

GeoAI für die Datenvalidierung

Key Concepts um Daten für AI „fit“ zu machen

Paris-Lodron-University Salzburg
Department of Geoinformatics – Z_GIS

Johannes Scholz

Department of Geoinformatics – Z_GIS
Paris-Lodron-University Salzburg

 johannes.scholz@plus.ac.at

 www.zgis.at || www.johannesscholz.net

 [@Joe_GISc](https://twitter.com/Joe_GISc)

 [@Joe_GISc@mastodon.online](https://mstdn.social/@Joe_GISc)

 <https://linkedin.com/in/johannes-scholz-gisc>

 [@joegisc.bsky.social](https://bsky.app/profile/joegisc.bsky.social)



Table of Contents

- What is GeoAI?
- Motivation

- Data Quality as critical Success Factor
 - GeoAI for Anomaly Detection
 - Bias Correction with GeoAI
 - GeoAI for Semantic Enrichment

- Applications in Selected Projects
 - Virtual Shepherd
 - RegioWoodTrain
 - iKlimEt

Geospatial Artificial Intelligence

- **“GeoAI can be regarded as a study subject to develop intelligent computer programs to mimic the processes of human perception, spatial reasoning, and discovery about geographical phenomena and dynamics**
 - to advance our knowledge,
 - to solve problems in human environmental systems and their interactions,
 - with a focus on spatial contexts and roots in geography or GIScience.” (Gao, 2021)
- **Spatially explicit models incorporating spatial contexts (Yan et al., 2018) can outperform traditional nonspatial AI models in many tasks:**
 - image classification,
 - geographic knowledge graph summarization (Yan et al., 2019),
 - and geographic question-answering problems (Mai et al., 2019).

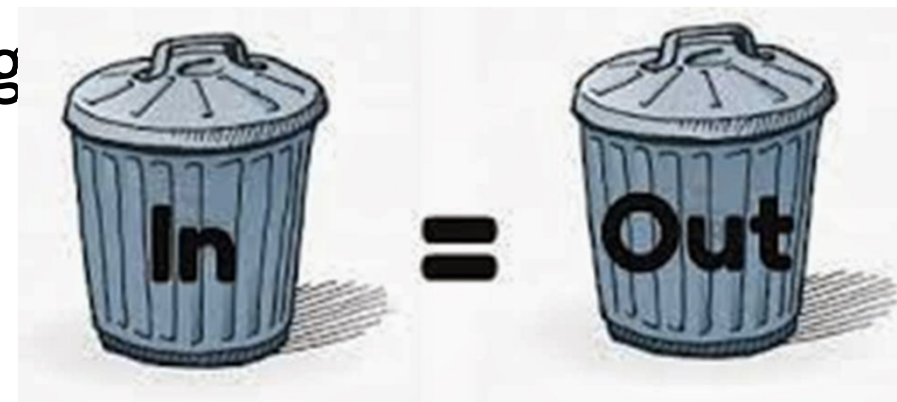


Motivation

AI Models are dependent on training and verification data

- Heterogeneity
- Incompleteness
- Bias
- Flaws

„Garbage in, Garbage out.“



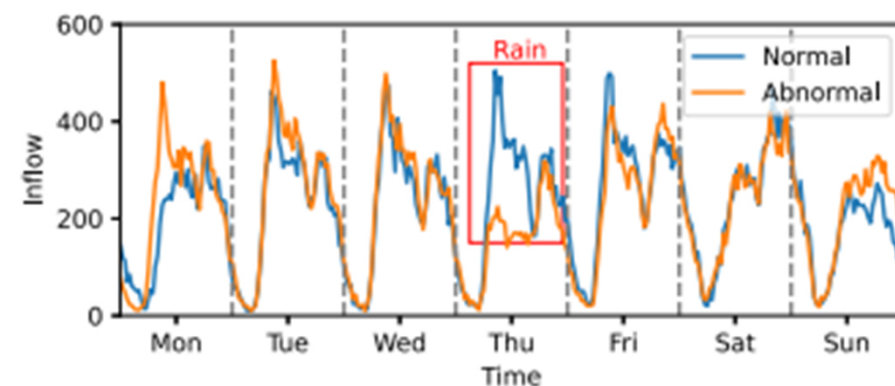
Data Quality as Critical Success Factor

- **Completeness:**
 - Missing values can distort patterns or hide important relationships.
- **Consistency:**
 - Inconsistent formats or conflicting entries complicate modeling and interpretation.
- **Representativeness:**
 - Skewed samples result in unfair or non-generalizable models
- **Timeliness:**
 - Outdated data fails to reflect current realities—especially critical in dynamic domains like mobility or energy. ng and interpretation.

GeoAI for Anomaly Detection

- **GeoAI leverages spatial and temporal patterns to identify outliers**
 - **Spatial context** (e.g. neighborhood similarity, geographic clustering)
 - **Temporal dynamics** (e.g. recurring patterns, seasonality)
- **Key Methods:**
 - **DBSCAN:** Density-based clustering to detect spatial outliers without needing labeled data.
 - **Autoencoders:** Neural networks trained to reconstruct input—large reconstruction errors signal anomalies.
 - **ST-GCN** (Spatio-Temporal Graph Convolutional Models) spatial dependencies and temporal evolution simultaneously, ideal for dynamic sensor networks.

Deng, L., Lian, D., Huang, Z., & Chen, E. (2022). Graph convolutional adversarial networks for spatiotemporal anomaly detection. *IEEE Transactions on Neural Networks and Learning Systems*, 33(6), 2416-2428.



Bias Correction with GeoAI (1)

- GeoAI integrates **spatial context** to **detect and mitigate bias** that arises from geographic (and/or demographic) imbalances.
- Spatial fairness-aware learning ensures that models treat regions and populations equitably, even when data availability varies.
- **Key Methods**
 - **Reweighting:** Adjusts the influence of overrepresented regions or groups to balance model learning.
 - **Fairness-aware algorithms:** Incorporate fairness constraints during training to reduce disparate impact.
 - **Spatial stratification:** Ensures that training samples are geographically diverse and representative.

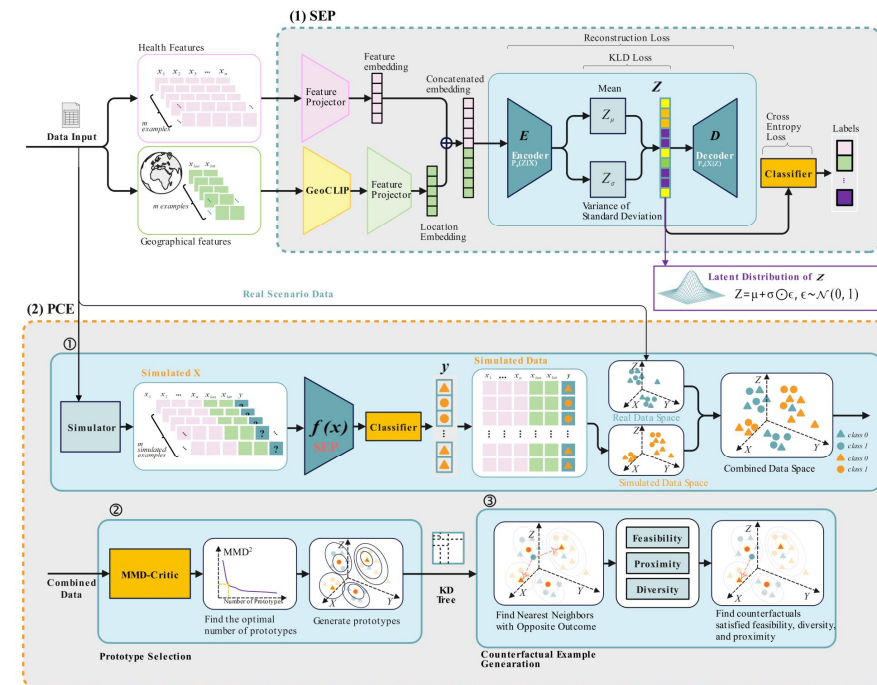
Bias Correction with GeoAI (2)

Some issues we should pay attention to:

- **Spatial Autocorrelation:** Nearby locations often share similar characteristics. Fairness-aware models must account for this to avoid overfitting to dense urban clusters.
- **Sensitive Attributes:** In geospatial contexts, attributes like income level, ethnicity, or infrastructure access may correlate with location—raising fairness concerns.
- **Representation Bias:** Volunteered geographic information (VGI) and sensor data often reflect the interests of more connected or affluent communities.

Counterfactual Fairness in Spatial Models:

- Ensure that predictions remain consistent if a location's demographic profile were different.



Ma, J., Guo, R., Zhang, A., & Li, J. (2023, August). Learning for counterfactual fairness from observational data. In *Proceedings of the 29th ACM SIGKDD conference on knowledge discovery and data mining* (pp. 1620-1630).

Ma, J., Guo, R., Wan, M., Yang, L., Zhang, A., & Li, J. (2022, February). Learning fair node representations with graph counterfactual fairness. In *Proceedings of the fifteenth ACM international conference on web search and data mining* (pp. 695-703).

Zhang, J., Mu, L., Zhang, D., Chen, Z., Rajbhandari-Thapa, J., Pagan, J. A., ... & Zhou, Z. (2025). SpaCE: a spatial counterfactual explainable deep learning model for predicting out-of-hospital cardiac arrest survival outcome. *International Journal of Geographical Information Science*, 1-32.

GeoAI for Semantic Enrichment

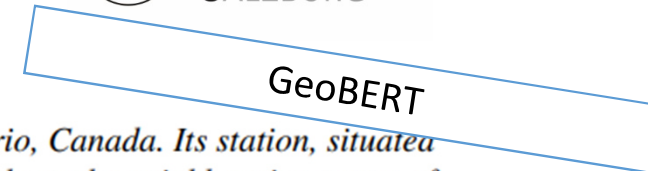
- **Semantic enrichment** refers to enhancing raw geospatial data with meaningful, contextual information - improving interpretability & usability for downstream tasks

Ontology + (Geo)Data = (Geo)Knowledge Graph

- **GeoAI Capabilities:**
 - **Text + Location Fusion:** Combine textual metadata (e.g., descriptions, tags) with geolocation to classify or cluster features.
 - **Embedding Techniques:** with NLP, LLMs or BERT generating semantic vectors for objects, places and/or events.
 - **Ontology Integration:** Link data to structured vocabularies (e.g., INSPIRE themes, GeoNames) for interoperability.

Qiu, Q., Zheng, S., Tian, M., Li, J., Ma, K., Tao, L., & Xie, Z. (2024). A deep neural network model for Chinese toponym matching with geographic pre-training model. *International Journal of Digital Earth*, 17(1), 2353111.

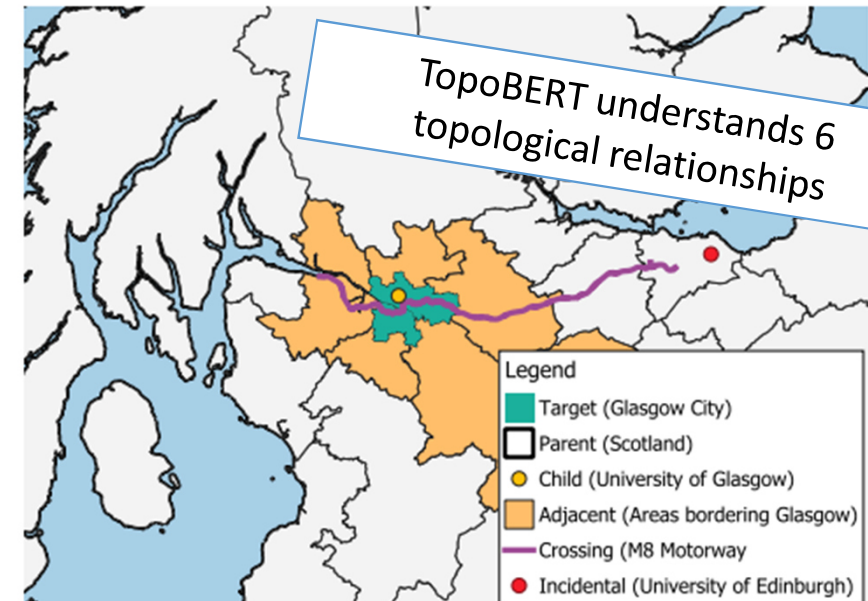
GeoAI for Semantic Enrichment



"London is a city in Ontario, Canada. Its station, situated on York Street, has rail links to the neighbouring towns of Woodstock, and onward to Toronto."

• GeoBERT

- built around a Bidirectional Encoder Representations from Transformers (BERT) model (Devlin et al., 2019)
- BERT can extract syntactical and semantic information from sentences, including:
 - subject/object/verb relationships (Nastase and Merlo, 2023)
 - and capturing structural linguistic information (Jawahar et al., 2019).
- BERT has also been shown to be effective in identifying spatial relationships within natural language (Shin et al., 2020),
 - "Tom is on the box"
 - "The cat is in the house"



Shingleton, J., & Basiri, A. (2024). Enhancing toponym identification: Leveraging Topo-BERT and open-source data to differentiate between toponyms and extract spatial relationships. *AGILE: GIScience Series*, 5, 1-10.
 Shingleton, J., & Basiri, A. (2025). How close is "close"? An analysis of the spatial characteristics of perceived proximity using Large Language Models. *AGILE: GIScience Series*, 6, 11.
 Qiu, Q., Zheng, S., Tian, M., Li, J., Ma, K., Tao, L., & Xie, Z. (2024). A deep neural network model for Chinese toponym matching with geographic pre-training model. *International Journal of Digital Earth*, 17(1), 2353111.

Applications in Selected Projects

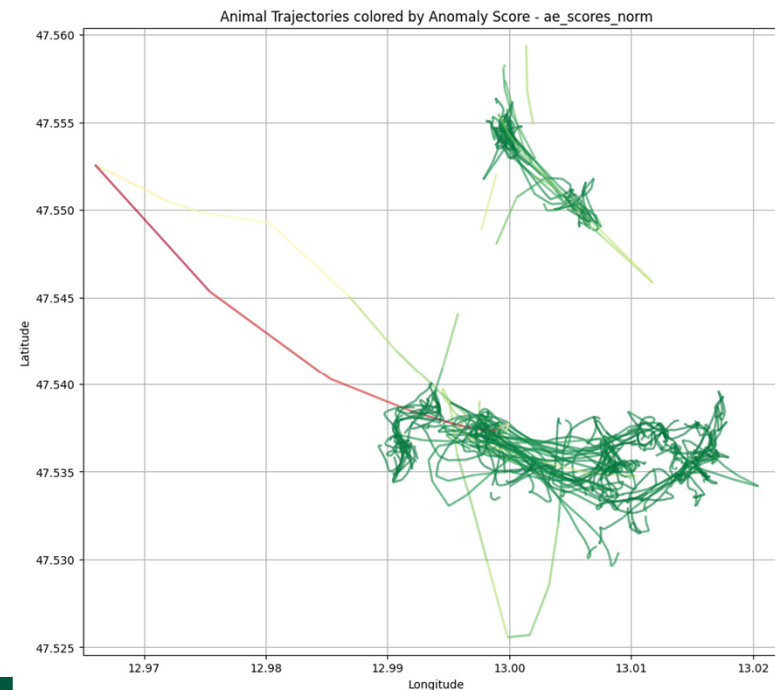
Virtual Shepherd

- Virtual Fencing and Virtual Shepherd that supervises livestock in Alpine regions
- Detection of anomalies in cow movement
 - Trajectories
 - Additional sensors (accelerometer, temperature, ...)
- GeoAI:
 - Autoencoder-based anomaly detection
 - Edge Devices(!)



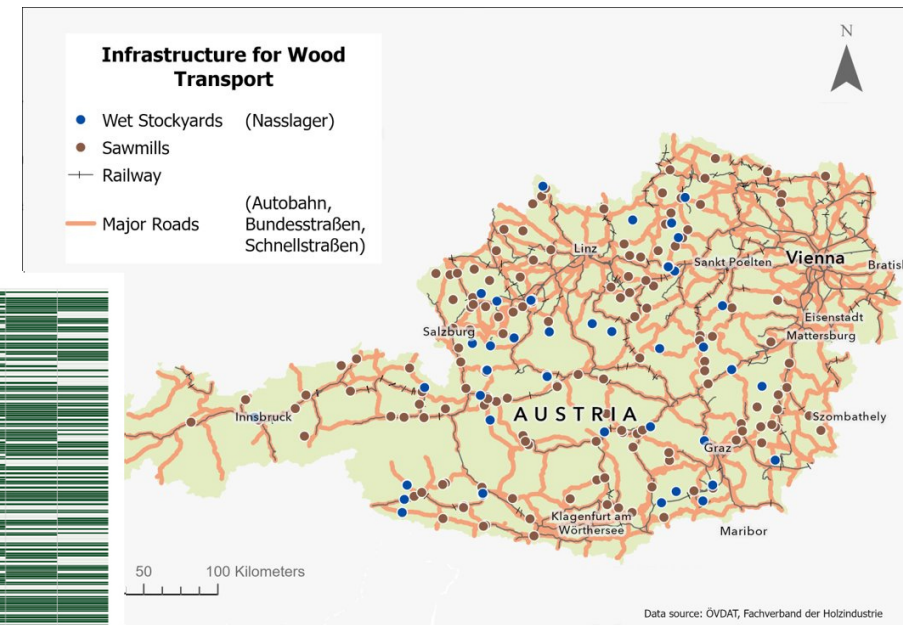
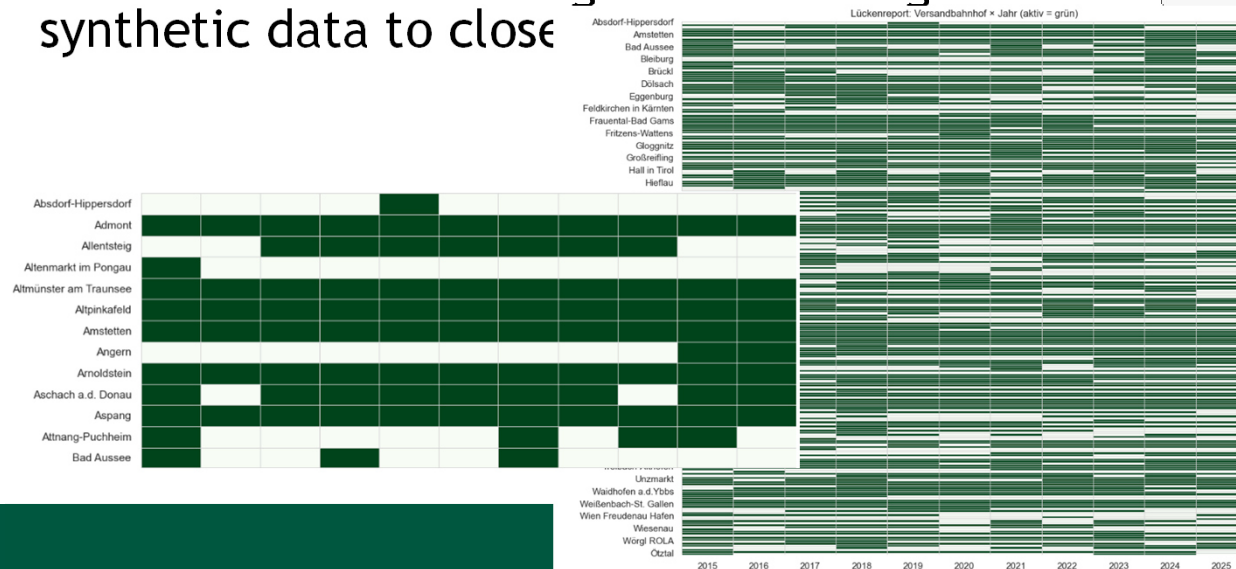
PARIS
LODRON
UNIVERSITÄT
SALZBURG

Fachbereich
Geoinformatik



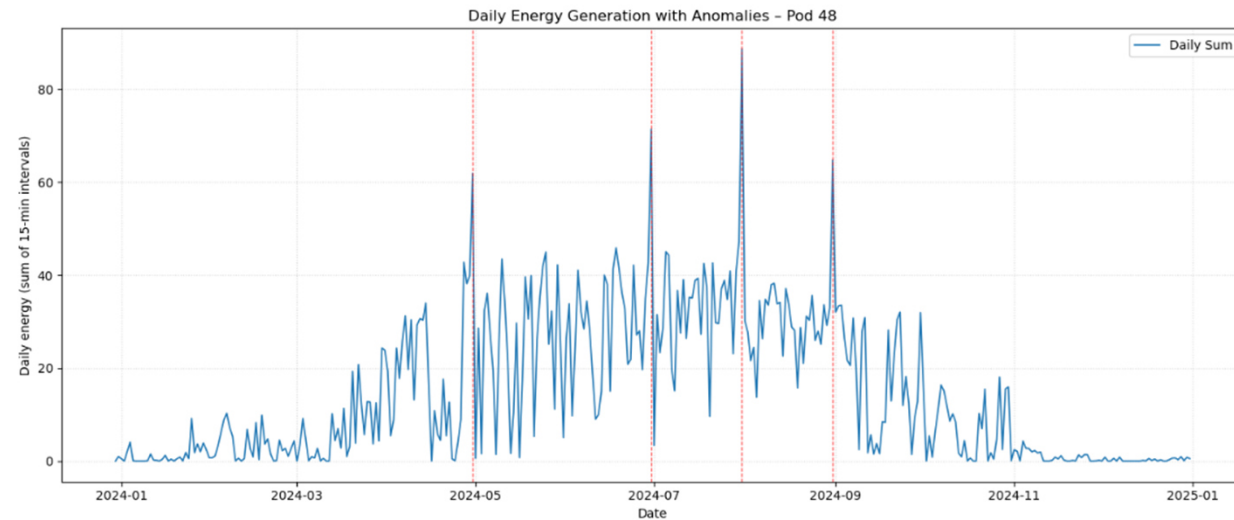
RegioWoodTrain

- The project develops cooperative, AI-driven strategies to shift wood transport toward climate-friendly rail logistics, improving resilience and sustainability in Austria's regional supply chains.
- ST-GNNs based on a graph-based representation of the data
- Identification of missing data and usage of synthetic data to close



iKlimEt

- The iKlimEt project develops AI-driven simulation tools for integrated, climate-resilient energy system planning, focusing on sector-coupled optimization and validating them through a case study in Styria to support Austria's 2040 climate neutrality goals.
- LSTM autoencoder detects anomalies in smart meter time series data (energy generation).
 - Divided into daily sliding windows (96 values of 15 minutes each) with a 12-hour overlap and then normalised so that all pods are comparable.
- Each sliding window therefore represents one day of energy generation → training data.
- Reconstruction errors were calculated, and windows with the highest errors top 3% were marked as anomalies.



Summary

- **Why GeoAI?**

- Enhances AI models with spatial reasoning & geographic context
- Tackles challenges in data quality, bias, and semantic richness

- **Core Use Cases**

- **Anomaly Detection:** DBSCAN, Autoencoders, ST-GCN
- **Bias Correction:** Reweighting, fairness-aware learning, spatial stratification
- **Semantic Enrichment:** GeoBERT, TopoBERT, Ontology integration

GeoAI bridges spatial intelligence and machine learning to improve data quality, fairness, and interpretability—critical for robust, ethical AI systems





PARIS
LODRON
UNIVERSITÄT
SALZBURG

Shaping Geospatial Futures

agit2026

Konferenz für Geoinformatik
Salzburg, 8. – 9. Juli

ZGIS

GeoAI für die Datenvalidierung

Key Concepts um Daten für AI „fit“ zu machen

Paris-Lodron-University Salzburg
Department of Geoinformatics – Z_GIS

Johannes Scholz

Department of Geoinformatics – Z_GIS
Paris-Lodron-University Salzburg

 johannes.scholz@plus.ac.at

 www.zgis.at | www.johannesscholz.net

 [@Joe_GISc](https://twitter.com/Joe_GISc)



[@Joe_GISc@mastodon.online](https://mstdn.social/@Joe_GISc)



<https://linkedin.com/in/johannes-scholz-gisc>



[@joegisc.bsky.social](https://bsky.app/profile/joegisc.bsky.social)

