Interpretable Deep Learning for 3D GNSS Troposphere Tomography: Bridging AI and Physics-Based Atmospheric Models

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Abstract

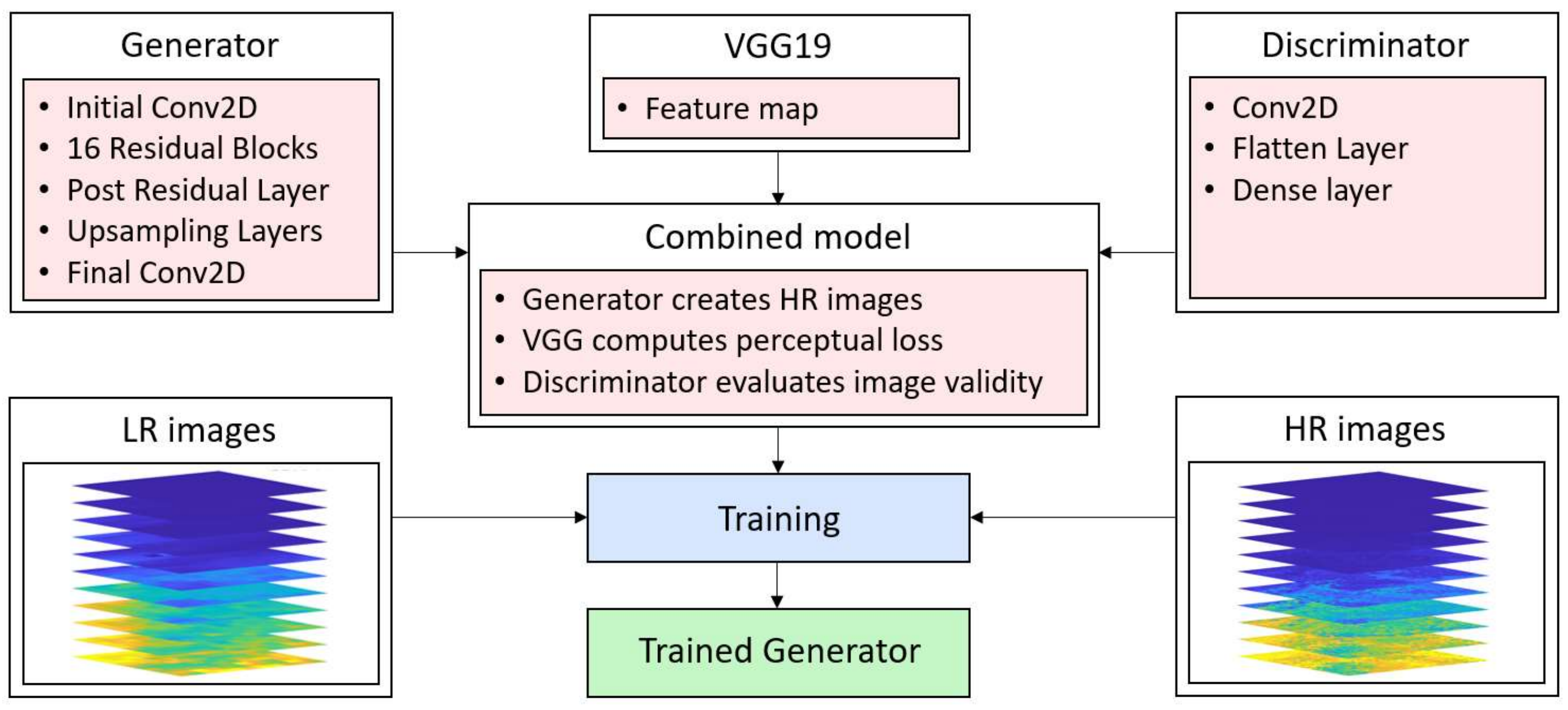
We present an XAI deep learning framework for enhancing GNSS-based 3-D tropospheric tomography that leverages both the predictive power of AI and the physical consistency of NWP models. Using a SRGAN, low-resolution (LR) tomography is refined into high-resolution (HR) wet refractivity fields. SRGAN outperforms traditional methods, with lower RMSE, especially in rainy conditions. Grad-CAM and SHAP reveal the model's focus aligns with physical atmospheric processes and seasonal feature importance. This framework increases trust in AI applications, and holds strong potential for integration into operational weather forecasting and data assimilation systems.

Introduction

Weather forecasting has advanced from physics-based models to AI-driven systems, yet predicting small-scale phenomena like convection remains challenging due to coarse input data. HR humidity information is crucial, and GNSS tropospheric products provide valuable measurements. While GNSS tomography reconstructs 3-D wet refractivity fields, outputs are often LR and smoothed, limiting the capture of rapid atmospheric changes. Downscaling methods, enhanced by machine learning and generative models like SRGANs, offer improved resolution, but interpretability is often lacking. This study introduces HR tropospheric tomography using the Weather Research and Forecasting (WRF) model outputs downscaled via SRGAN, applied to Poland under varying weather conditions. XAI techniques, including Grad-CAM and SHAP, are employed to interpret predictions. The motivation is to improve small-scale weather forecasting by combining HR humidity data with advanced downscaling, and to generate accurate, interpretable HR forecasts that can be used in the data assimilation process of weather forecasting models.

Data sets and Methodology

We used GNSS tomography data as LR inputs and WRF model outputs as HR references, training an SRGAN with a generator (16 residual blocks and two upsampling stages) and a discriminator guided by adversarial and perceptual losses to super-resolve the LR images from 0.8° × 0.5° to 0.2° × 0.125°. **The downscaling factor is 4.**



Generator
- Initial Conv2D
- 16 Residual Blocks
- Post Residual Layer
- Upsampling Layers
- Final Conv2D

VGG19
- Feature map

Discriminator
- Conv2D
- Flatten Layer
- Dense layer

Combined model
- Generator creates HR images
- VGG computes perceptual loss
- Discriminator evaluates image validity

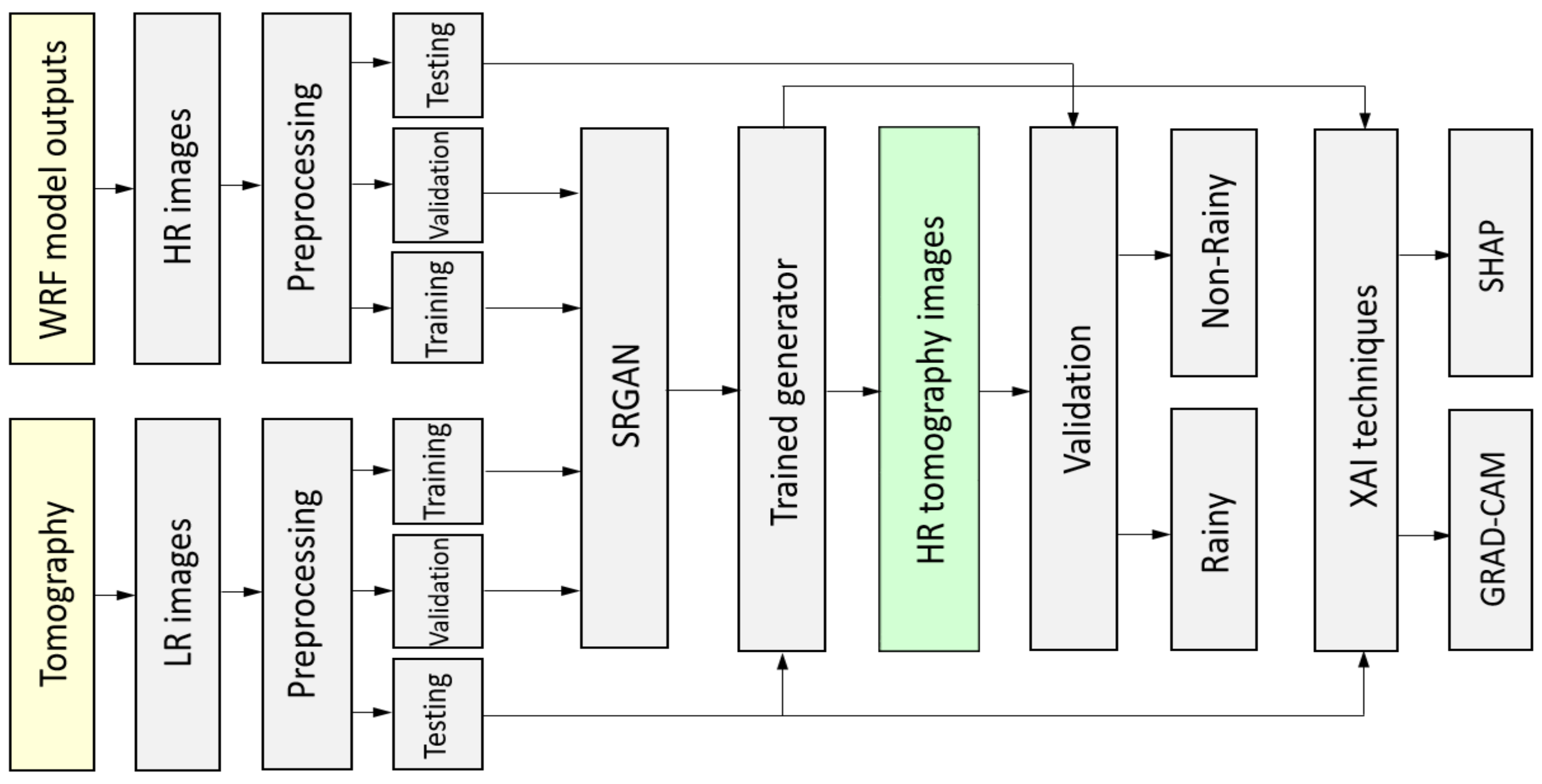
LR images

Training

Trained Generator

HR images

Figure 1: Overview of the steps followed in the procedure



WRF model outputs

HR images

Preprocessing

Testing

Validation

Training

Tomography

LR images

Preprocessing

Training

Validation

Testing

SRGAN

Trained generator

HR tomography images

Validation

Non-Rainy

Rainy

XAI techniques

SHAP

GRAD-CAM

Figure 2: Model structure for downscaling

Study Area

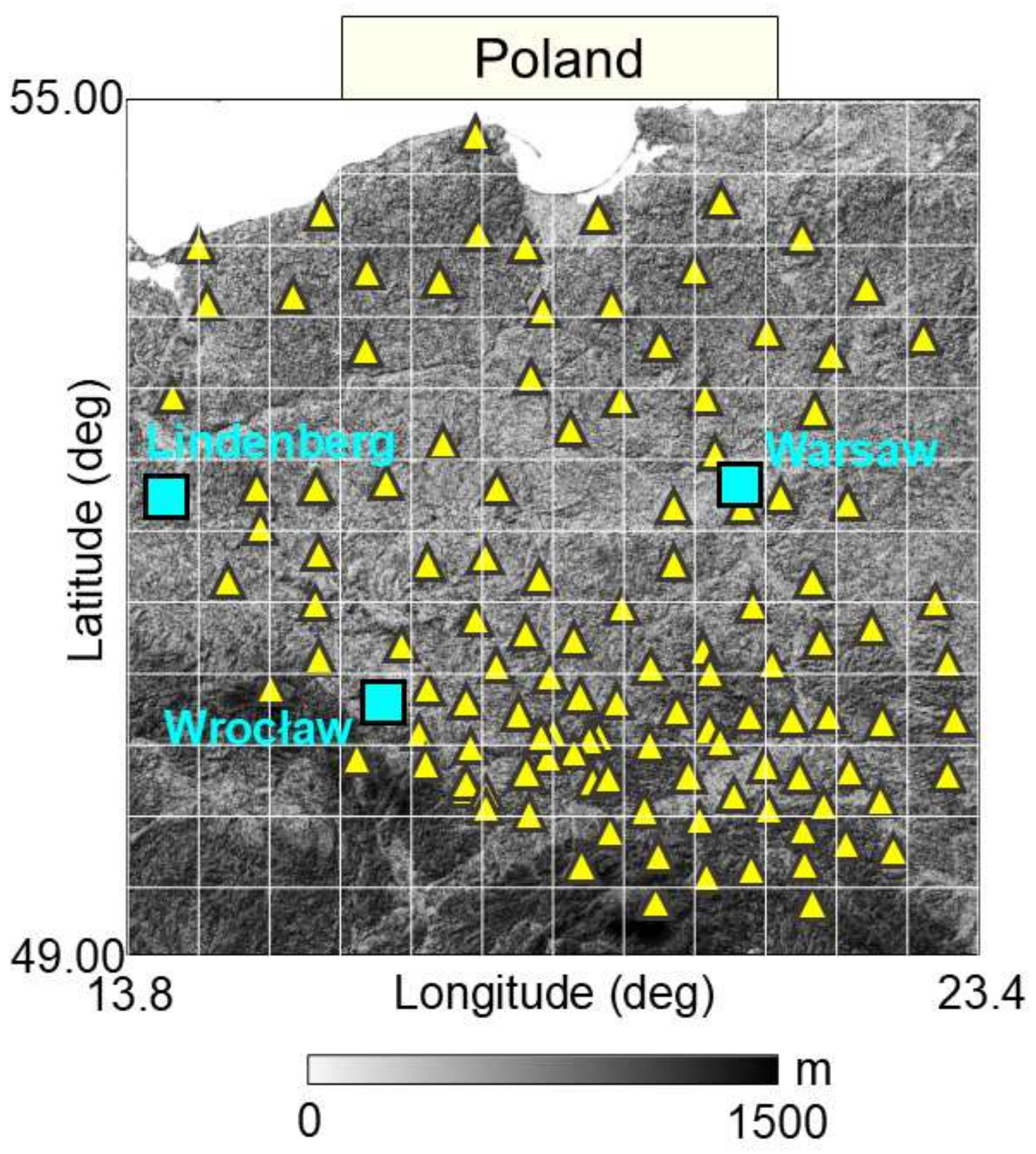


Figure 3: Distribution of GNSS stations (triangles) and radiosonde stations (squares).

Results

Validation against radiosonde measurements shows RMSE values of 3.78 ppm in rainy conditions and 3.31 ppm in non-rainy conditions at heights below 3000 meters. Downscaling using SRGAN significantly improved the resolution and accuracy of the tomography, outperforming Lanczos3 interpolation, as reflected in RMSE reductions of up to 62%. Logarithmic-scale density plots further illustrate the improved alignment of SRGAN predictions with reference datasets, showing reduced dispersion and a more symmetric concentration around the 1:1 line. XAI analyses using highlight that the model emphasizes regions of high wet refractivity and sharp gradients.

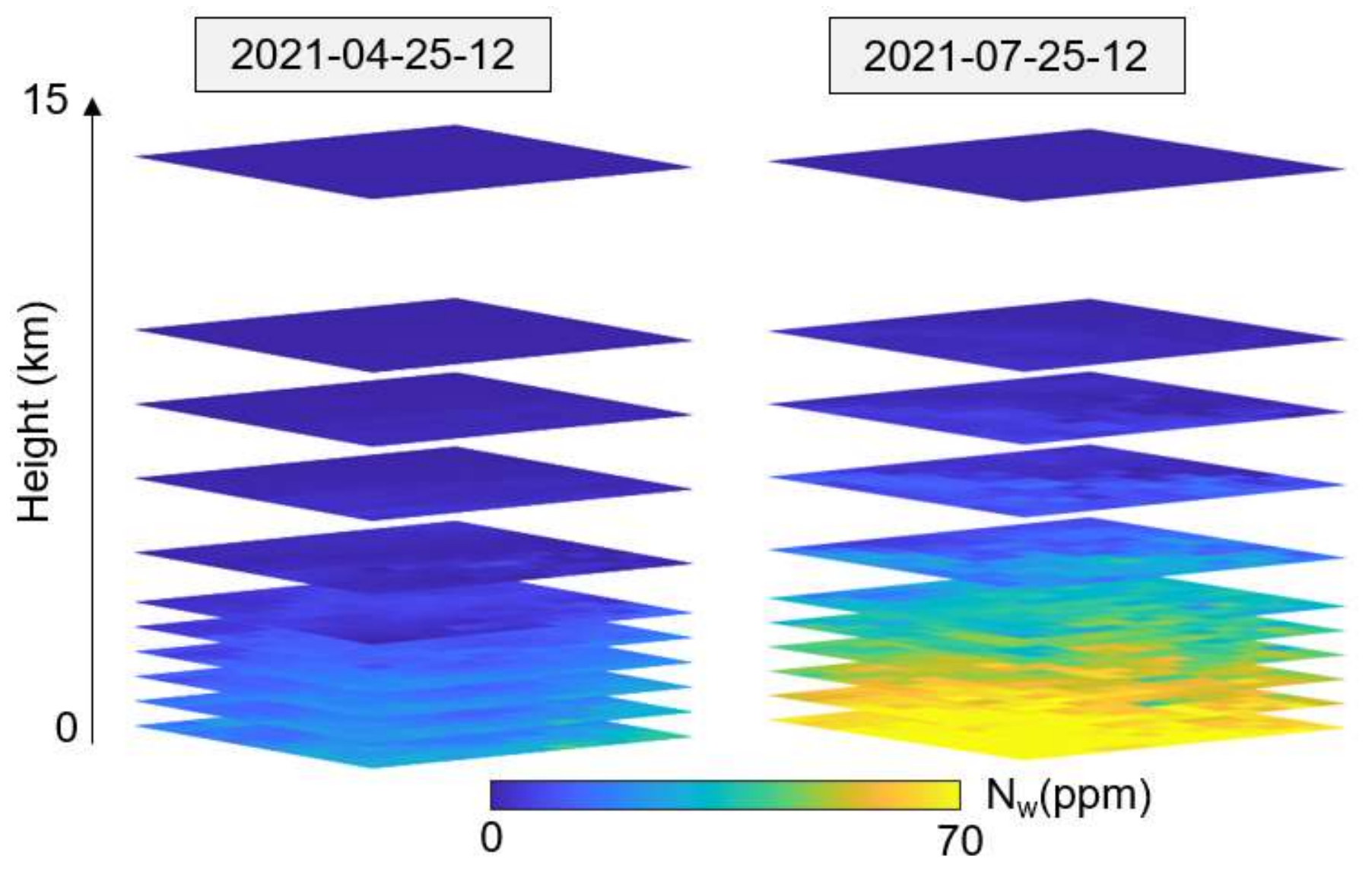


Figure 4. Tomography results in two samples epochs (2021-04-25-12 and 2021-07-25-12) in YYYYMMDDHH format

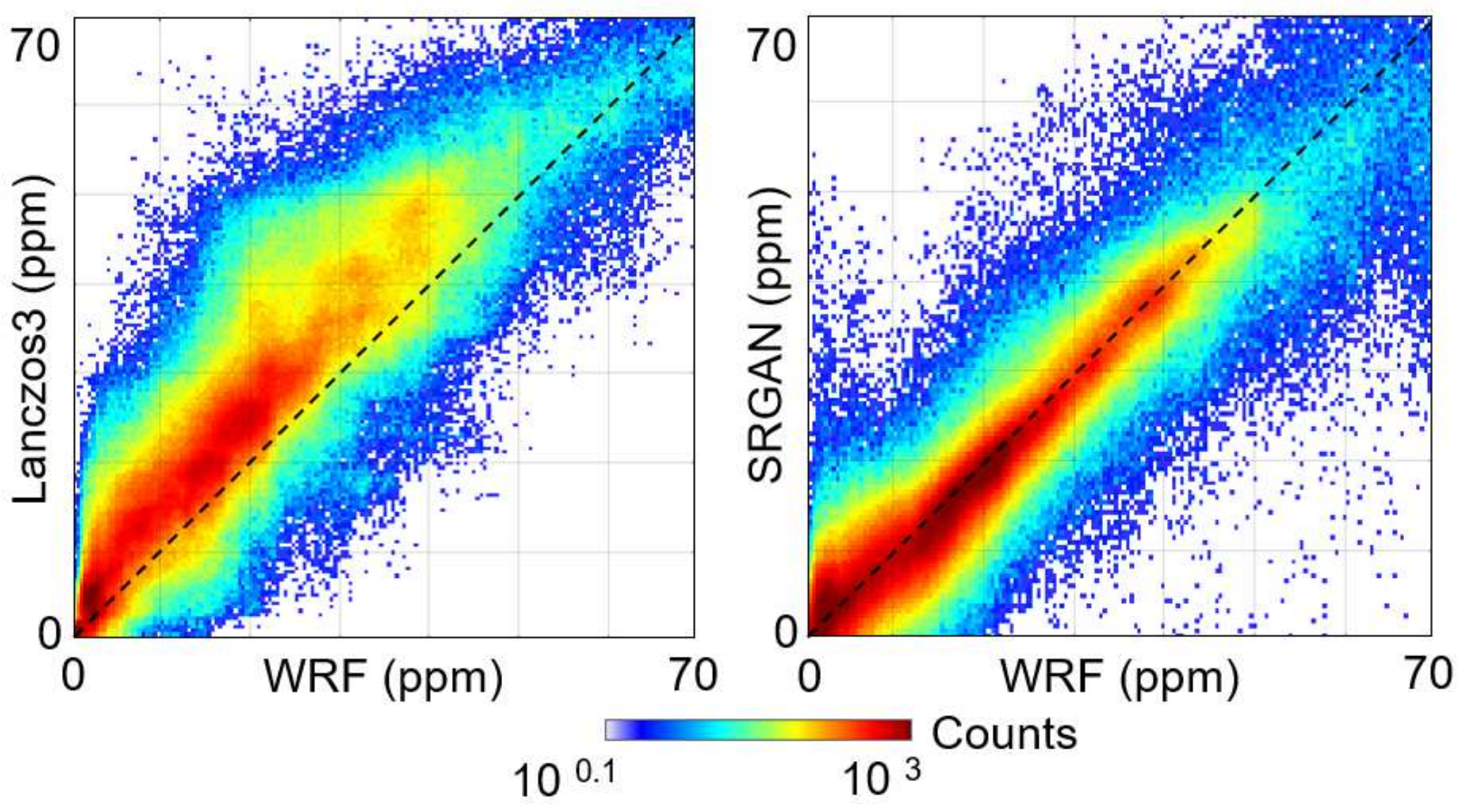


Figure 5: Log-scale density plots

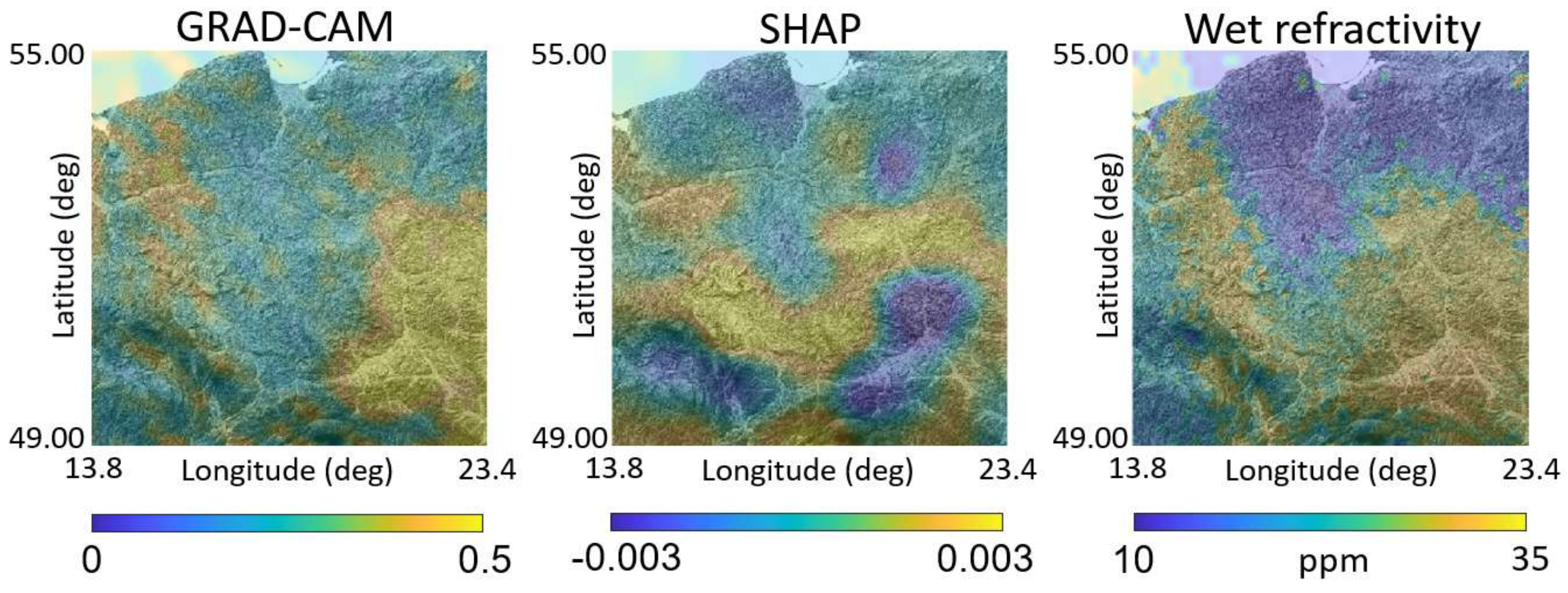


Figure 6: Example of the results of the XAI methods for Poland (2021-09-29-17)

Discussion and Conclusion

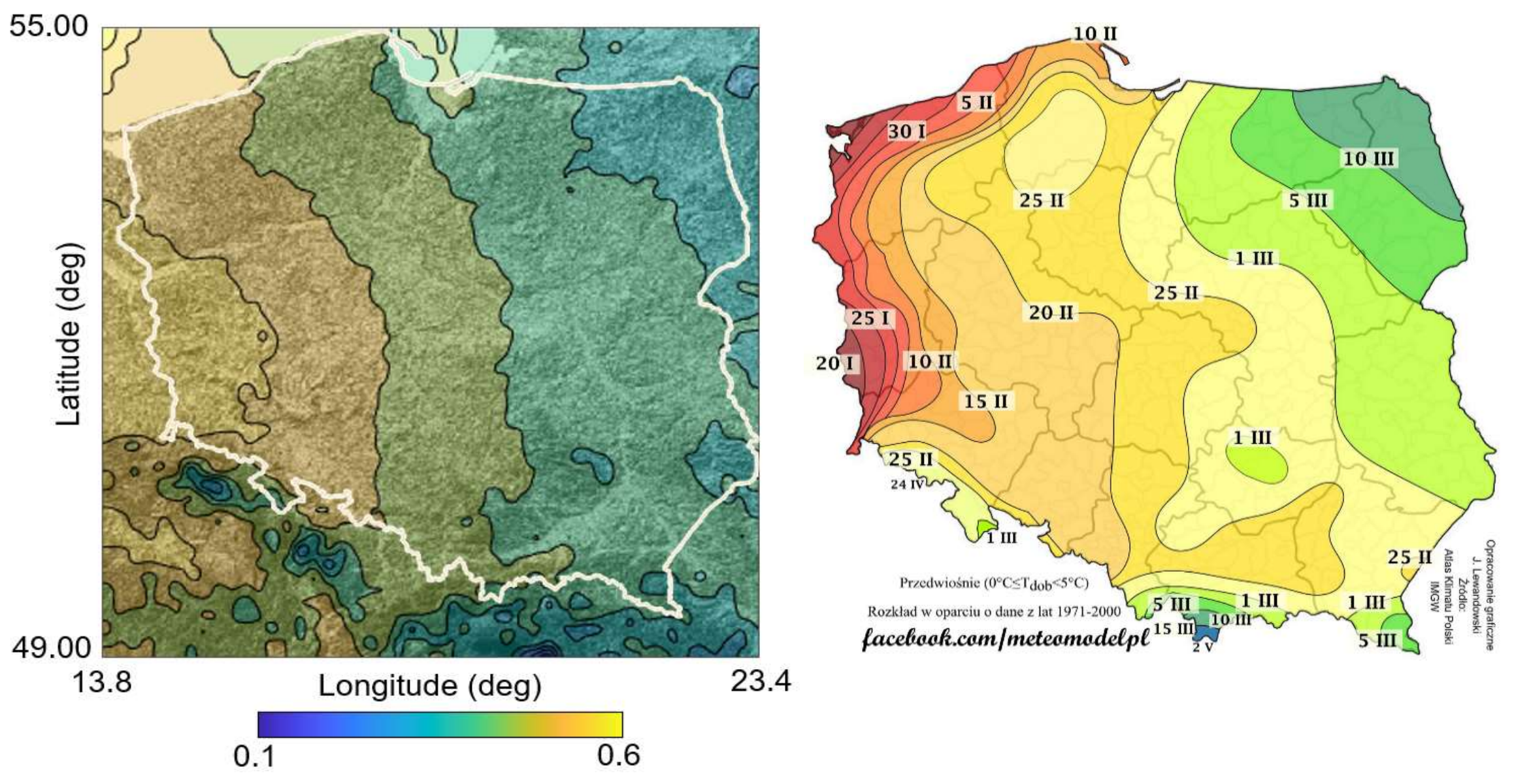


Figure 7. Average Grad-CAM results (left) and average dates of the beginning of early spring (right)

Average Grad-CAM results show higher importance in the western regions and a gradual decrease toward the east. This pattern reflects the country's maritime–continental climate transition, where moist Atlantic air creates more complex atmospheric conditions in the west and leads to an earlier spring in the western part, causing the model to focus more on these areas. SRGAN effectively enhances tomography resolution and outperforms Lanczos3, improving agreement with reference data. It overcomes a key GNSS tomography limitation without altering the model structure, enabling more reliable analysis and support for accurate weather forecasting.

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