MAPPING HUMAN HEALTH RISK FROM CONTAMINATION OF DRINKING WATER SOURCES IN DEVELOPING COUNTRIES

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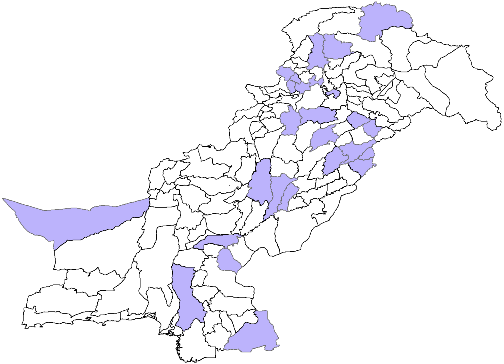

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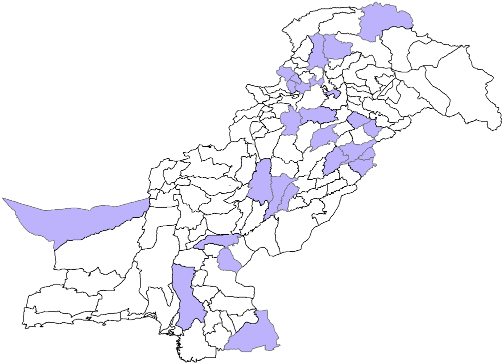

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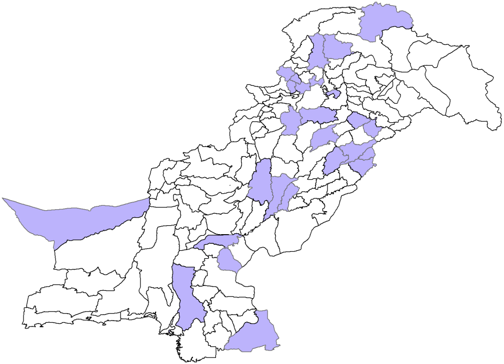

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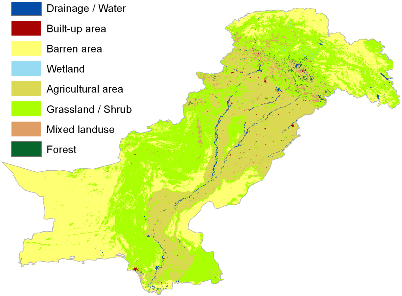

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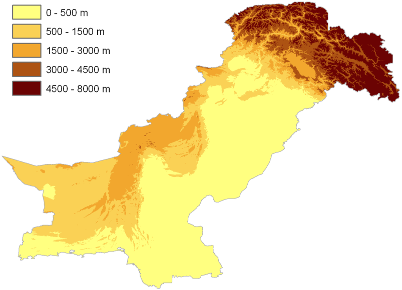

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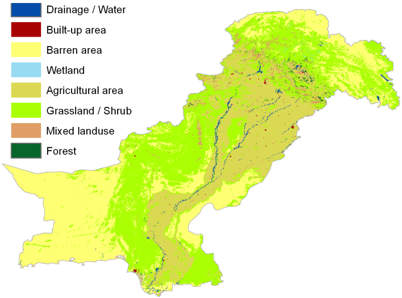

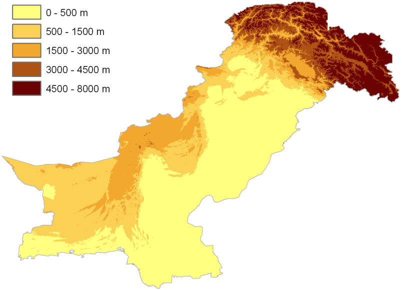

Land cover (ISCGM 2014) BL, AL, ML Elevation (Rodriguez et al. 2005)

Global soil properties (Batjes 2000) SOC, SCC, WC, pH

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- R package GWmodel (Gollini et al. 2013)

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- Standard deviation of prediction z-scores (SDZ) unity indicates high certainty

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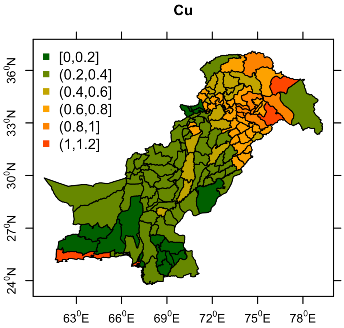

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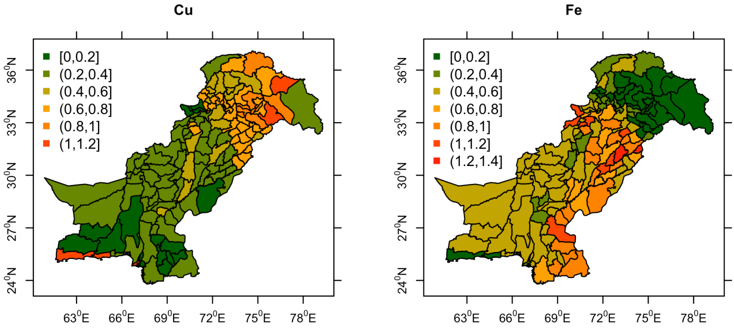

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RQ>1 at risk $RQ \leq 1$ negligible risk

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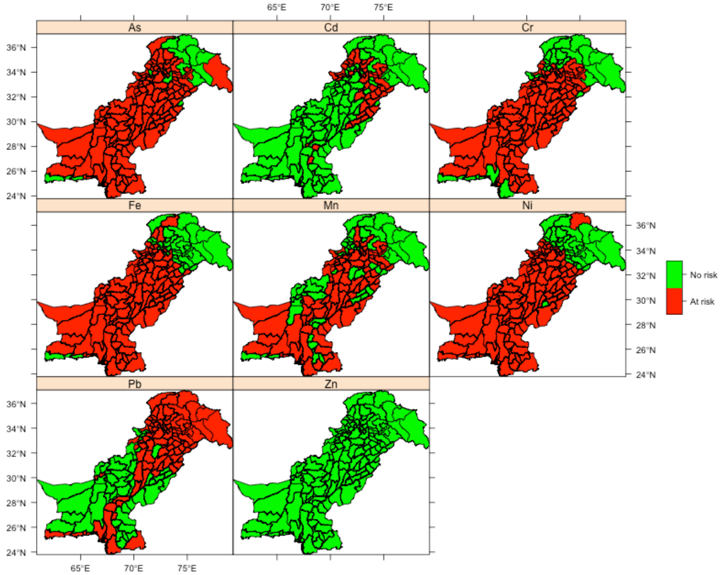

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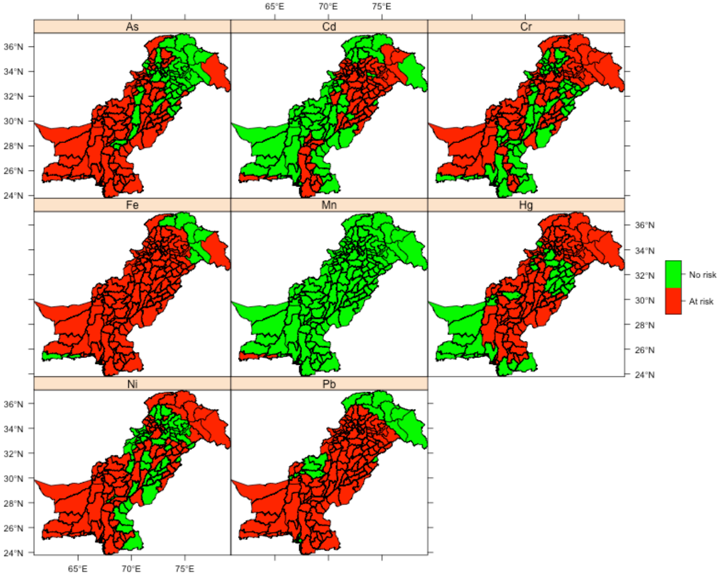

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- $SDZ \geq 0.7$ except for cadmium and zinc in ground water, and cadmium and manganese in surface water
- Calibrated spatial predictors are in agreement with the causes of trace metal contamination e.g. As_SW~SOC + pH (Husain et al. 2012)

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- May also indicate indirect effects e.g. via consumption of vegetables irrigated with contaminated water (Amin et al., 2012)

For more: Bhowmik et al. 2015, Sci. Tot. Env. *under review*

Collaborators: Ambreen Alamdar, Ioannis Katsoyiannis, Heqing Shen, Nadeem Ali, Syeda Maria Ali, Habib Bokhari, Ralf B. Schäfer, Syed Ali Musstjab Akber Shah Eqani

Thank you

Questions?