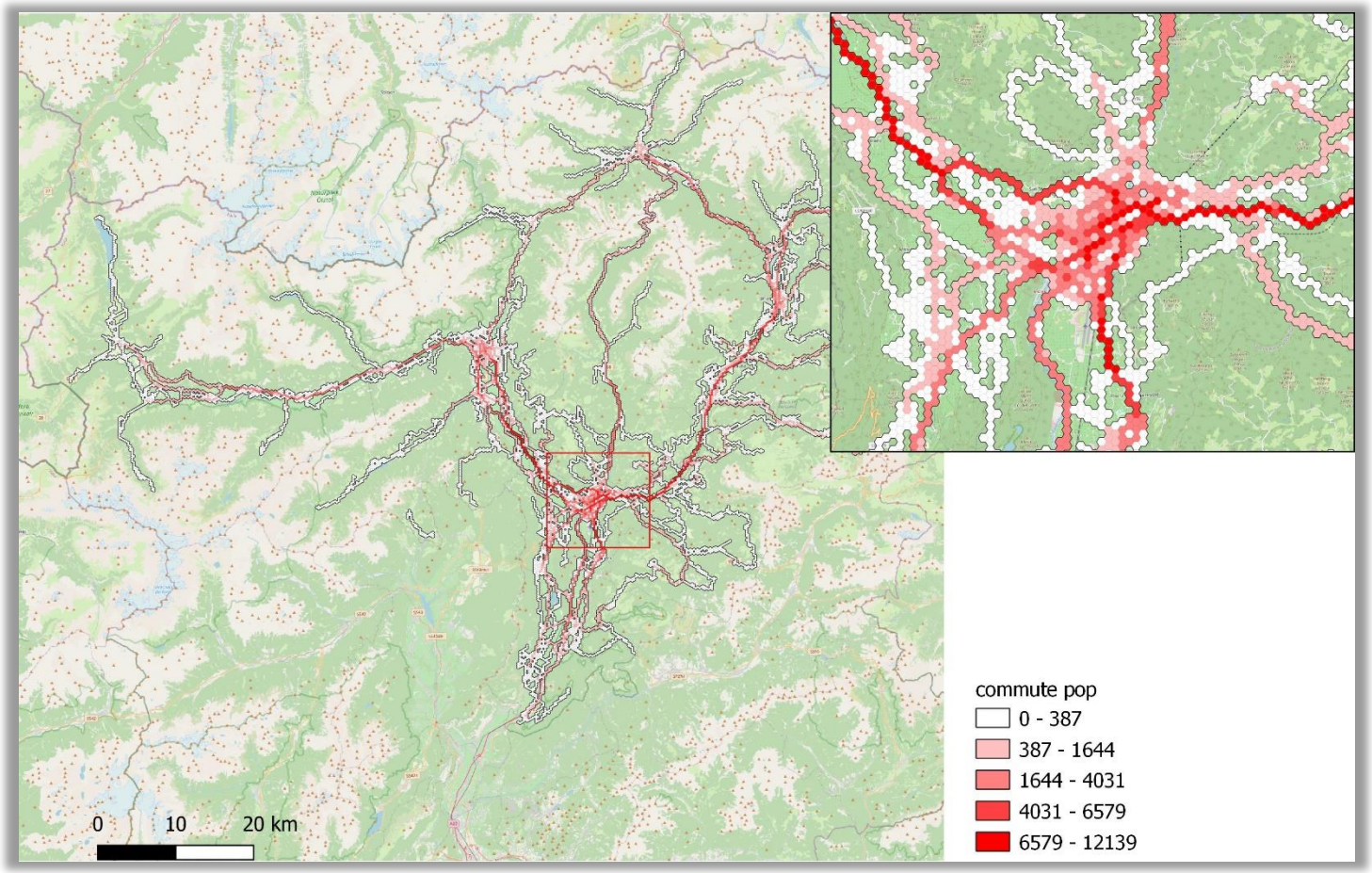




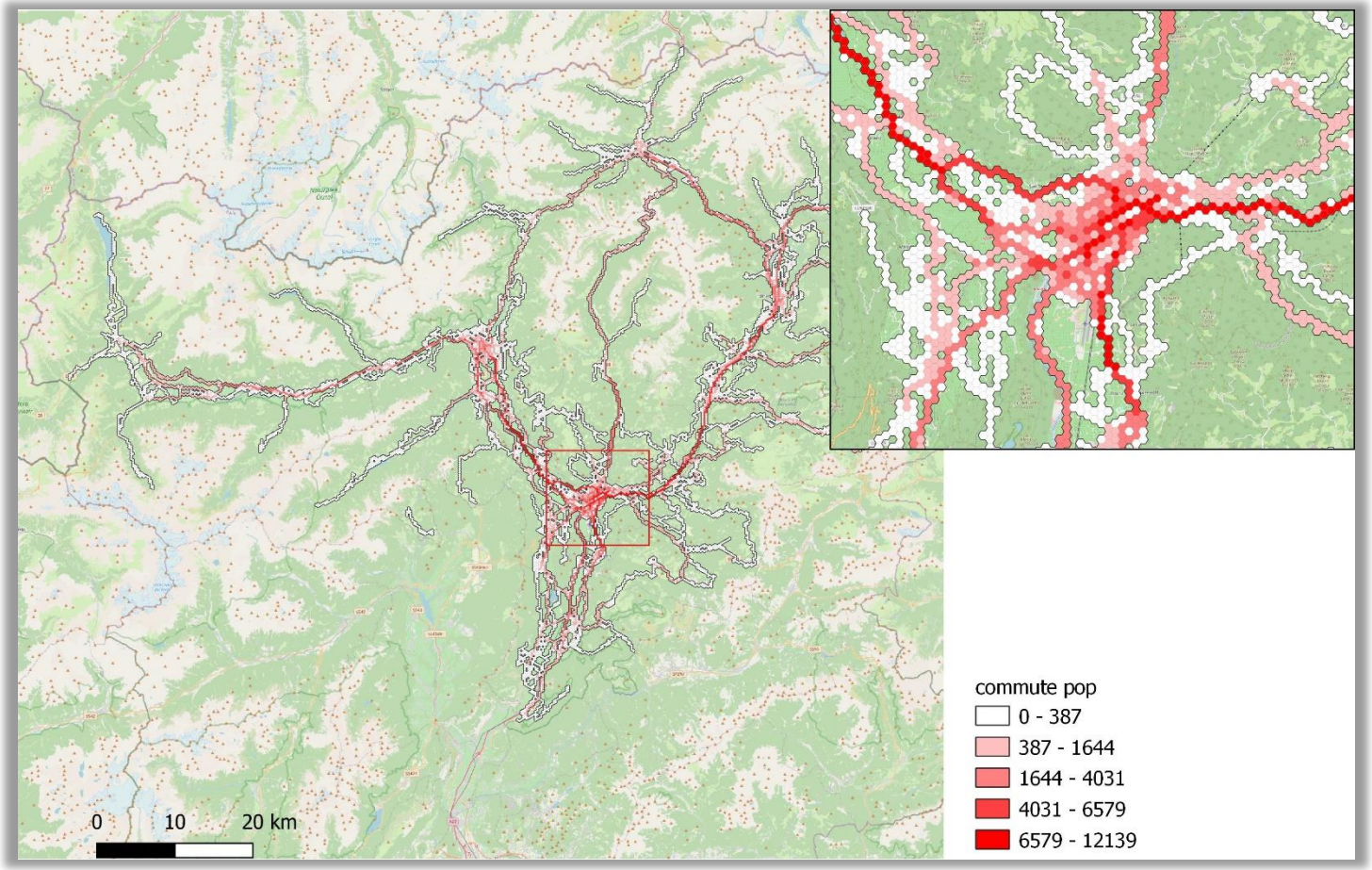
Commuters data from **Ufficio Osservazione Mercato del Lavoro** (South Tyrol, IT)

Need a flexible, border-independent solution



Need a flexible, border-independent solution

- **Dynamic best-effort**
  From basic to refined behaviour depending on data availability



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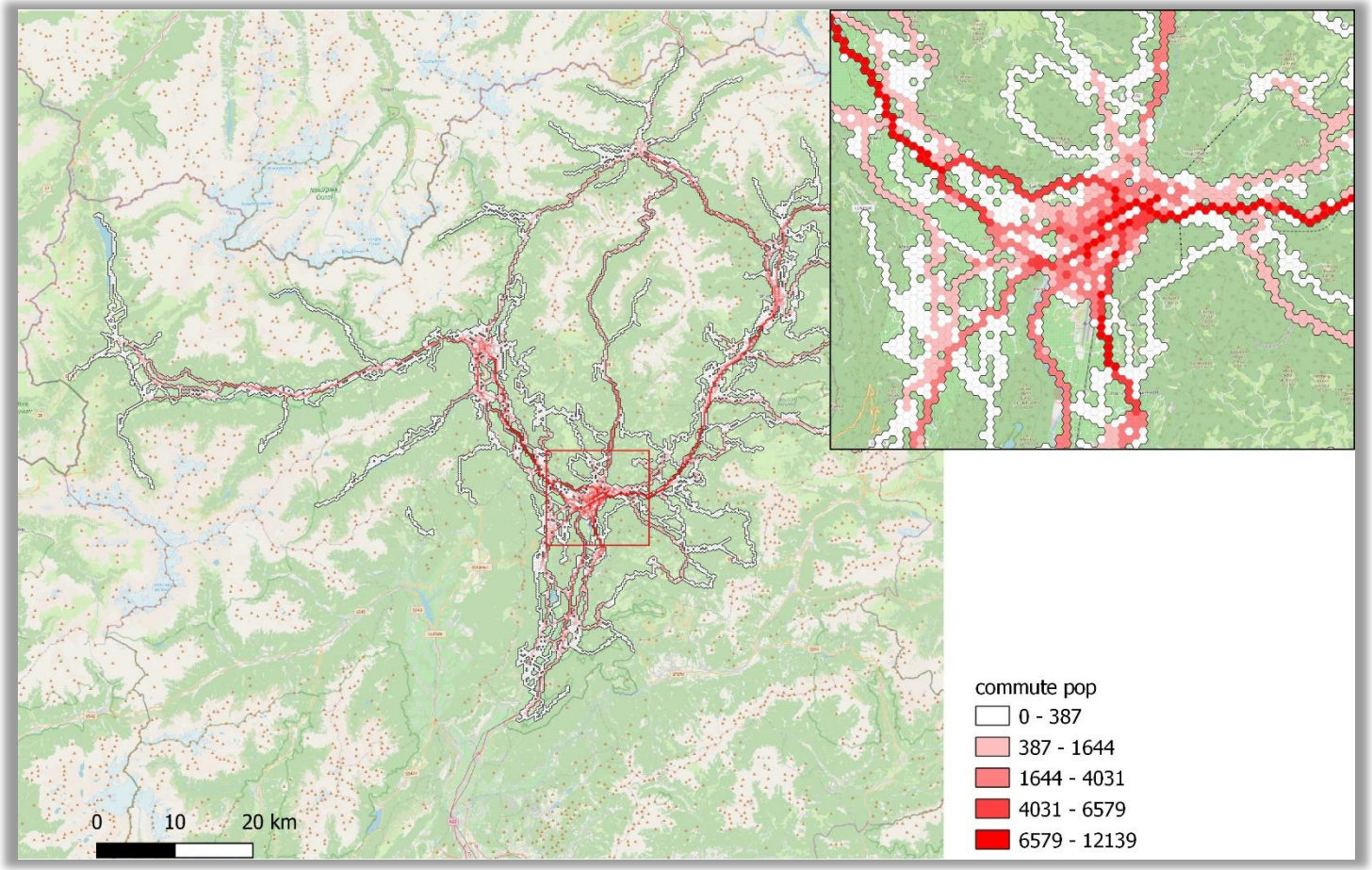
  Possible data-driven model configuration on a country-base



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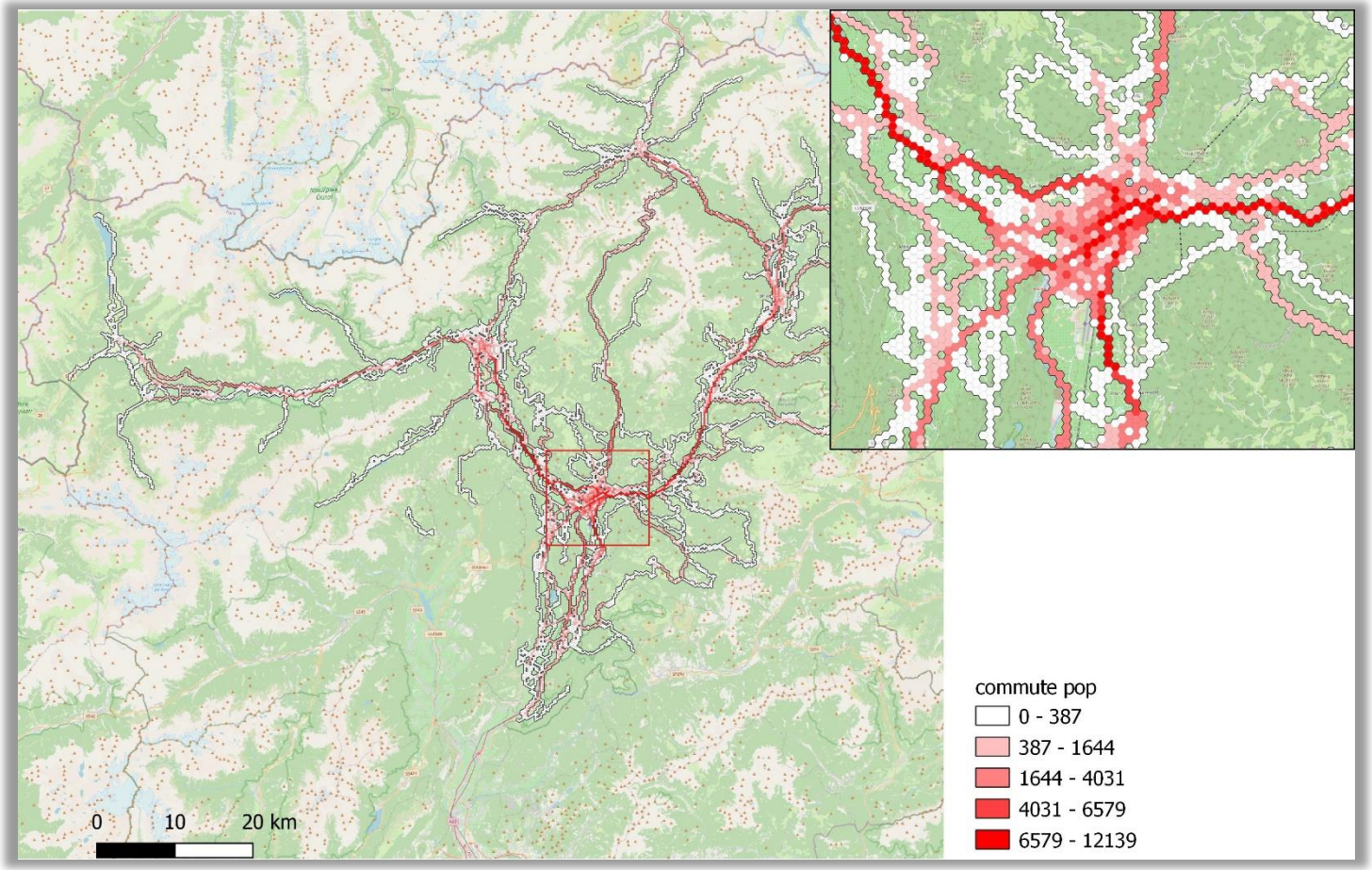
- **Multi-scale**
  Allow visual analysis at multiple scales (medium to small)



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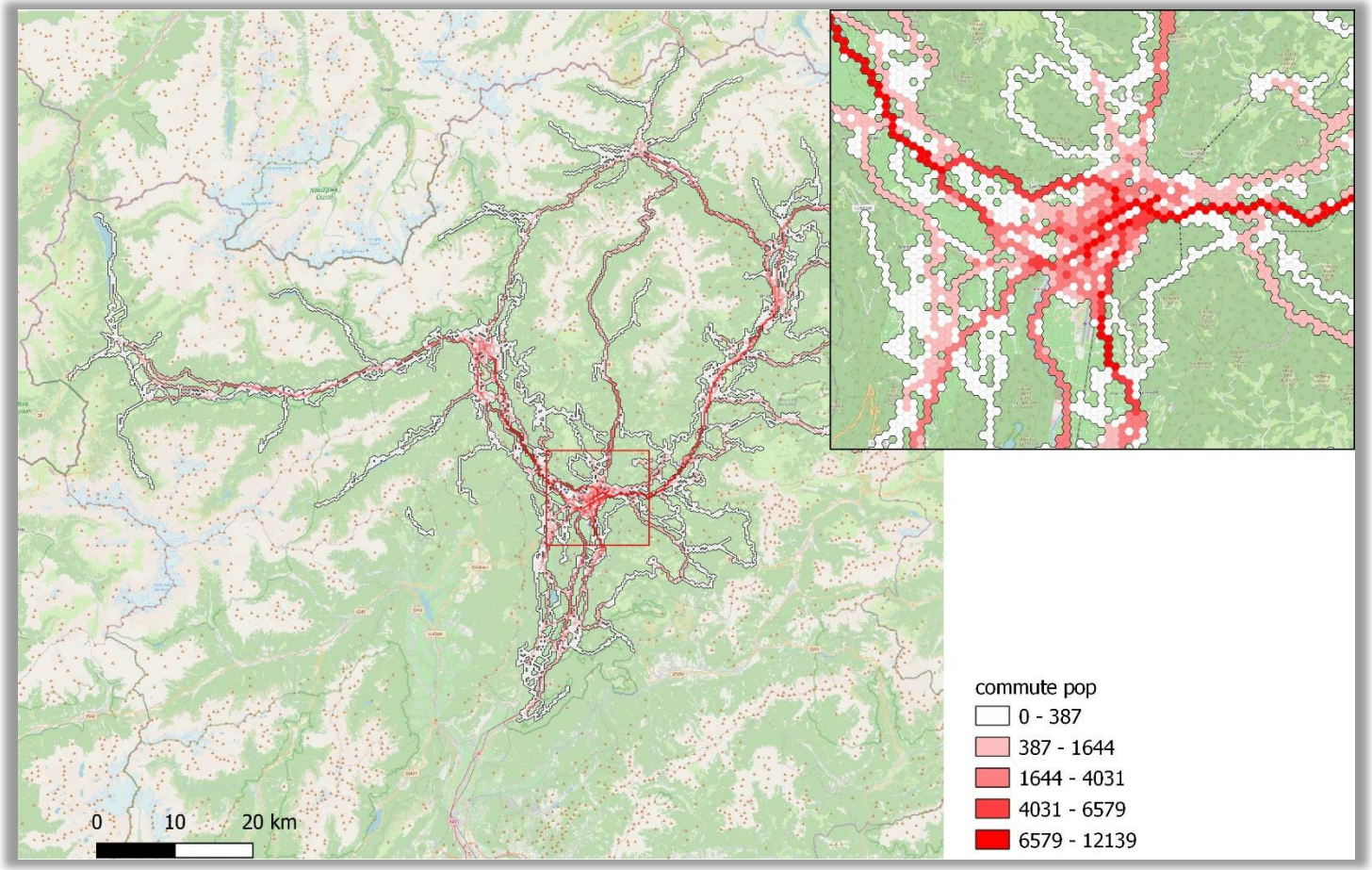
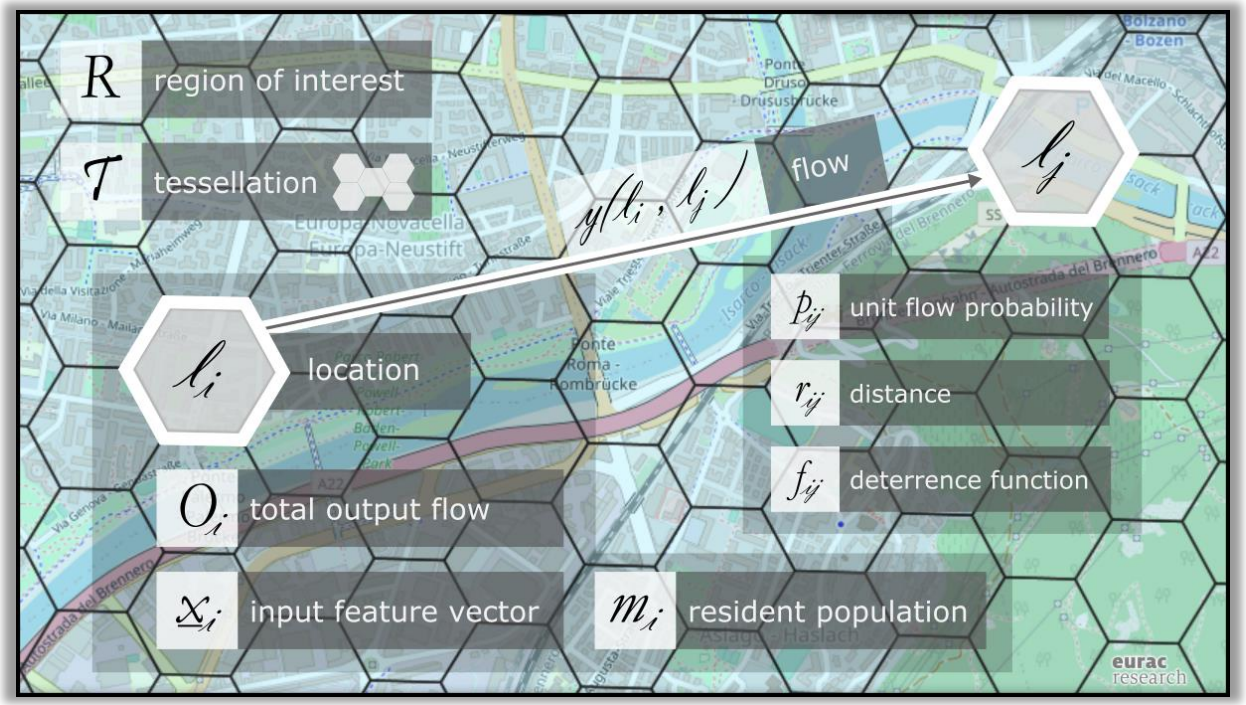
- **Multi-scale**
  Allow visual analysis at multiple scales (medium to small)
- **Re-compute easily**
  Pseudo real-time what-if scenarios visualizations



A gravity model ?

Asset / timeframe			Week days			Weekend and holidays		
			Morning	Afternoon	Night	Morning	Afternoon	Night
$\underline{w_u}$	Land Use	$w_u^1 : urban$	$1/\oiint l$	$1/\oiint l$	$1/\oiint l$	$1/\oiint l$	$1/\oiint l$	$1/\oiint l$
		$w_u^2 : industrial$	$1/\oiint l$	$1/\oiint l$	$1/\oiint l$	0	0	0
		$w_u^3 : vegetated$	$1/\oiint l$	$1/\oiint l$	0	$1/\oiint l$	$1/\oiint l$	0
		$w_u^4 : crop/forest$	0	0	0	$1/\oiint l$	$1/\oiint l$	0
		$w_u^5 : water$	0	0	0	$1/\oiint l$	$1/\oiint l$	0
$\underline{w_n}$	Roads	$w_n^1 : main$	$1/\oint l$	$1/\oint l$	0	$1/\oint l$	$1/\oint l$	$1/\oint l$
		$w_n^2 : residential$	$1/\oint l$	$1/\oint l$	$1/\oint l$	$1/\oint l$	$1/\oint l$	$1/\oint l$
		$w_n^3 : pedestrian$	$1/\oint l$	$1/\oint l$	$1/\oint l$	$1/\oint l$	$1/\oint l$	$1/\oint l$
$\underline{w_t}$	Transport	$w_t^1 : stations$	1	1	1	1	1	1
		$w_t^2 : stops$	1	1	0	1	1	0
		$w_t^3 : parkings$	1	1	1	1	1	1
$\underline{w_h}$	Health	$w_h^1 : hospitals$	5	5	1	5	5	1
		$w_h^2 : clinics$	1	1	0	1	1	0
		$w_h^3 : pharmacies$	1	1	0	1	1	0
		$w_h^4 : retirement$	1	1	0	1	1	0
$\underline{w_s}$	Education	$w_s^1 : kita/schools$	1	1	0	0	0	0
		$w_s^2 : higher\ edu.$	1	1	0	0	0	0
$\underline{w_b}$	Food	$w_b^1 : bars/cafes$	1	1	0	1	1	0
		$w_b^2 : restaurants$	0	1	1	0	1	1
$\underline{w_c}$	Retail	$w_c^1 : malls$	5	5	0	5	5	0
		$w_c^2 : shops$	1	1	0	1	1	0
$\underline{w_a}$	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^2 : industrial	$1/\oiint l$	$1/\oiint l$	$1/\oiint l$	0	0	0
		w_u^3: vegetated	$1/\oiint l$	$1/\oiint l$	0	$1/\oiint l$	$1/\oiint l$	0
		w_u^4 : crop/forest	0	0	0	$1/\oiint l$	$1/\oiint l$	0
		w_u^5 : water	0	0	0	$1/\oiint l$	$1/\oiint l$	0
$\underline{w}_n$	Roads	w_n^1 : main	$1/\oint l$	$1/\oint l$	0	$1/\oint l$	$1/\oint l$	$1/\oint l$
		w_n^2 : residential	$1/\oint l$	$1/\oint l$	$1/\oint l$	$1/\oint l$	$1/\oint l$	$1/\oint l$
		w_n^3 : pedestrian	$1/\oint l$	$1/\oint l$	$1/\oint l$	$1/\oint l$	$1/\oint l$	$1/\oint l$
$\underline{w}_t$	Transport	w_t^1 : stations	1	1	1	1	1	1
		w_t^2 : stops	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
		w_t^3 : parkings						
$\underline{w}_h$	Health	w_h^1 : hospitals						
		w_h^2 : clinics						
		w_h^3 : pharmaci						
		w_h^4 : retiremen						
$\underline{w}_s$	Education	w_s^1 : kita/schoo						
		w_s^2 : higher ed						
$\underline{w}_b$	Food	w_b^1 : bars/caf						
		w_b^2 : restauran						
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		w_c^2 : shops						
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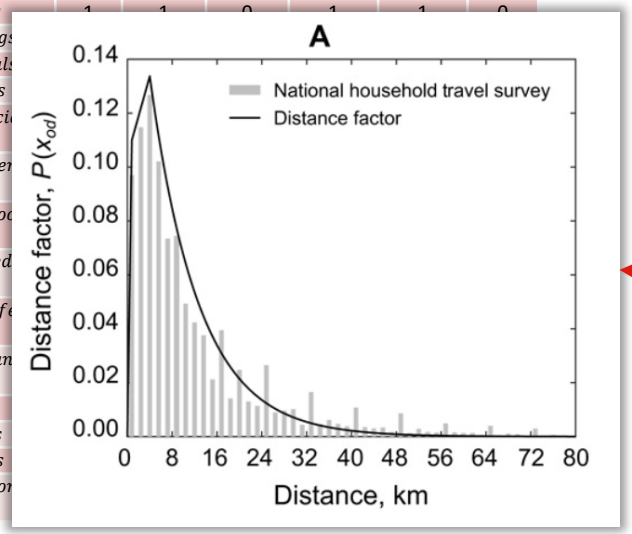
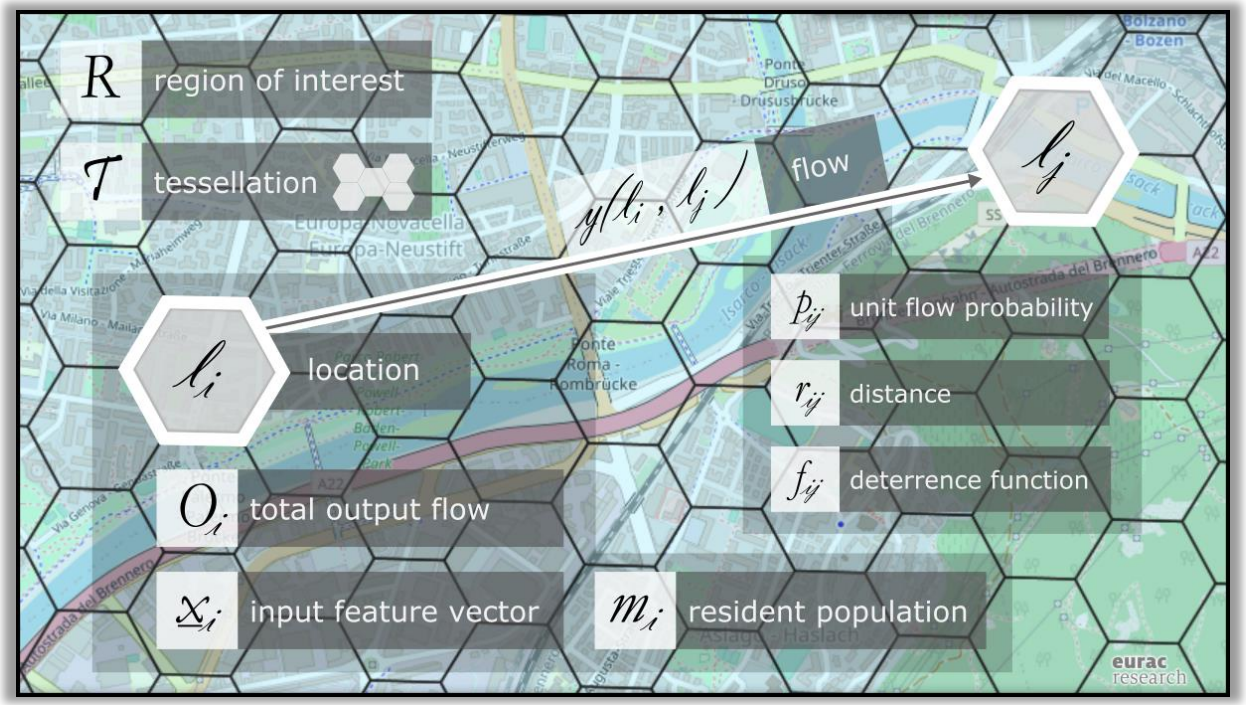
		w_a^2 : attractio						



Ganin et al. (2017)
doi:10.1126/sciadv.1701079



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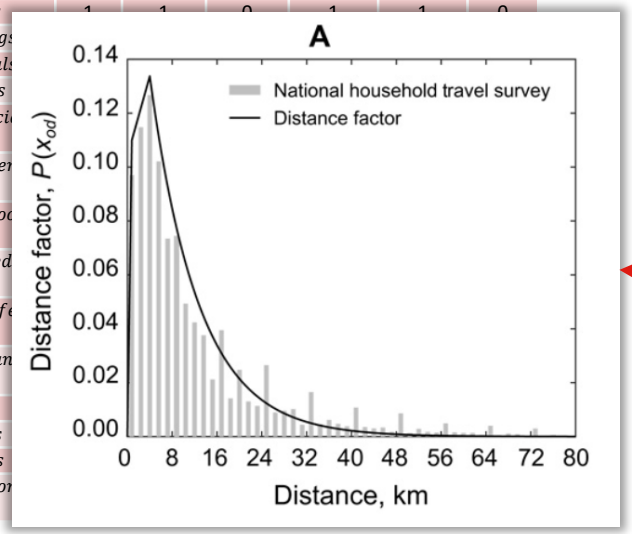
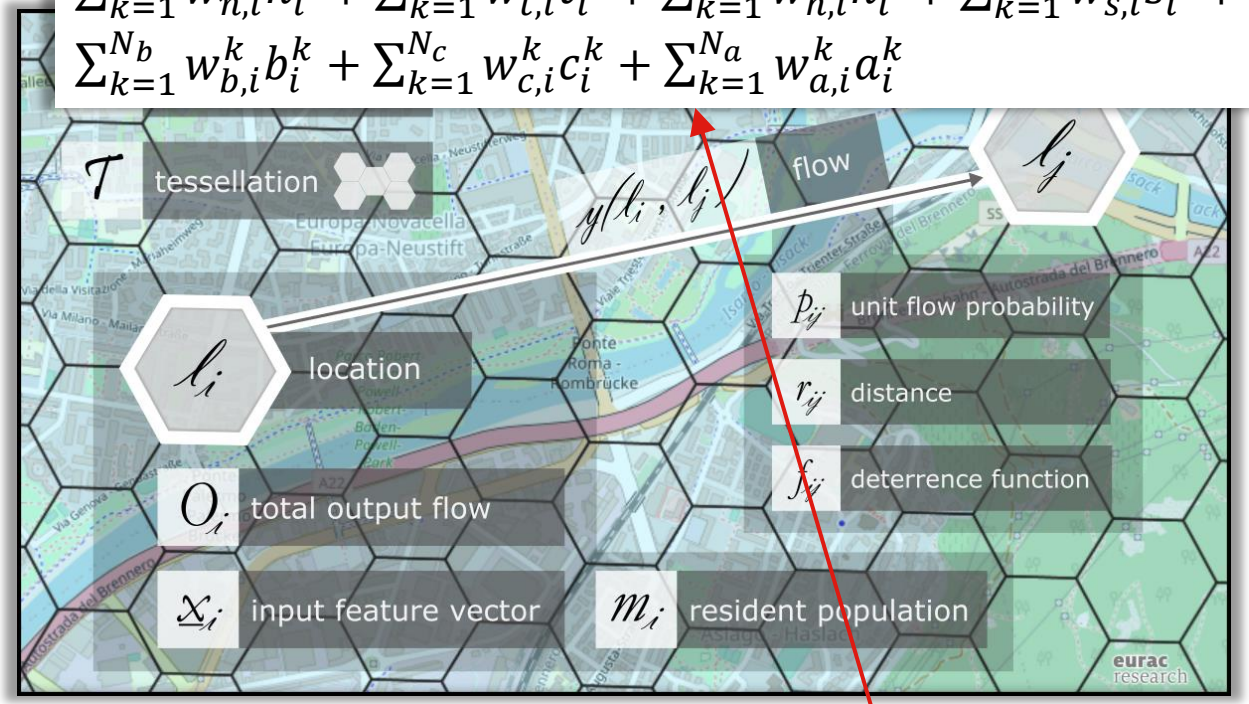
A gravity model ?

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

Asset / timeframe			Week days			Weekend and holidays		
			Morning	Afternoon	Night	Morning	Afternoon	Night
$\underline{w}_u$	Land Use	w_u^1 : urban	$1/\oiint l$	$1/\oiint l$	$1/\oiint l$	$1/\oiint l$	$1/\oiint l$	$1/\oiint l$
		w_u^2 : industrial	$1/\oiint l$	$1/\oiint l$	$1/\oiint l$	0	0	0
		w_u^3: vegetated	$1/\oiint l$	$1/\oiint l$	0	$1/\oiint l$	$1/\oiint l$	0
		w_u^4 : crop/forest	0	0	0	$1/\oiint l$	$1/\oiint l$	0
		w_u^5 : water	0	0	0	$1/\oiint l$	$1/\oiint l$	0
$\underline{w}_n$	Roads	w_n^1 : main	$1/\oint l$	$1/\oint l$	0	$1/\oint l$	$1/\oint l$	$1/\oint l$
		w_n^2 : residential	$1/\oint l$	$1/\oint l$	$1/\oint l$	$1/\oint l$	$1/\oint l$	$1/\oint l$
		w_n^3 : pedestrian	$1/\oint l$	$1/\oint l$	$1/\oint l$	$1/\oint l$	$1/\oint l$	$1/\oint l$
$\underline{w}_t$	Transport	w_t^1 : stations	1	1	1	1	1	1
		w_t^2 : stops	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
		w_t^3 : parkings						
$\underline{w}_h$	Health	w_h^1 : hospitals						
		w_h^2 : clinics						
		w_h^3 : pharmaci						
		w_h^4 : retiremen						
$\underline{w}_s$	Education	w_s^1 : kita/schoo						
		w_s^2 : higher ed						
$\underline{w}_b$	Food	w_b^1 : bars/caf						
		w_b^2 : restauran						
$\underline{w}_c$	Retail	w_c^1 : malls						
		w_c^2 : shops						
$\underline{w}_a$	Tourism	w_a^1 : hotels						
		w_a^2 : attractio						



Ganin et al. (2017)
doi:10.1126/sciadv.1701079



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

A Multicommodity Network Flow (MCNF) model?

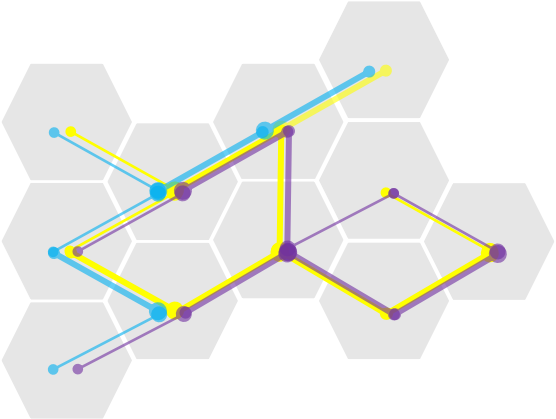
A Multicommodity Network Flow (MCNF) model?

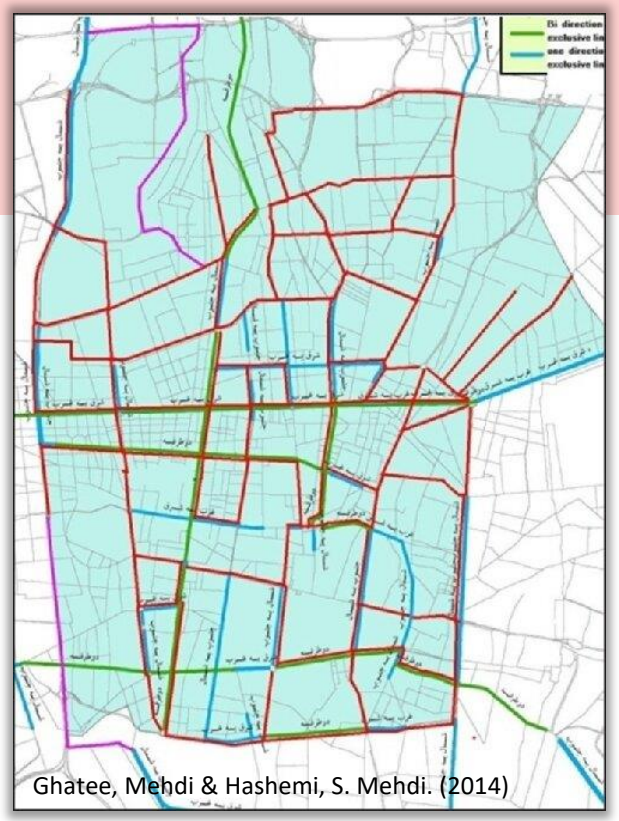
✓ Capture different segments of population flow

A Multicommodity Network Flow (MCNF) model?

✓ Capture different segments of population flow

- Daily commuters
- Tourists
- Trucks
- External
- …





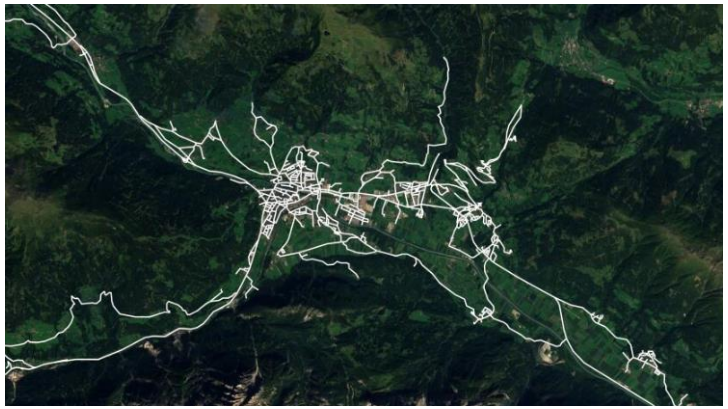
Ghatee, Mehdi & Hashemi, S. Mehdi. (2014)

C Output of the *TransAlp* project

Exposure

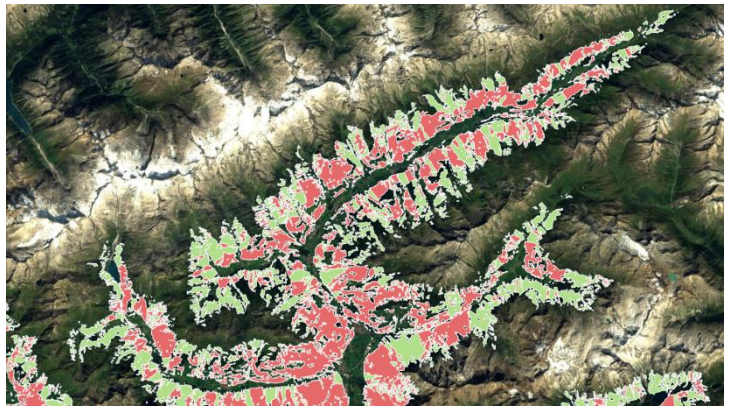
Cross-border harmonization of assets

roads network

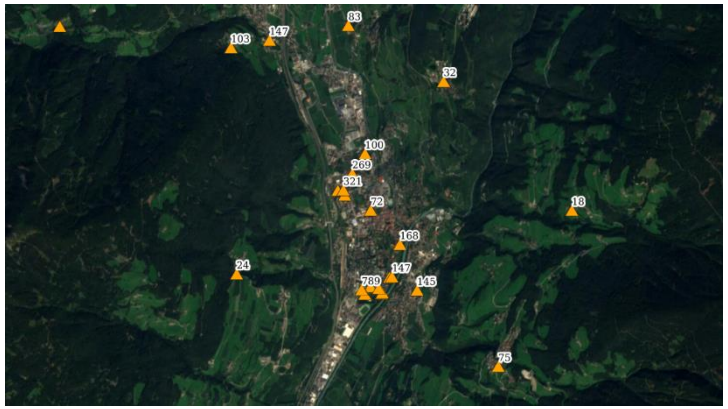


human settlements

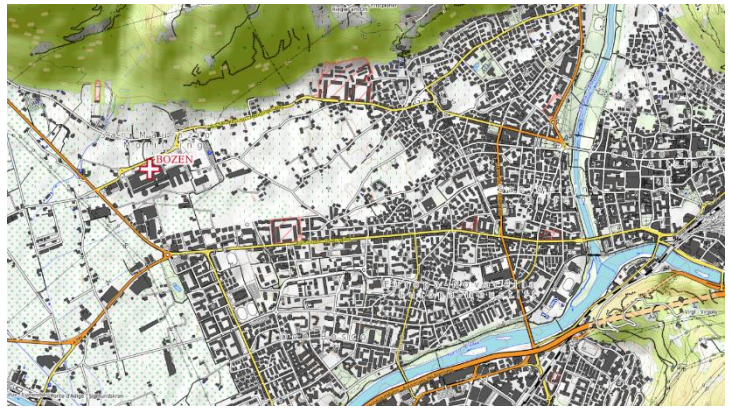
protection forest



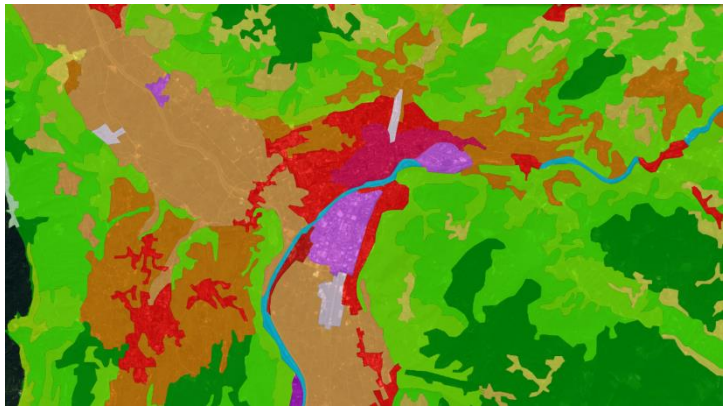
schools / kindergarten



hospitals / daycare



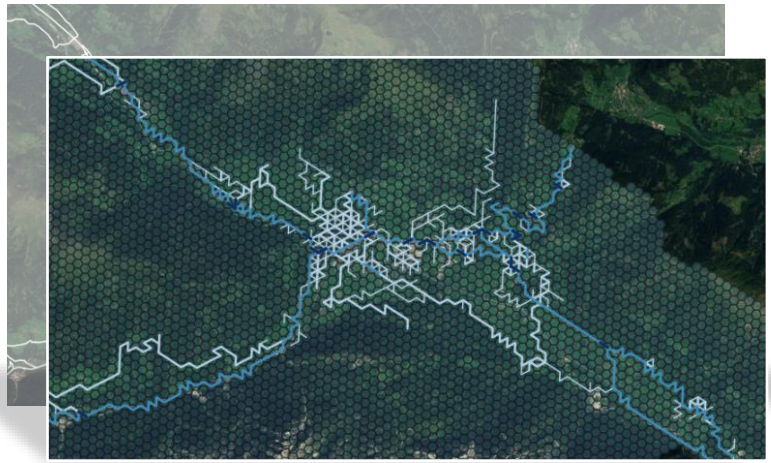
land cover



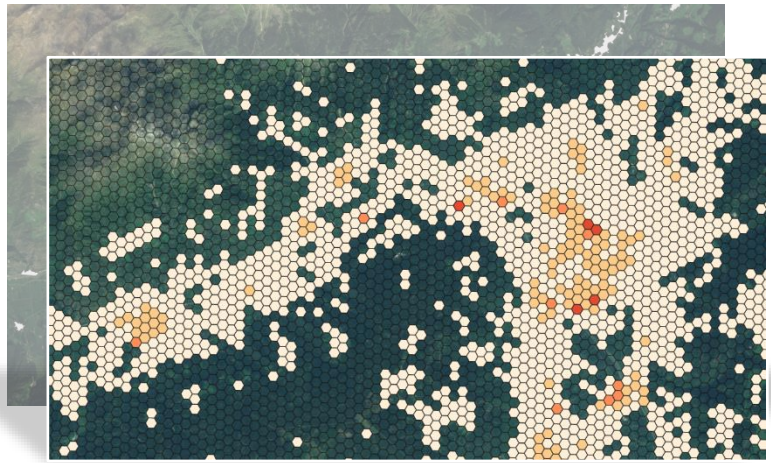
Exposure

Cross-border harmonization of assets

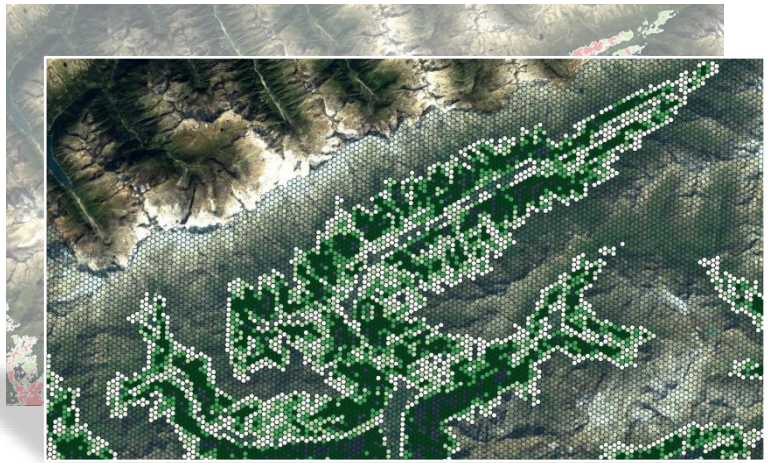
roads network



human settlements



protection forest



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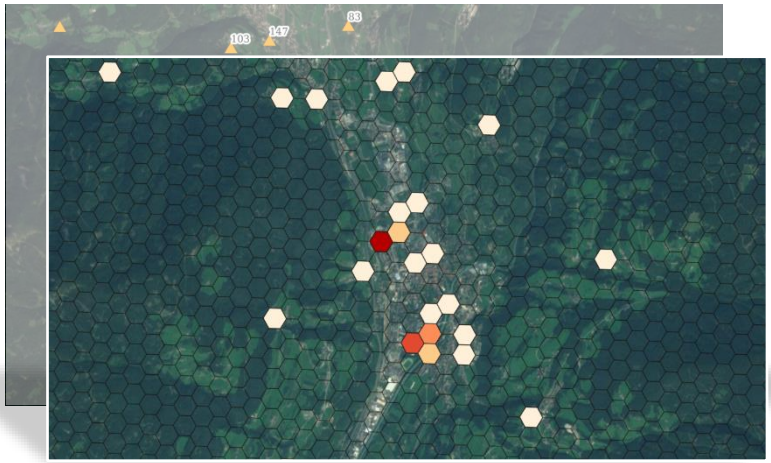

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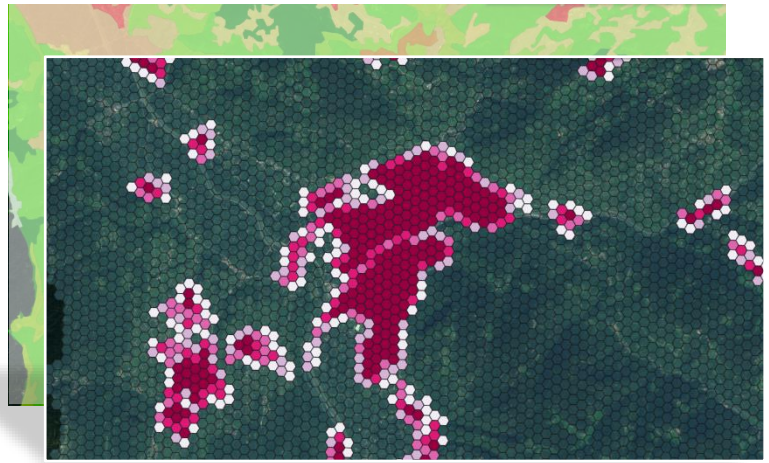
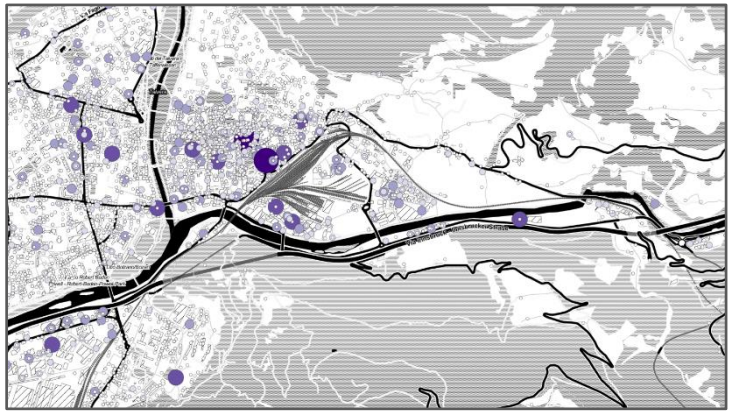


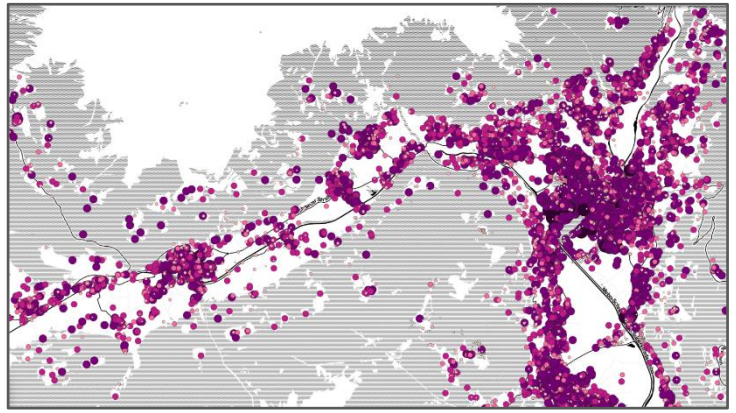
Exposure

Predicting dynamic population flow

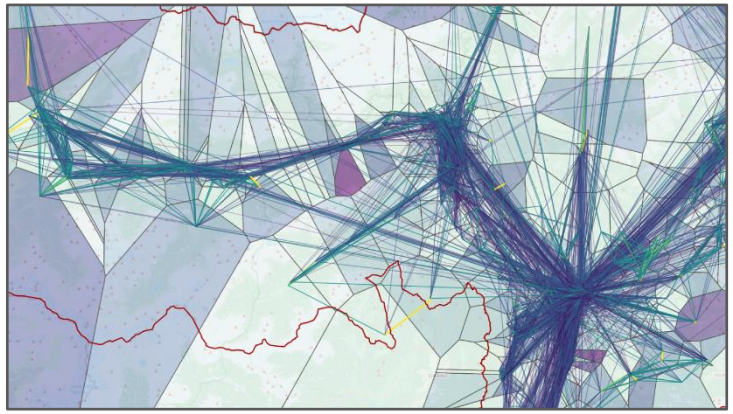
employees



residents



commuting trips



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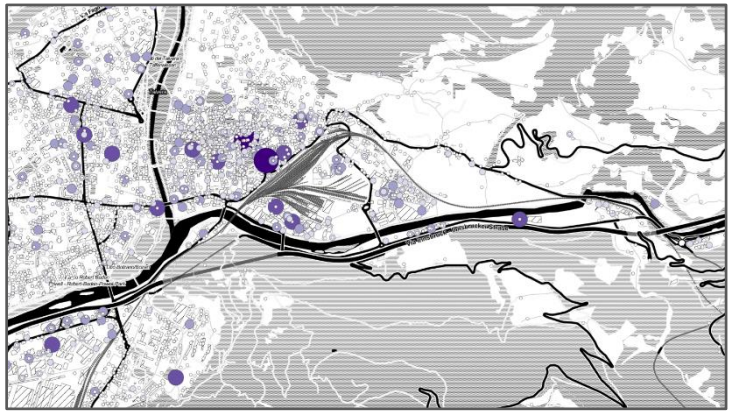

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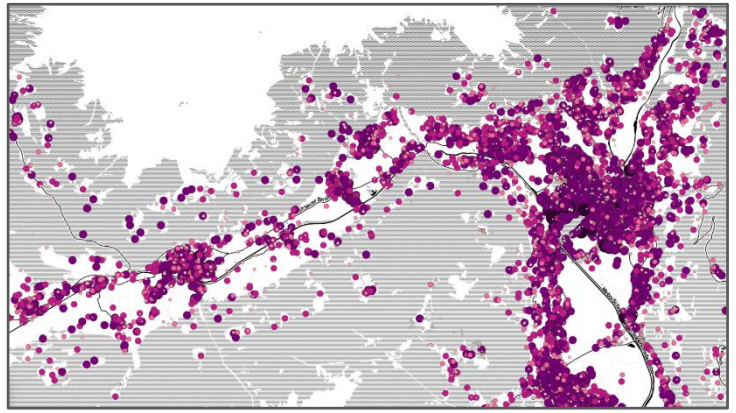
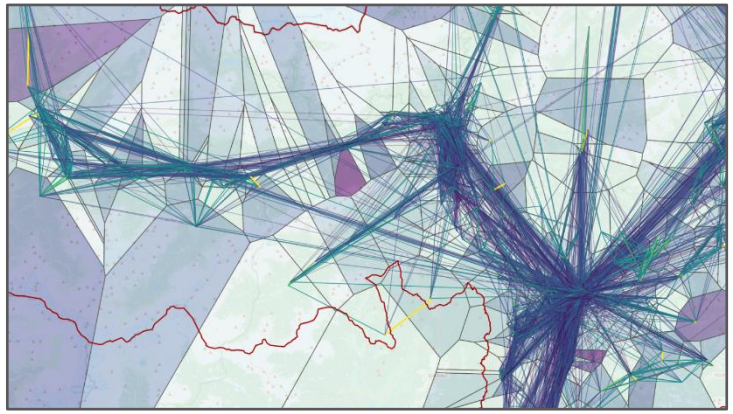
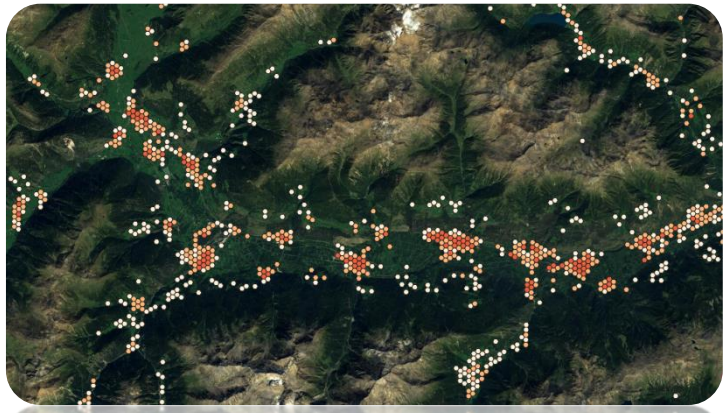


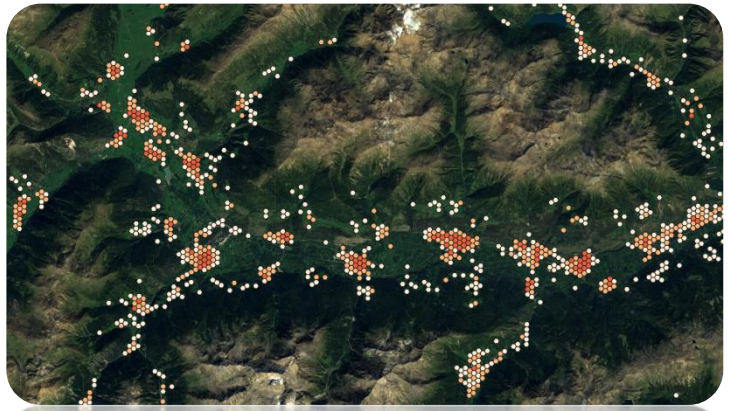
commuting trips



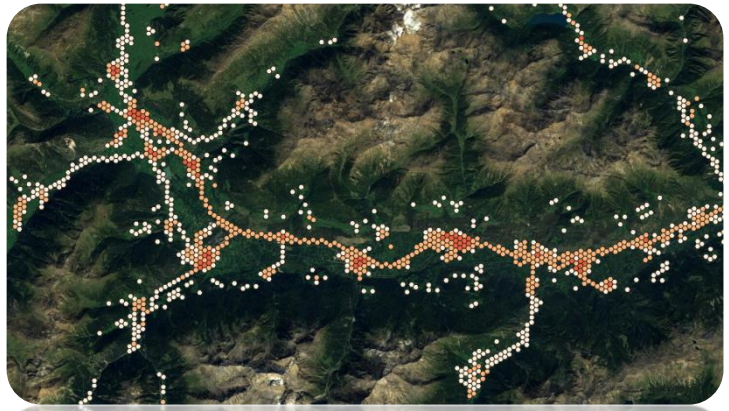
daytime pop.



nighttime pop.



commuting pop.



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Predicting dynamic population flow

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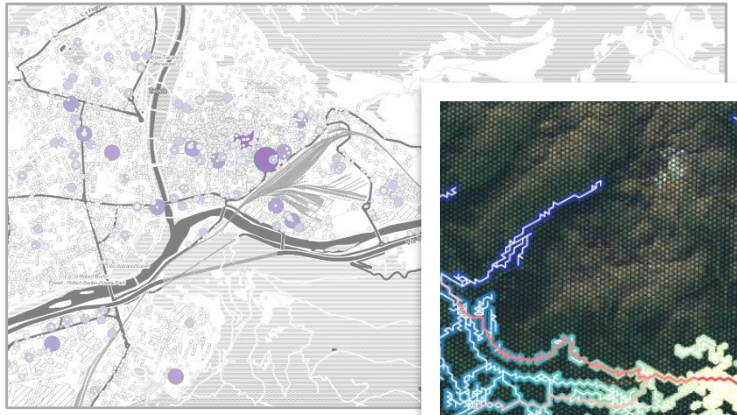

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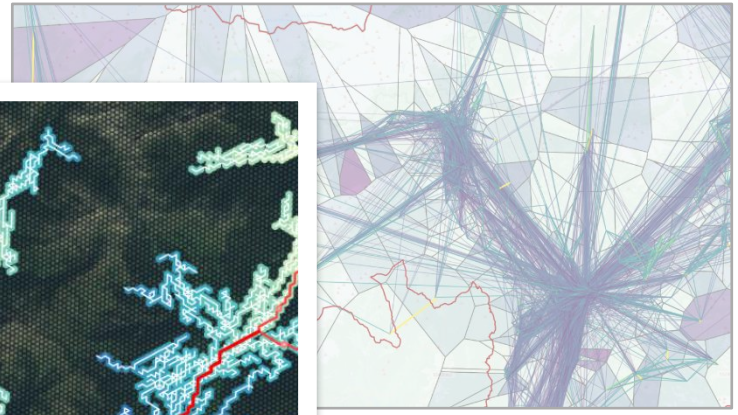

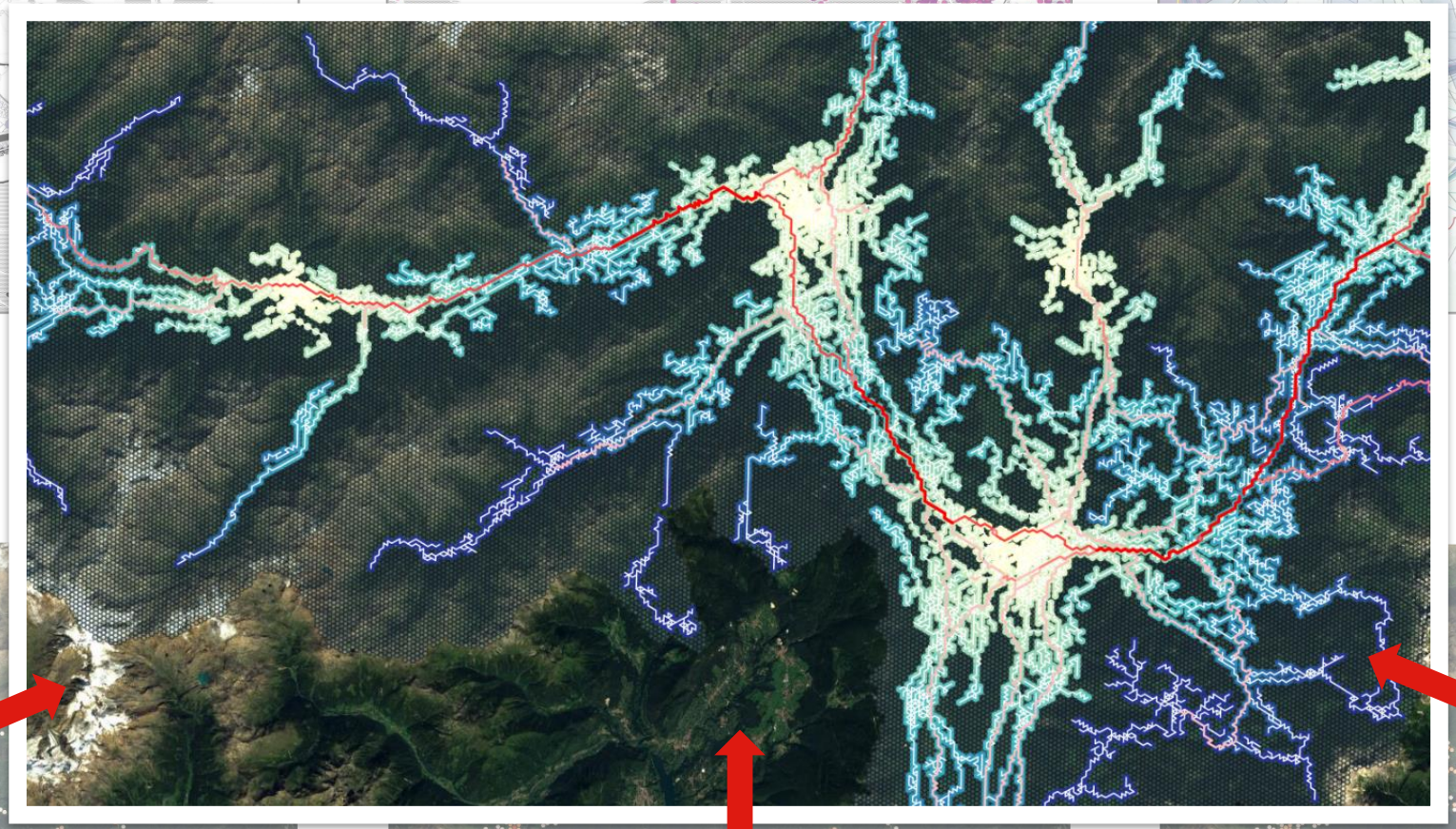

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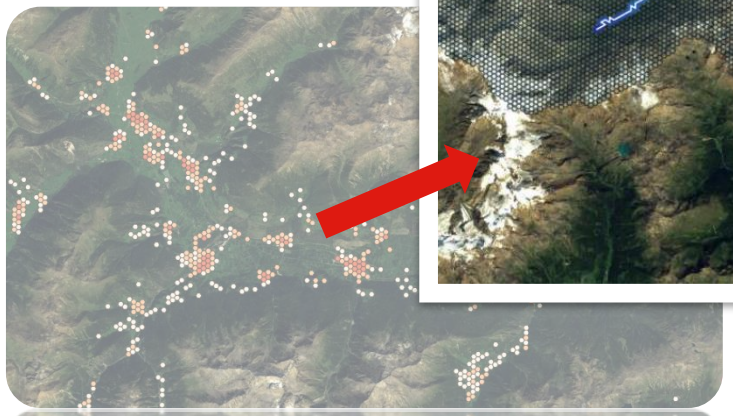
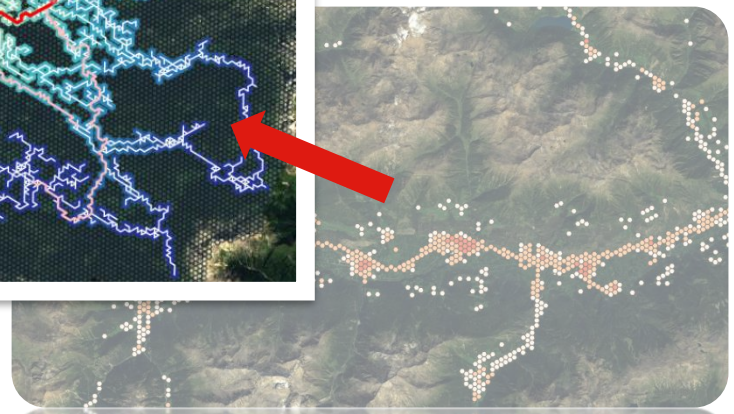
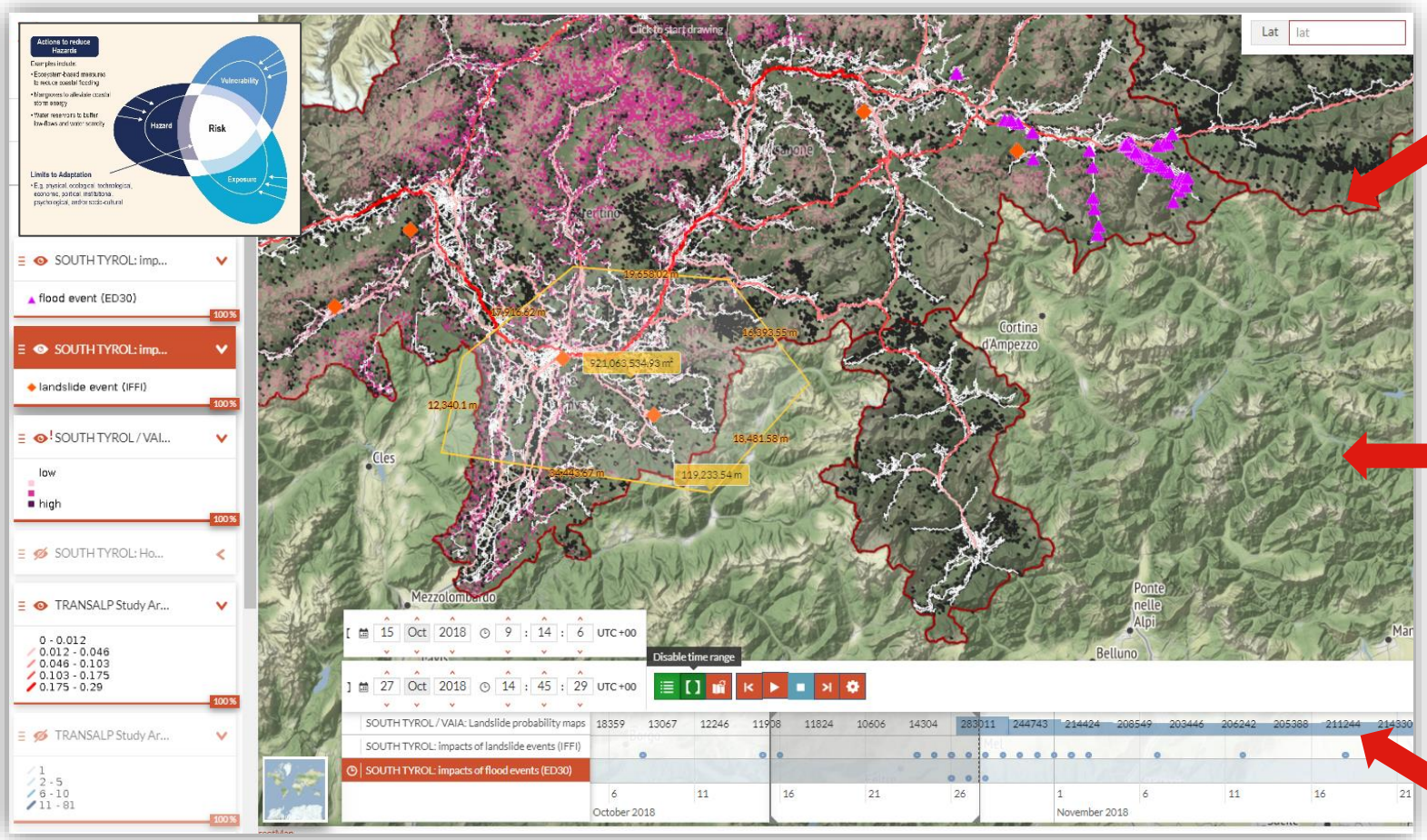


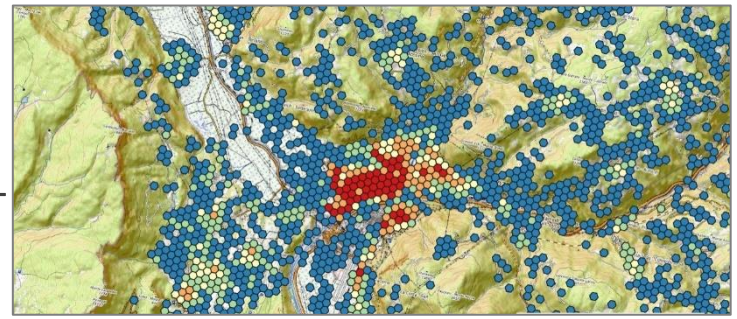


Exposure

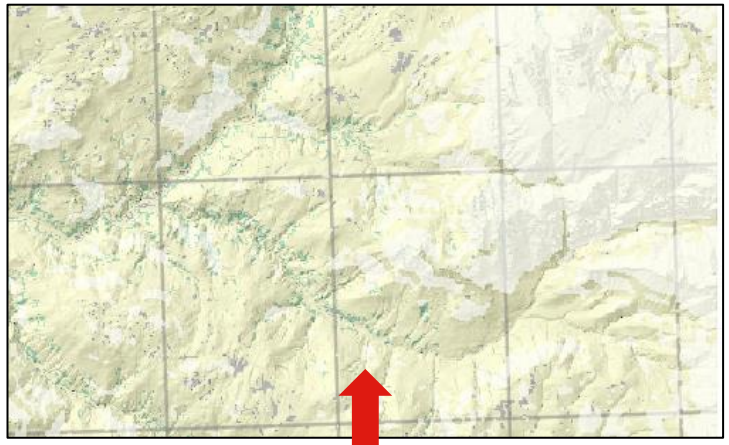
Putting it all together: towards an impact forecasting tool



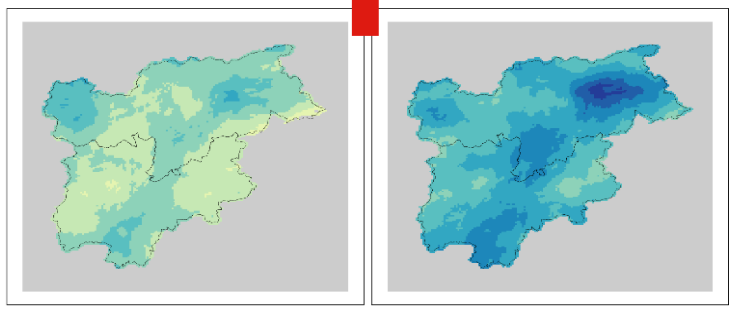
exposure



hazards



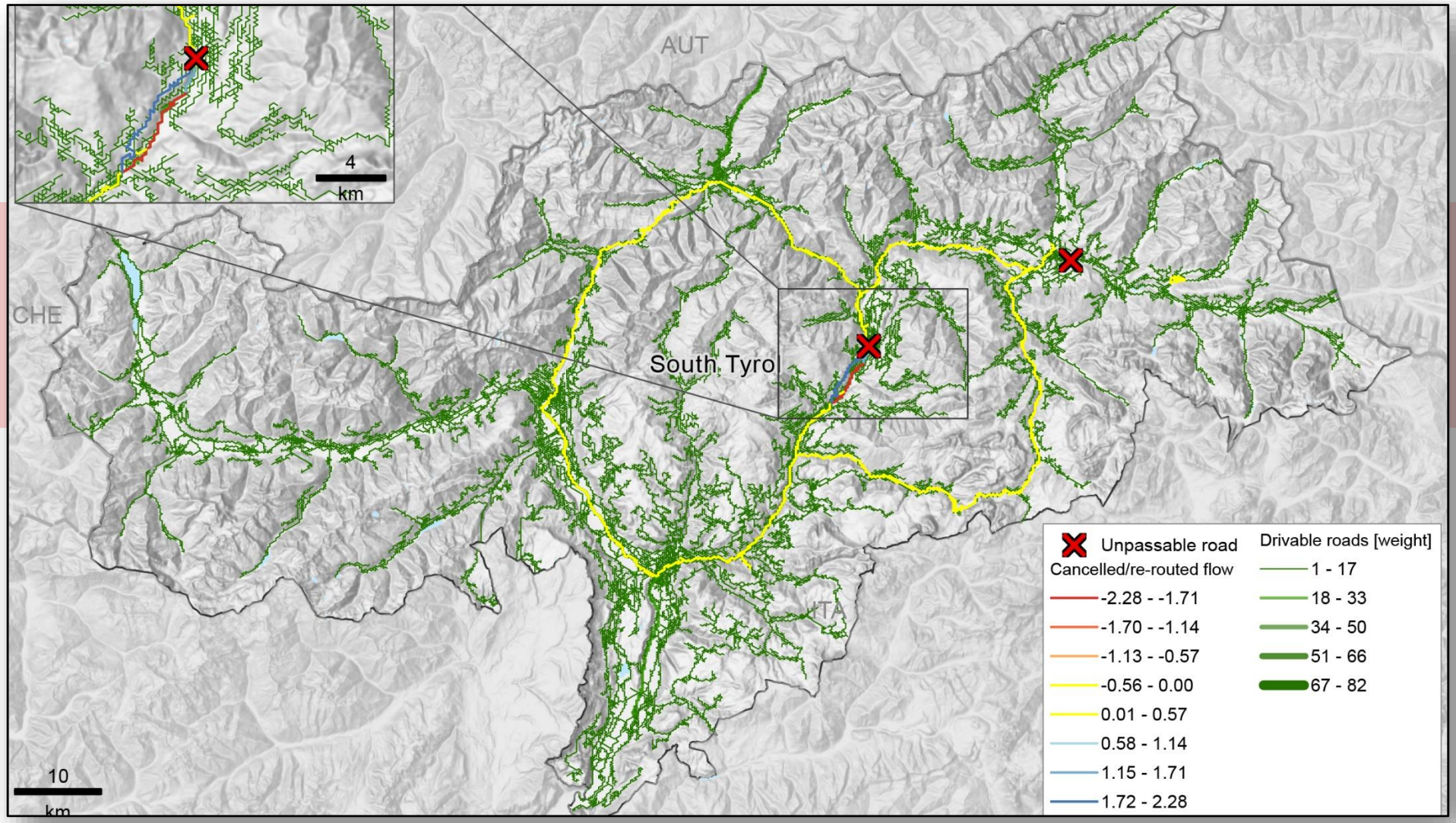
climate extremes



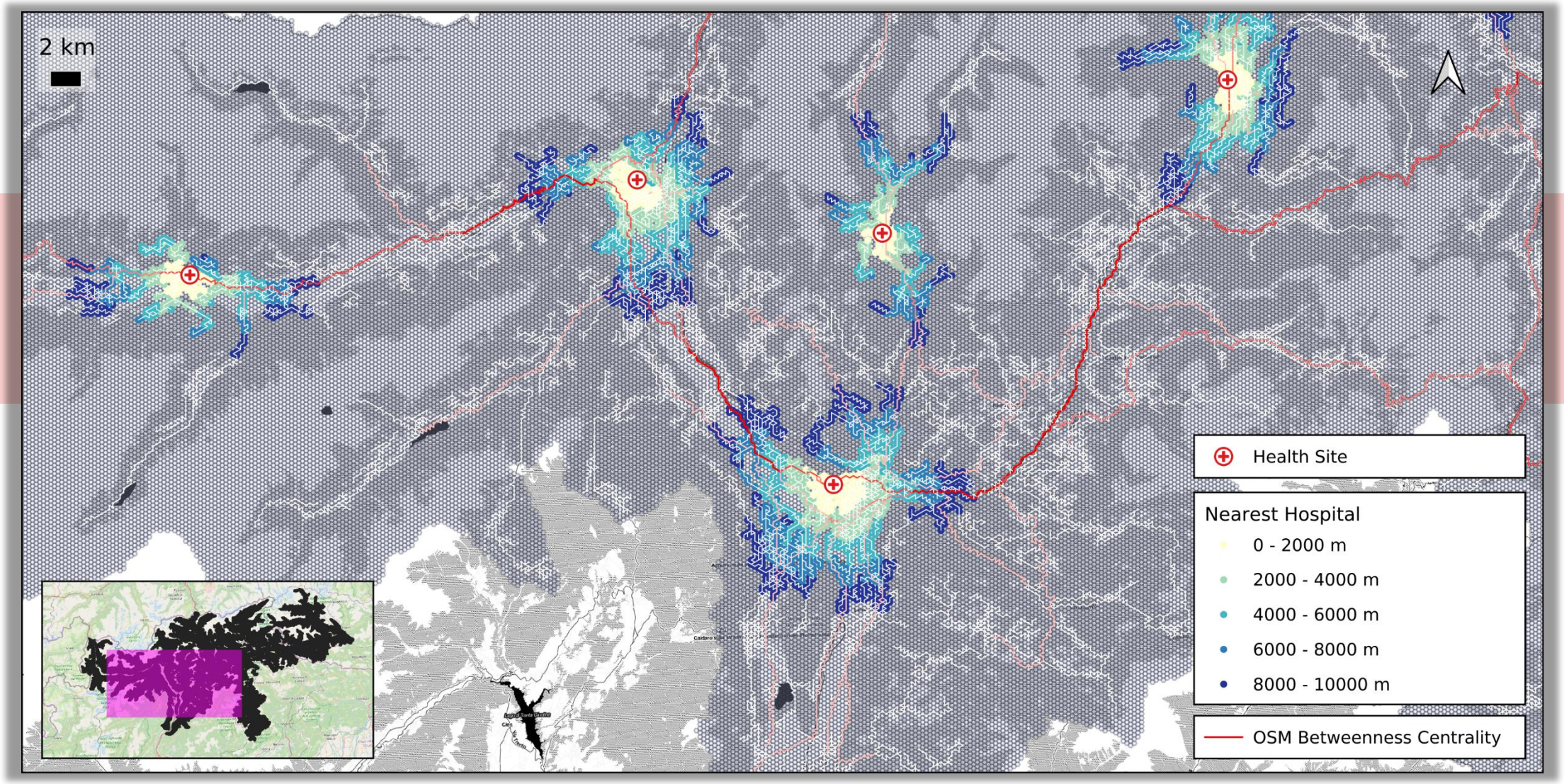
https://maps.eurac.edu/maps/1274

D Forward looking

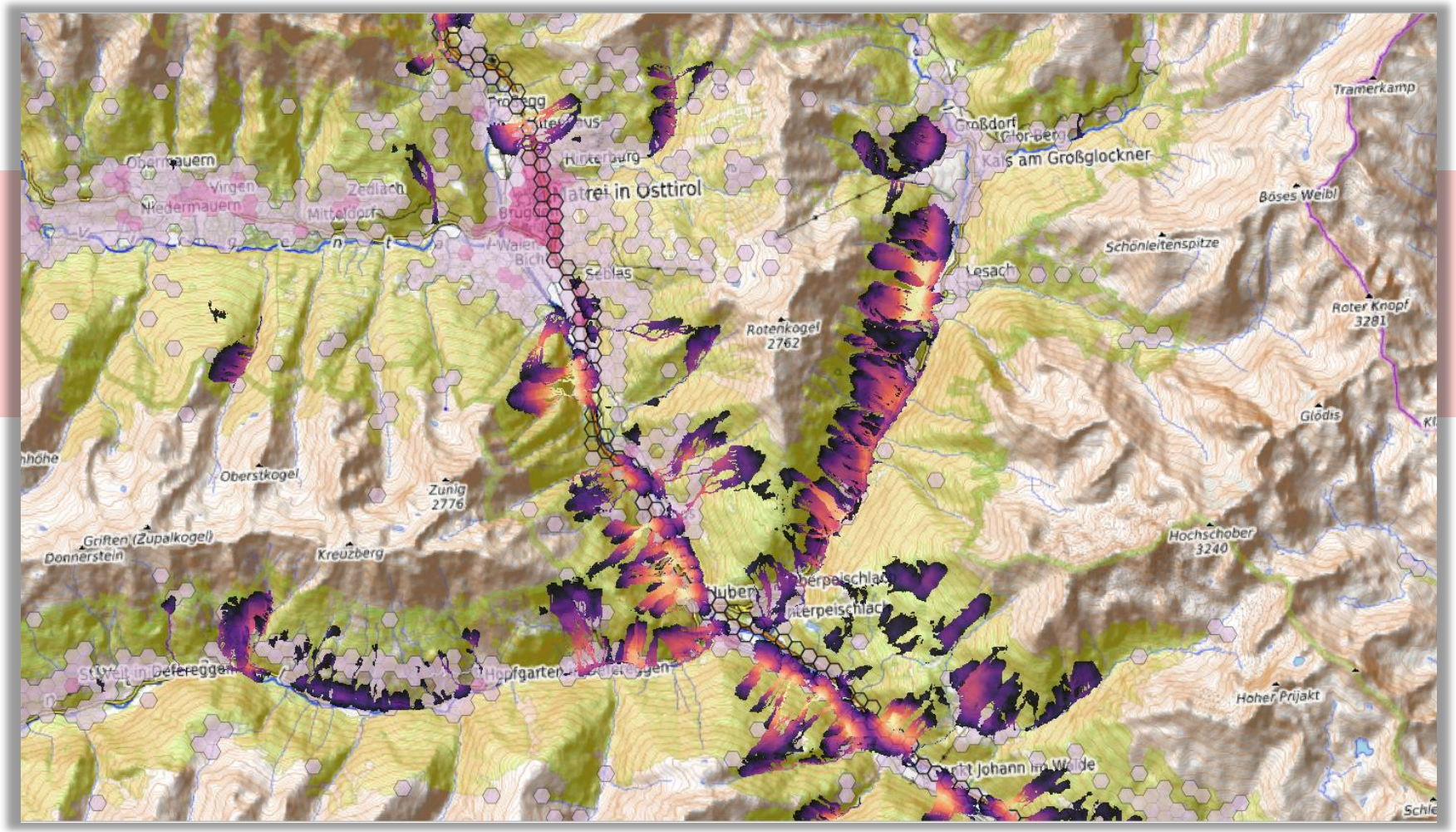
Resilience and efficiency in transport networks



From exposure to vulnerability



Large-scale hazard risk simulations



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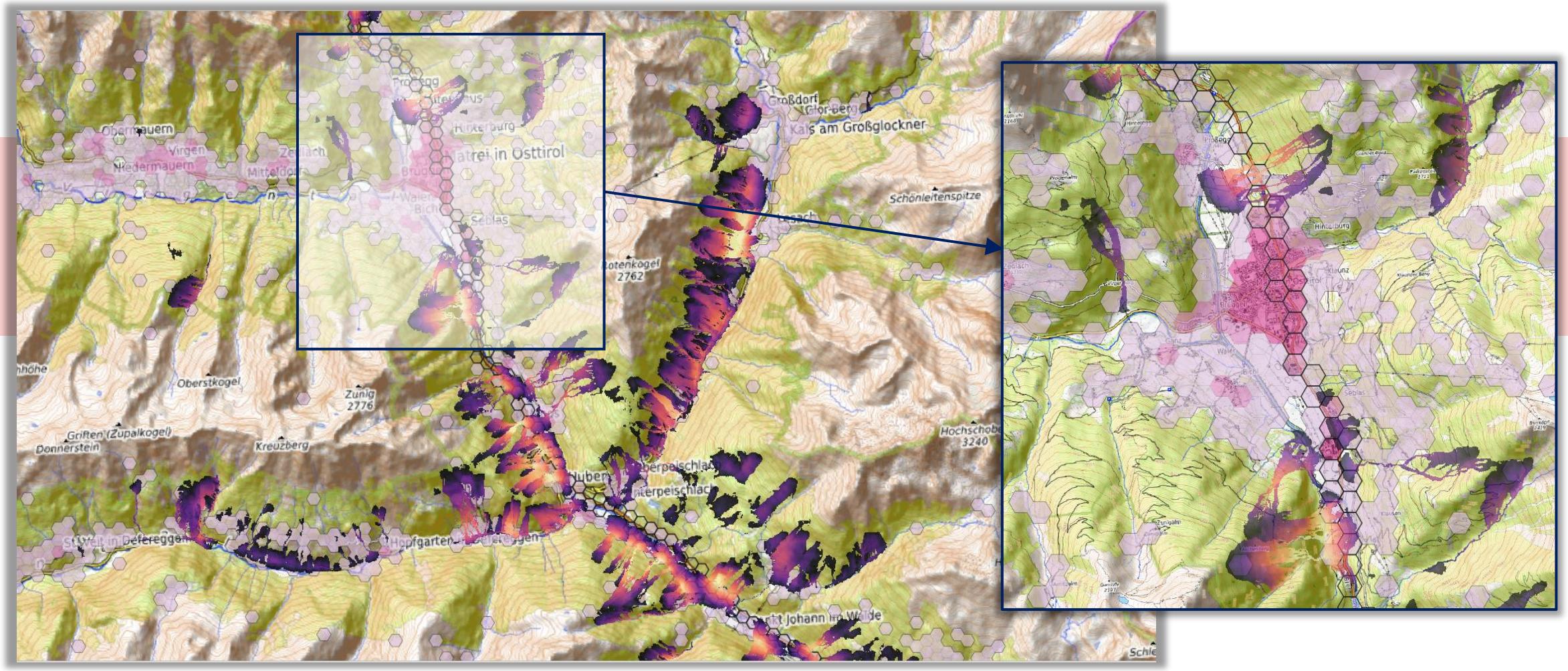
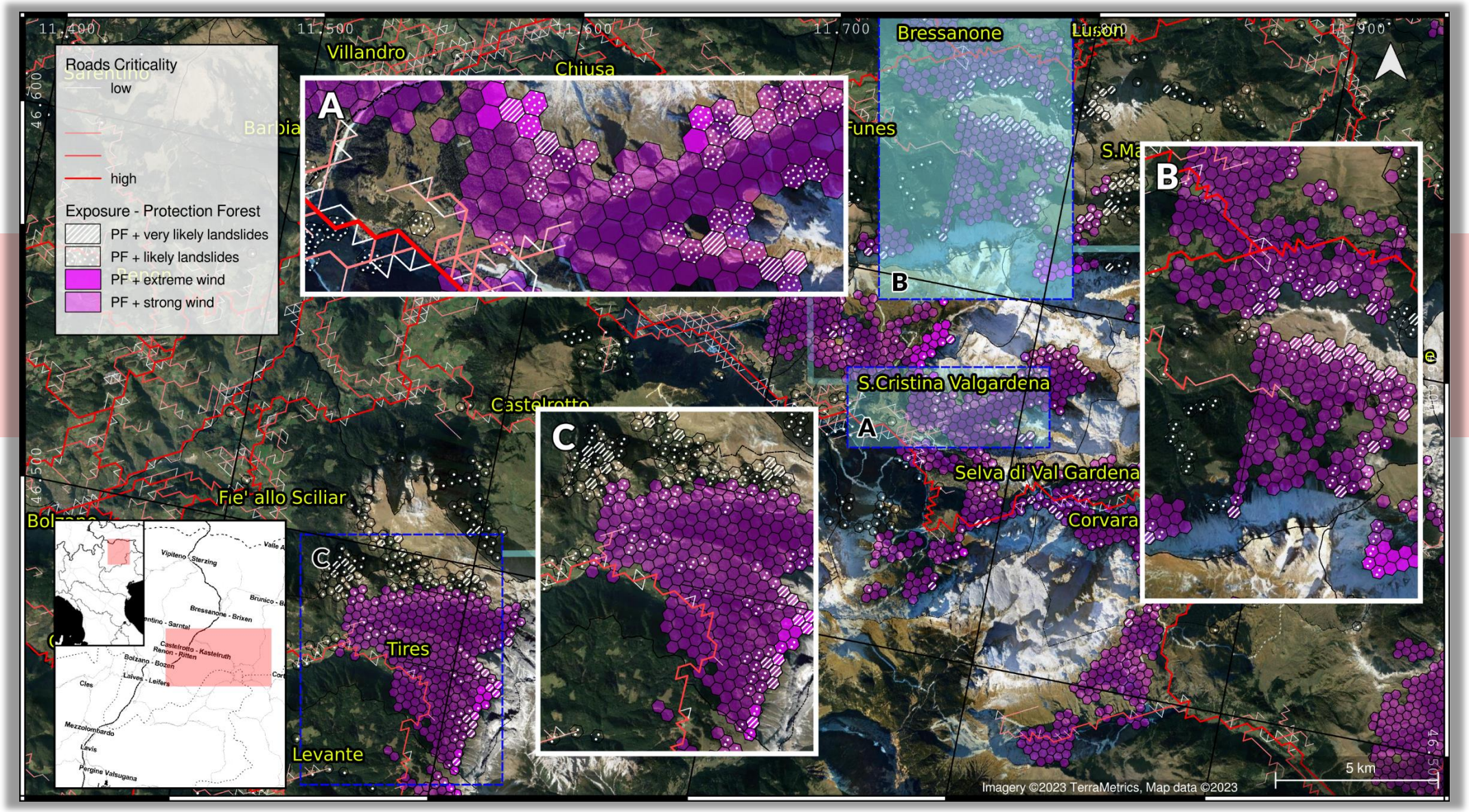


Multi-hazards risk nowcasting



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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