Spatially Explicit Forecasting of Impervious Surface Area Growth in Developed Regions Using Deep Learning: A Case Study of North Rhine-Westphalia, Germany

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1 Motivation

The expansion of built-up land and associated **impervious surface area (ISA)** degrades environmental quality, affects human well-being, and strains infrastructure, while growth continues to be required for housing, production, and leisure. At international and national levels, policies aim to reduce ISA growth and achieve net-zero land take in the long term, making spatially explicit forecasts of future ISA growth essential to evaluate the feasibility of these objectives and to support spatial planning. **Convolutional Long Short-Term Memory (ConvLSTM)** networks model spatial and temporal dependencies in sequential raster data and are therefore well suited for future ISA prediction (Shi et al. 2015). Prior ConvLSTM studies demonstrate feasibility, but they focus on fast-growing metropolitan regions (Boulila et al. 2021; Kim et al. 2022) or rely on short, sparsely sampled time series that hinder training stability (O'Neill et al. 2025). Consequently, the performance of ConvLSTM models in **developed regions** characterized by comparatively low rates of ISA growth remains insufficiently understood.

Research Question

Can a **ConvLSTM** trained on **long ISA time series** forecast ISA growth **in a developed, slow-growing region,** and which static **driving factors** improve it?

2 Study Area

North Rhine-Westphalia (NRW) (Fig. 1)

- 18 million inhabitants (most populous state, 2022)
- 34,112 km^2 (4th largest state)
- Heterogeneous:
  - Lowlands vs. uplands
  - Polycentric urban regions vs. rural areas
- Mainly tertiary sector, developed infrastructure
- Projected population decline
- Slow and diffuse ISA growth (~10% in 1986 → 14% in 2021)

→ Well suited testing region in contrast to the fast-growing regions of prior studies

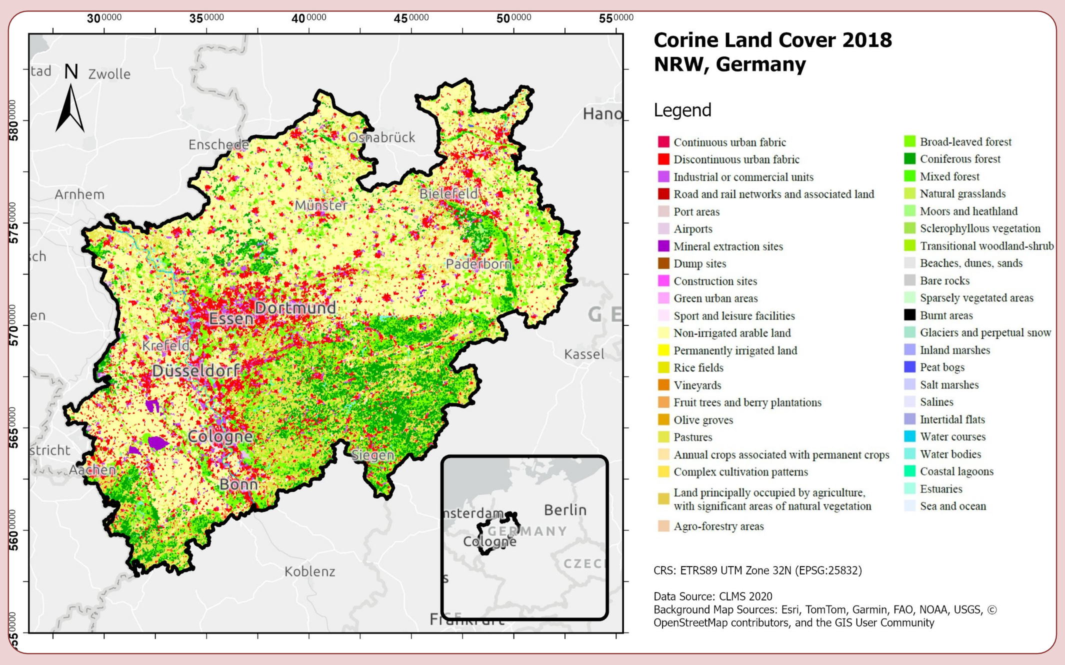

Fig. 1: Land Cover 2018 in North Rhine-Westphalia, Germany (data source: CLMS 2020)

3 Data & Preprocessing

- GISA-new **annual binary ISA maps, 1985–2021**, at 30 m resolution based on **Landsat** archive (Ren et al. 2025) (Fig. 2)
- NRW tiled into 128 x 128 pixel tiles with 20 % overlap yielding 3,308 tiles per year
- Creation of spatiotemporal sequences at 5-year spacing with **four inputs (X)** and **three forecast targets (Y)** at horizons **+5 (H1), +10 (H2), +15 years (H3)** (Fig. 3)
- A one-year **sliding window** over start years generates overlapping sequences per tile (seven start years × 3,308 tiles)
- 13,230 training, 3,310 validation and 6,616 test sequences (two most recent sequences per tile held out for testing)
- Six one-year snapshot **driving factors (DFs)** as additional input channels (Fig. 4)
  - **Population density** (socioeconomic)
  - **Standard land value** (socioeconomic)
  - **Slope** (geophysical)
  - **Distance to major roads** (proximity)
  - **Distance to rail transit** (proximity)
  - **Forested area** (geophysical)

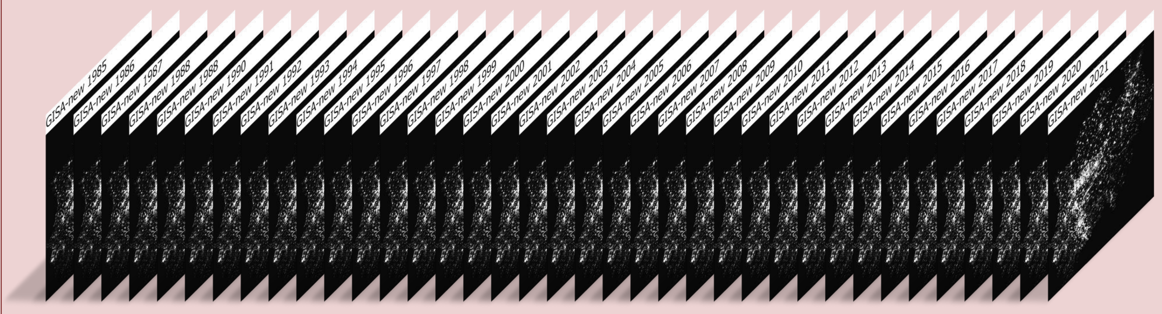

Fig. 2: Annual binary ISA maps for NRW from 1985–2021 (data source: Ren et al. 2025)

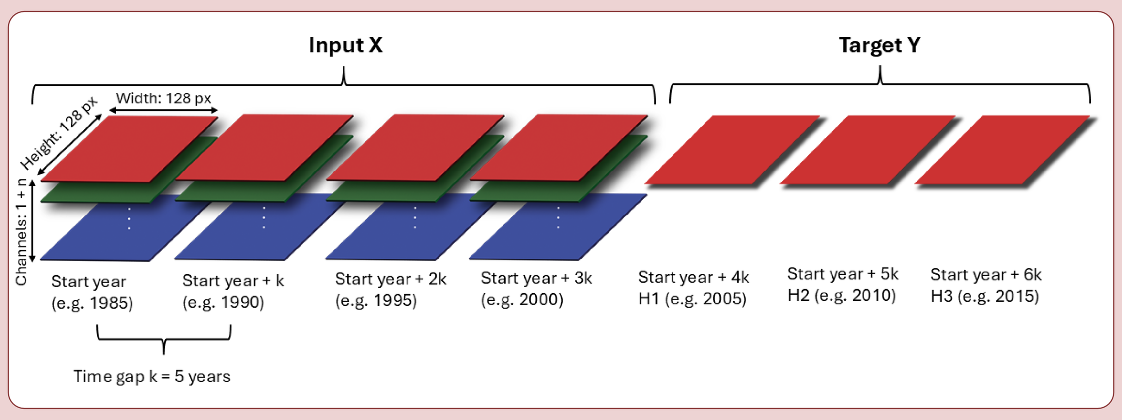

Fig. 3: Example input (X) and target (Y, three horizons) sequence at 5-year spacing

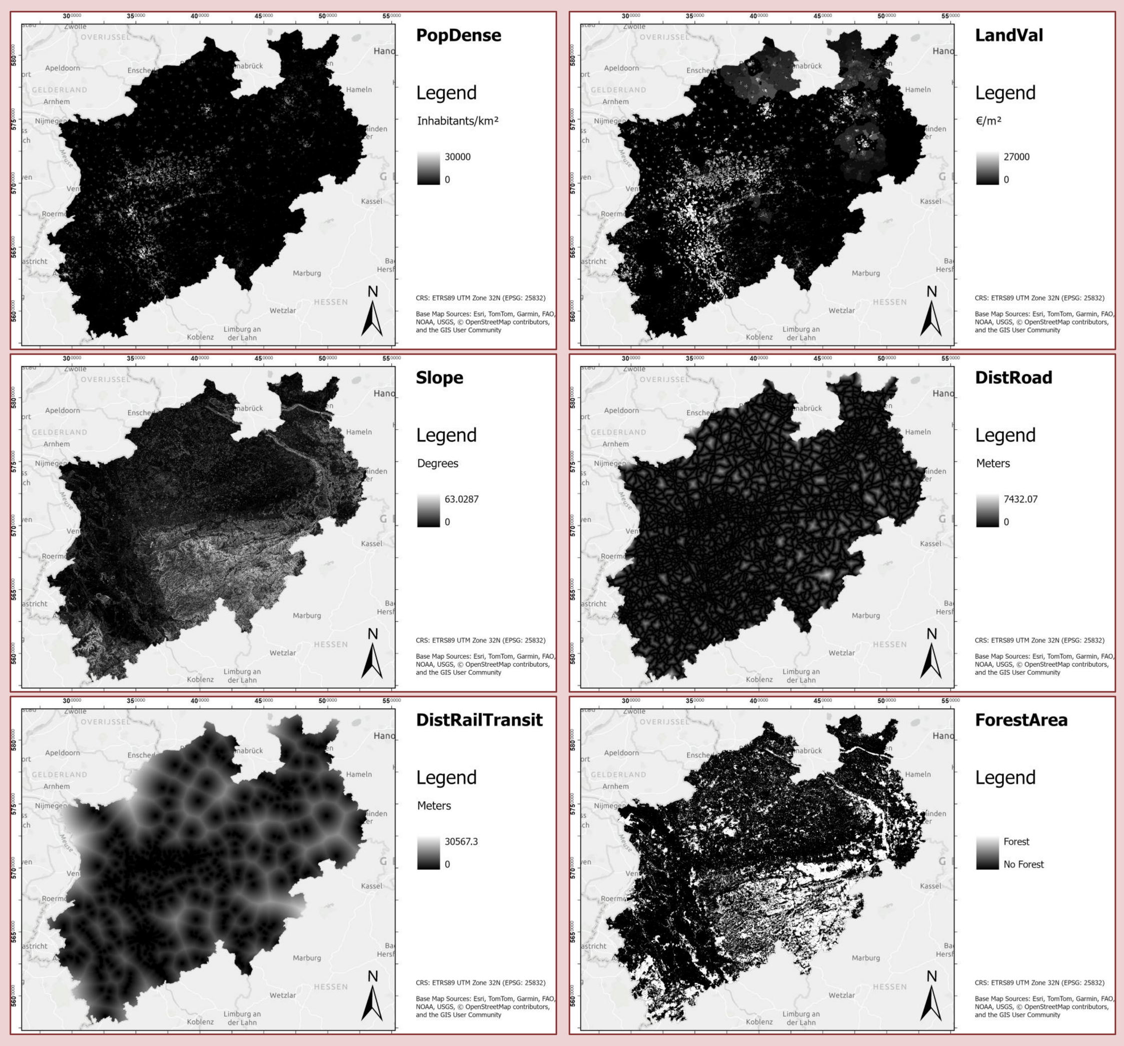

Fig. 4: The six static driving factors for NRW (2011)

4 Methodology

- **Sequence-to-sequence ConvLSTM** with an encoder-decoder architecture, producing dense 128 × 128 per-pixel ISA probability maps (Fig. 5)
- **Three ConvLSTM architectures** of increasing depth were compared against a **persistence baseline** that copies the last observed ISA map forward; an intermediate-depth model performed best, and all variants beat the baseline
- **Ablation study**: the best model was retrained with each **DF** individually and combined, to assess whether and which factors improve forecasting quality
- **Trained** with the Adam optimizer (learning rate 0.001) and binary cross-entropy, batch size 32, with early stopping; the output threshold was selected on validation to maximize Intersection over Union (IoU)
- **Evaluated** on held-out test sequences using **IoU** (primary), **precision**, **recall**, **F1**, and **overall accuracy (OA)**
- Full-scale training ran on an **NVIDIA H100 GPU** (RAMSES HPC, IT Center University of Cologne)

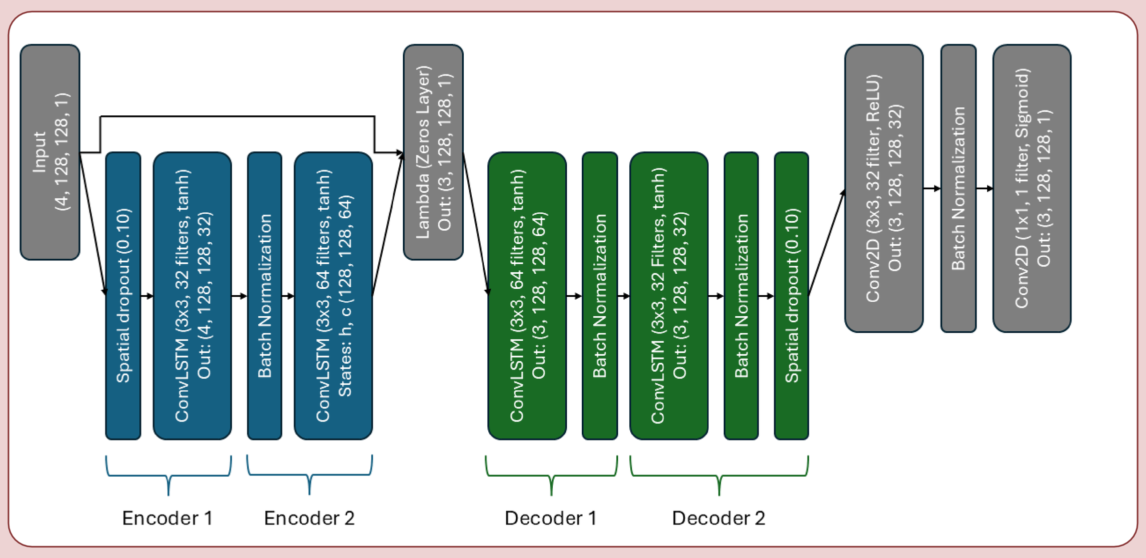

Fig. 5: Sequence-to-sequence ConvLSTM architecture

5 Results & Discussion

- All ConvLSTM variants **outperformed the persistence baseline** at every horizon (Tab. 1, Fig. 6)
  → **the models predicted new ISA** rather than only copying the last observed state
- Adding **DFs** gave little improvement at +5 years but **increasing benefit at +10 and +15 years**
- Absolute IoU was high but should be interpreted with caution, since ISA change per step is small; the meaningful signal is the consistent gain over the persistence baseline
- **Long time series** likely **overcame the training-stability problems** reported for short-series ConvLSTMs (O'Neill et al. 2025), supporting long historical depth as the key enabler
- In a developed region, demand- and constraint-related factors likely added more prediction value than accessibility variables

Tab. 1: Test metrics of each ConvLSTM variant at H3

Configuration	IoU	Precision	Recall	F1	OA
+ Slope	**0.912**	**0.994**	**0.917**	**0.954**	**0.987**
+ All driving factors	0.911	0.993	0.916	0.953	0.987
+ Population density	0.905	0.995	0.910	0.950	0.987
+ Standard land value	0.903	0.997	0.906	0.949	0.986
+ Forested area	0.903	0.996	0.906	0.949	0.986
+ Distance to rail transit	0.903	0.996	0.906	0.949	0.986
+ Distance to major roads	0.902	0.996	0.905	0.949	0.986
ConvLSTM (ISA only)	**0.902**	**0.997**	**0.905**	**0.949**	**0.986**
Persistence baseline	0.900	1.000	0.900	0.947	0.986

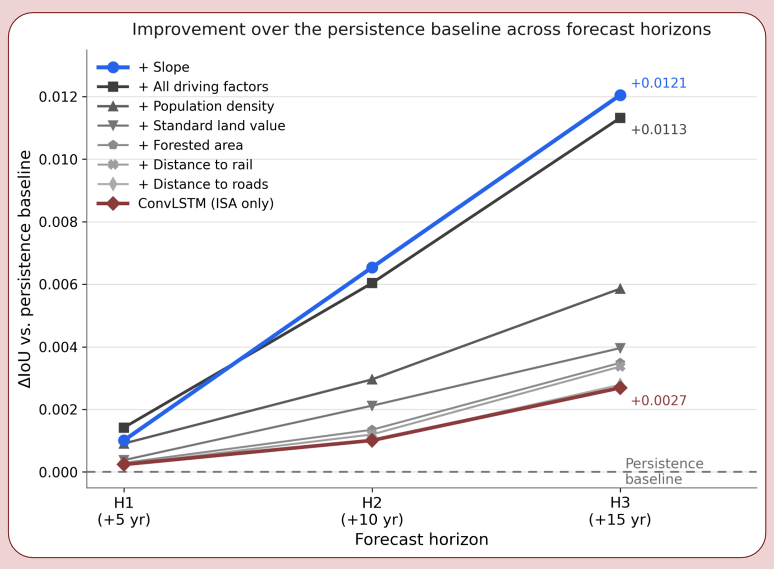

Fig. 6: IoU difference for each ConvLSTM configuration over the persistence baseline

Answer to Research Question

- A **ConvLSTM** trained on **long ISA time series** is able to forecast ISA in a **slow-growing developed region**
- The driving factor **Slope** improves forecasts the most

6 Conclusion & Outlook

- **ConvLSTM** beats the persistence baseline at every horizon, and the **advantage grows with forecast horizon**
- Static driving factors improved performance at **longer horizons**, and **slope** was the most influential factor in this setting
- **Outlook**: incorporating dynamic drivers (e.g. population time series) and additional socioeconomic and institutional variables, and designing input sequences that target longer, policy-relevant horizons directly

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