

GeoAI für die Datenvalidierung

Key Concepts um Daten für AI „fit“ zu machen

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Geospatial Artificial Intelligence

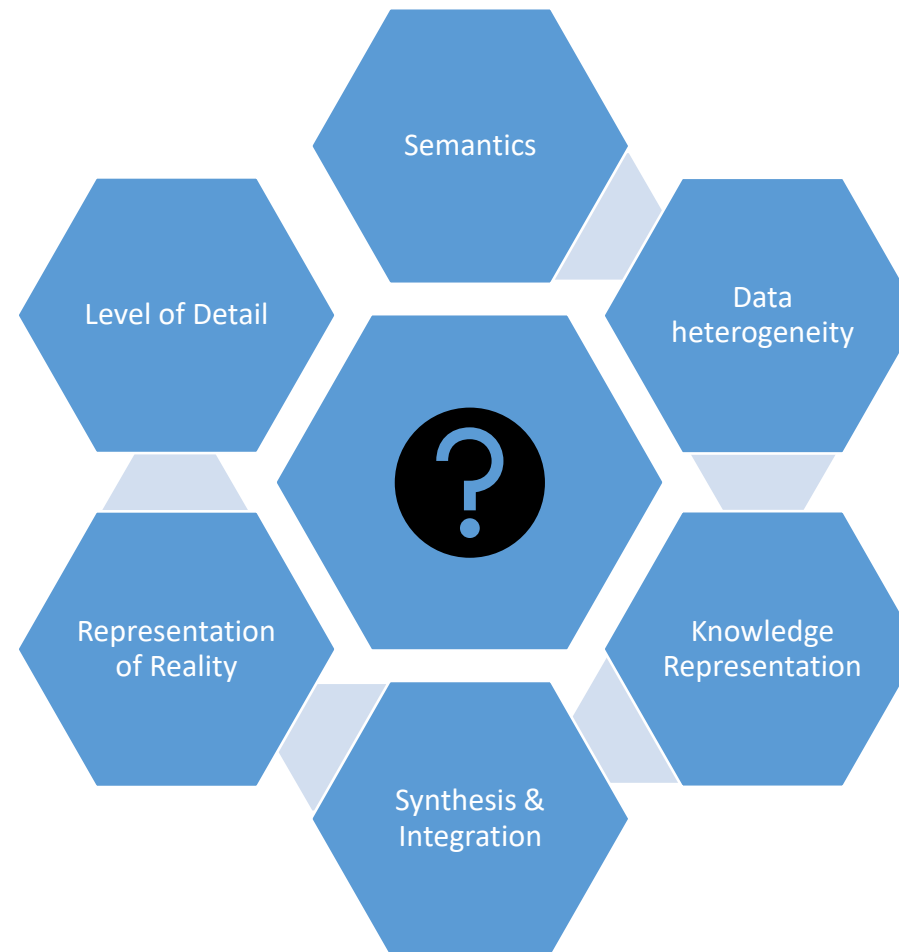
- **“GeoAI can be regarded as a study subject to develop intelligent computer programs to mimic the processes of human perception, spatial reasoning, and discovery about geographical phenomena and dynamics**
 - to advance our knowledge,
 - to solve problems in human environmental systems and their interactions,
 - 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).

GeoAI – Additional Questions?

- Questions that may surface when:

- Representing
- Manipulating
- Storing
- Analyzing, and
- Visualizing

Geographic Data ...!

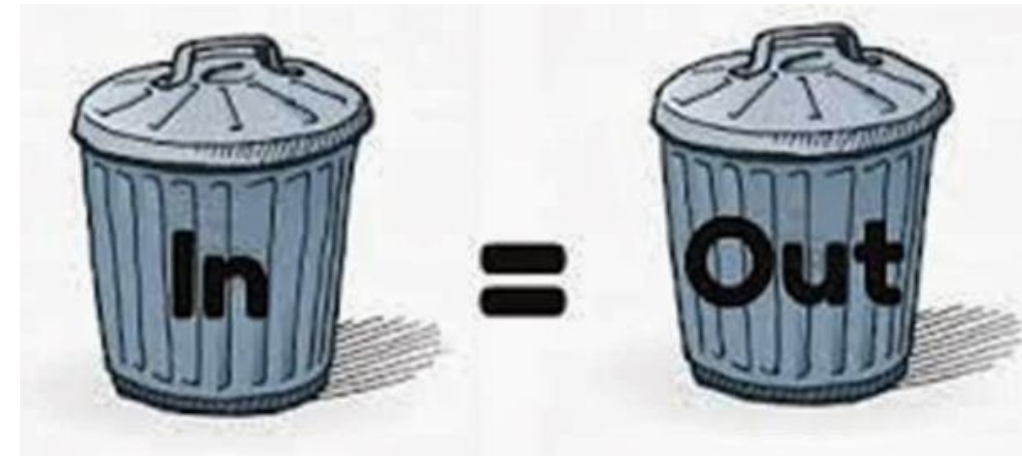


Motivation

„Garbage in, Garbage out.“

AI Models are dependent on training and verification data

- Heterogeneity
- Incompleteness
- Bias
- Flaws



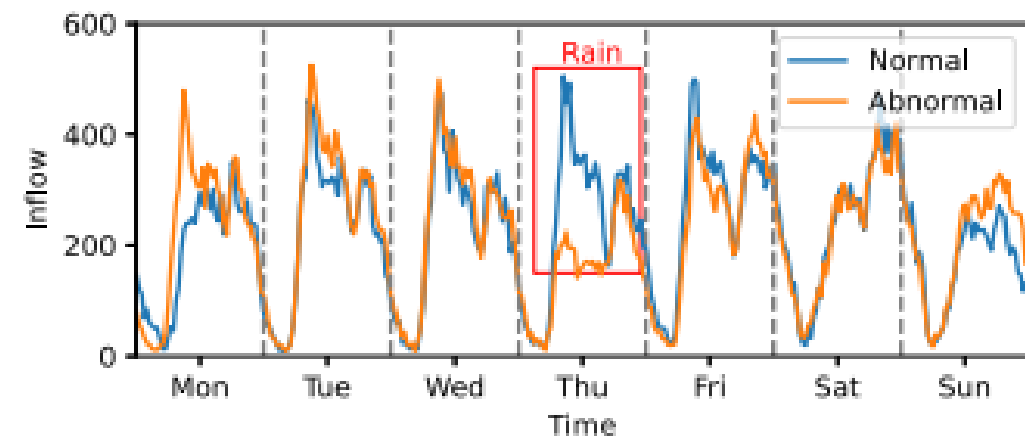
Data Quality as Critical Success Factor

- **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 - Outdated data fails to reflect current realities—especially critical in dynamic domains like mobility or energy.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 Networks): 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.

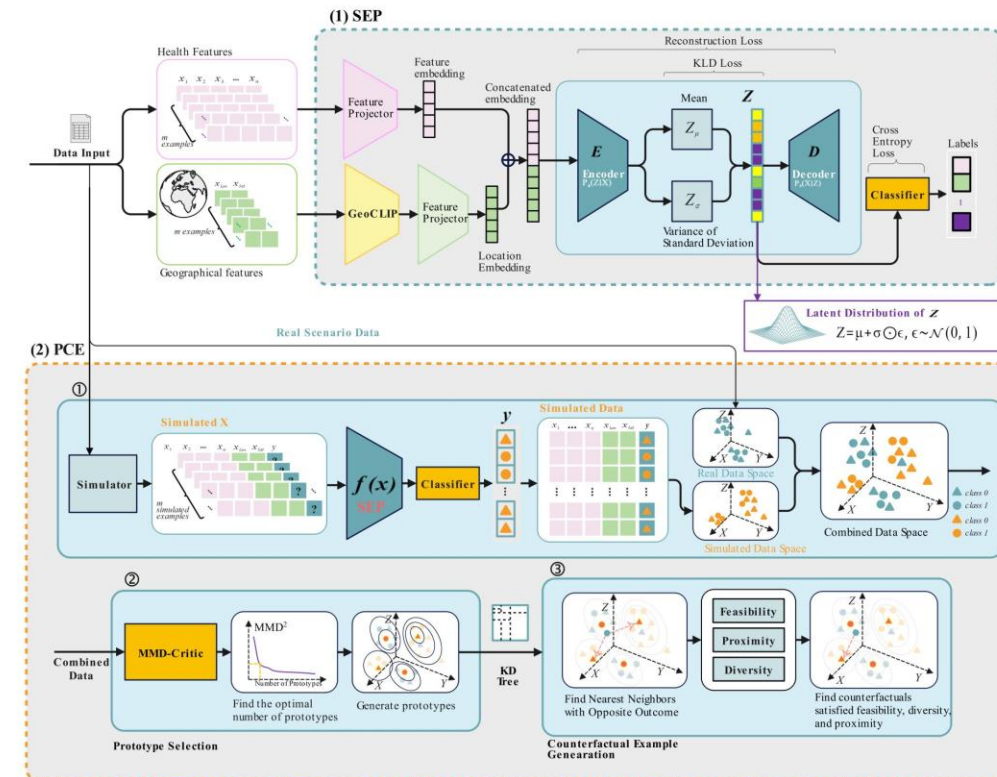


Bias Correction with GeoAI (1)

- 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.

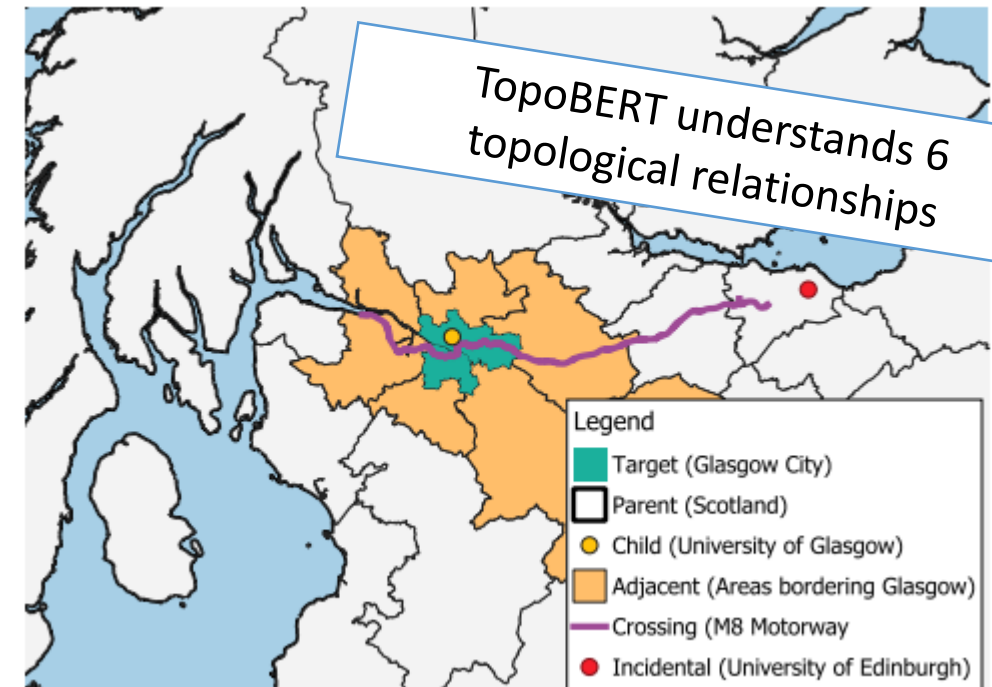
GeoAI for Semantic Enrichment

• 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"

GeoBERT

"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."



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



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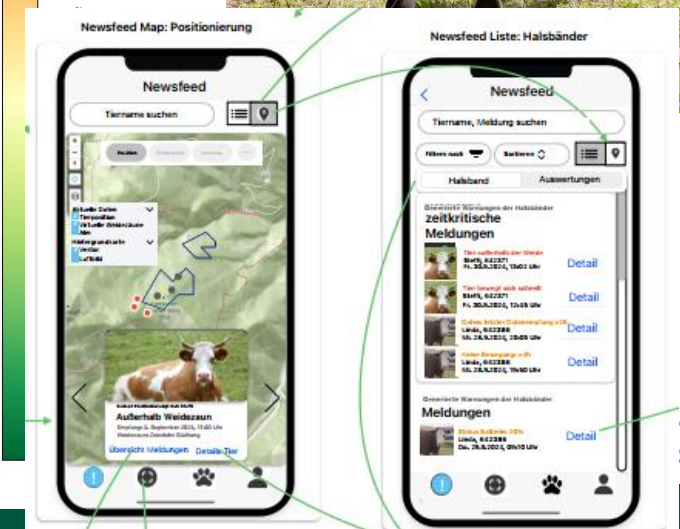
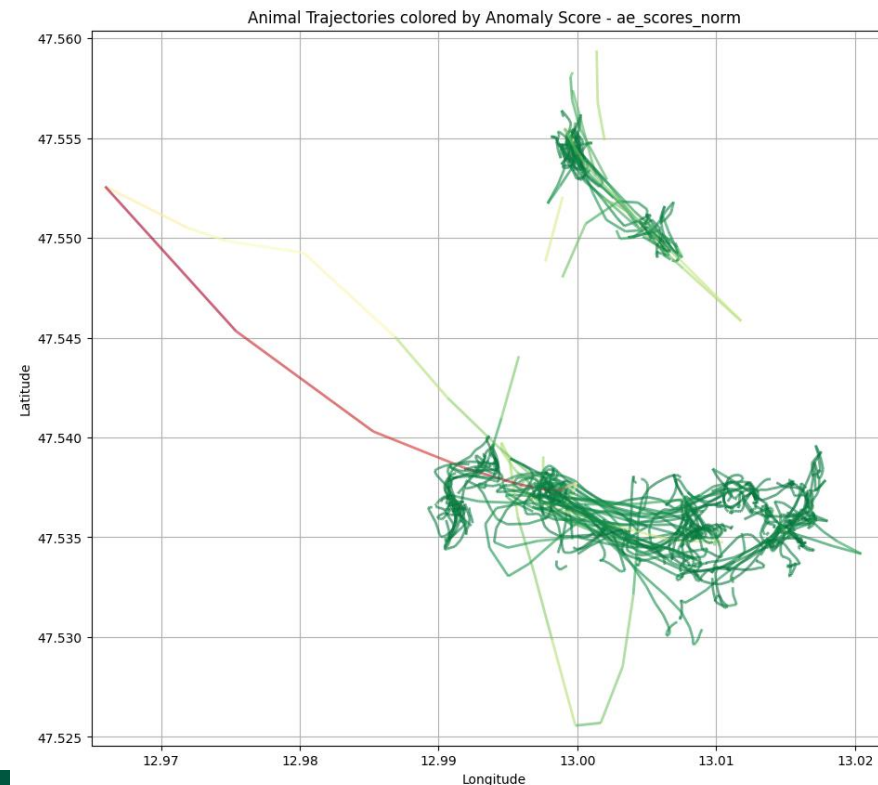
Fachbereich
Geoinformatik

TU
WIEN Informatics

MOVING
LAYERS

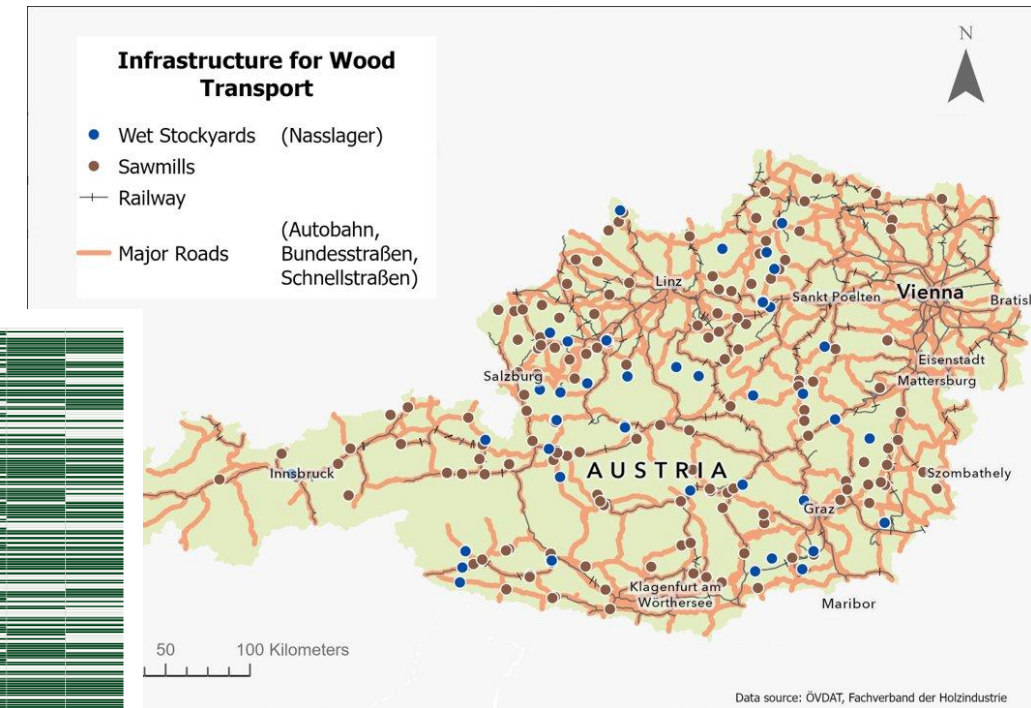
VIEHFINDER

- 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(!)

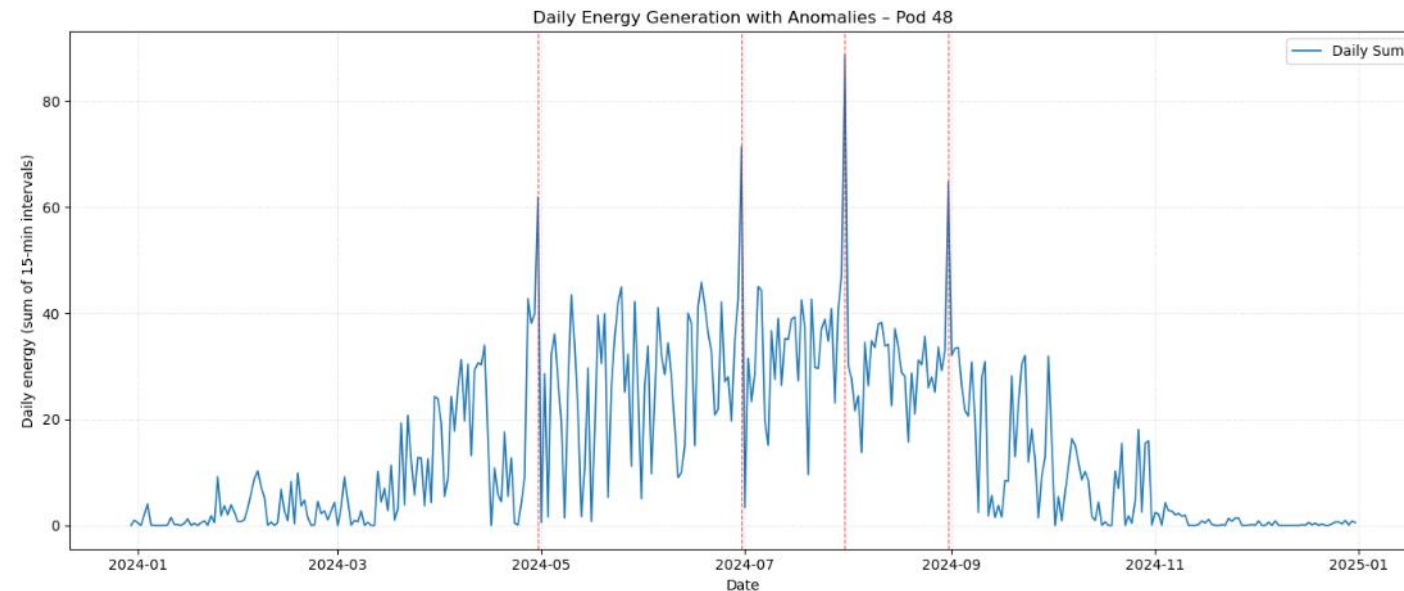


RegioWoodTrain

- 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 some “data gaps”



- 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





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