



Evaluating the performance of a numerical weather prediction model for precipitation and temperature in Luxembourg and the Greater Region: insights from WRF and WRFDA 3D-VAR

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Abstract. This study evaluates the Weather Research and Forecasting (WRF) model, with and without WRFDA 3D-VAR data assimilation (DA), for precipitation and temperature forecasts in Luxembourg and the Greater Region during the July 2021 flood event. Conventional observations (CONV), Global Navigation Satellite System (GNSS) Zenith Total Delay (ZTD), and their combination (CONV + ZTD) were assimilated using a 6-hour rapid-update cycle over a full month (20 June–20 July 2021), and verified against independent surface stations withheld from the assimilation, together with radar and GPM IMERG data. For precipitation, DA improved categorical skill: CONV yielded the largest gains in bias (+37.4 %) and probability of detection (+18.3 %), at the cost of a higher false alarm ratio, while CONV + ZTD gave more moderate but balanced improvements. Absolute-error metrics (RMSE, MAE, SMAPE) changed little and mostly not significantly, indicating that DA improves event detection rather than magnitude. For temperature, all configurations reduced bias, ZTD being the most effective (+97.4 %). Station-level Wilcoxon signed-rank tests confirm that the bias and detection gains are statistically significant ($p < 0.001$). The results demonstrate the complementary roles of conventional and GNSS-based observations for regional numerical weather prediction.

1 Introduction

Floods are considered one of the most catastrophic and devastating natural disasters, causing massive loss of infrastructure, loss of life, and economic disruption (IPCC, 2021; Duan et al., 2022; Khayyam, 2020). Climate change has intensified flood events, posing an increasingly serious challenge to communities around the world. Flash floods are often viewed as one of the most severe types of hazards due to their abrupt onset, infrequency, localized impact, intense rainfall, and high peak river discharge. Their movements are swift, violent, and difficult to predict (Ali et al., 2017). Flash floods can result in additional hazards like landslides, mudslides, infrastructure damage, and even loss of life (Kuksina and Golosov, 2020). Nonetheless, the greatest uncertainty in predicting flash floods continues to be the unpredictability of future rainfall both in location and time (Hapuarachchi et al., 2011). Flash floods kill, on average, 50 people in Europe every year (European Environment Agency (EEA), 2017) with 2021 marking a particularly devastating year as approximately 250 lives were lost due to such events.



(EM-DAT, 2021). Moreover, The likelihood of flood risks is expected to rise in cities that are still developing (Tom et al., 2022)

25 The IPCC AR6 (2021) report underscores that climate change has increased the frequency and intensity of extreme precipitation events across Europe, contributing to more frequent and severe floods. In particular, river basins like the Rhine have experienced heightened flood risks due to a combination of heavy rainfall, earlier snow melt, and saturated soil conditions. In July 2021, multiple European countries experienced devastating floods due to prolonged and intense rainfall. This event represents a dual crisis, where sudden shocks like floods coincide with ongoing, long-term challenges (Pot et al., 2023) as it was at least partly driven by climate change (Faranda et al., 2022; Tradowsky et al., 2023; Kreienkamp et al., 2021) which is an ongoing, underlying crisis (Ferreira et al., 2022) However, climate change adaptation efforts often focus on immediate, known risks, without fully considering how those risks might change in the future (Boin et al., 2020). This is despite the fact that climate change is making floods more intense and frequent and is likely to cause more disasters like the ones in July 2021 (United Nations Environment Programme, 2022; Lee and Romero, 2023; Fettweis and Doutreloup, 2022; Ludwig et al., 2023). The July 2021 floods in Luxembourg and the surrounding regions were linked to a 1-2 day heavy rainfall event, which scientists attribute to a warming climate. Flood events with major damage in Luxembourg, were recorded for January 1993, December 1993, January 1995, January 2003, January 2011, June 2018 and July 2021 (Ministerium für nachhaltige Entwicklung und Infrastrukturen (MDDI) and Wasserwirtschaftsverwaltung Luxemburg, 2015; Apel et al., 2022; Mathias, 2019). The flood in Luxembourg in July 2021, was a part of a much larger event affecting Belgium, Germany, France and the Netherlands driven by unprecedented rainfall in the region (Tradowsky et al., 2023) resulting in significant loss of life and damage to infrastructure (Koks et al., 2022). Figure 1 illustrates the primary affected regions, with red dots and circles marking key locations within these countries.

The discharge levels at the Rhine tributaries and rivers across these countries, including Luxembourg, were up to four times larger than any previously recorded events, leading to significant devastation. The flood caused nearly 253 fatalities and more than \$45.8 billion in damages (EM-DAT, 2021). The primary cause of the flood was heavy rainfall over a short period, overwhelming existing flood defenses and catching local experts by surprise (Bertola et al., 2023; Apel et al., 2022; Kreibich et al., 2022). For the initial analysis of the 14–15 July 2021 hydro-meteorological event, rainfall data were compiled from the nearby Belvaux and Obercorn stations, providing a 67-year record of daily observations maintained by the Administration of Technical Agricultural Services (Luxembourg Institute of Science and Technology (LIST), 2021). The July 2021 flood was characterized by extraordinary precipitation levels, with cumulative rainfall of 68.1 mm observed in Oberkorn, Luxembourg. This event has a return period of 92 years for summer and 43 years for the entire hydrological year, indicating its rarity. Prior to the flood, the Bibeschbach catchment area was highly saturated, nearly double the average, increasing flood risk. The seven-day cumulative rainfall was also exceptional, with a return period over 100 years. The Bibeschbach showed an immediate and intense hydrological response, with peak flows significantly higher than previous records. Other basins, such as Weierbach and Huewelerbach, experienced varying degrees of hydrological stress. Peak flow events had return periods exceeding 50 years, and in some cases over 100 years, across several watersheds, underscoring the event's exceptional nature (Luxembourg Institute of Science and Technology (LIST), 2021).

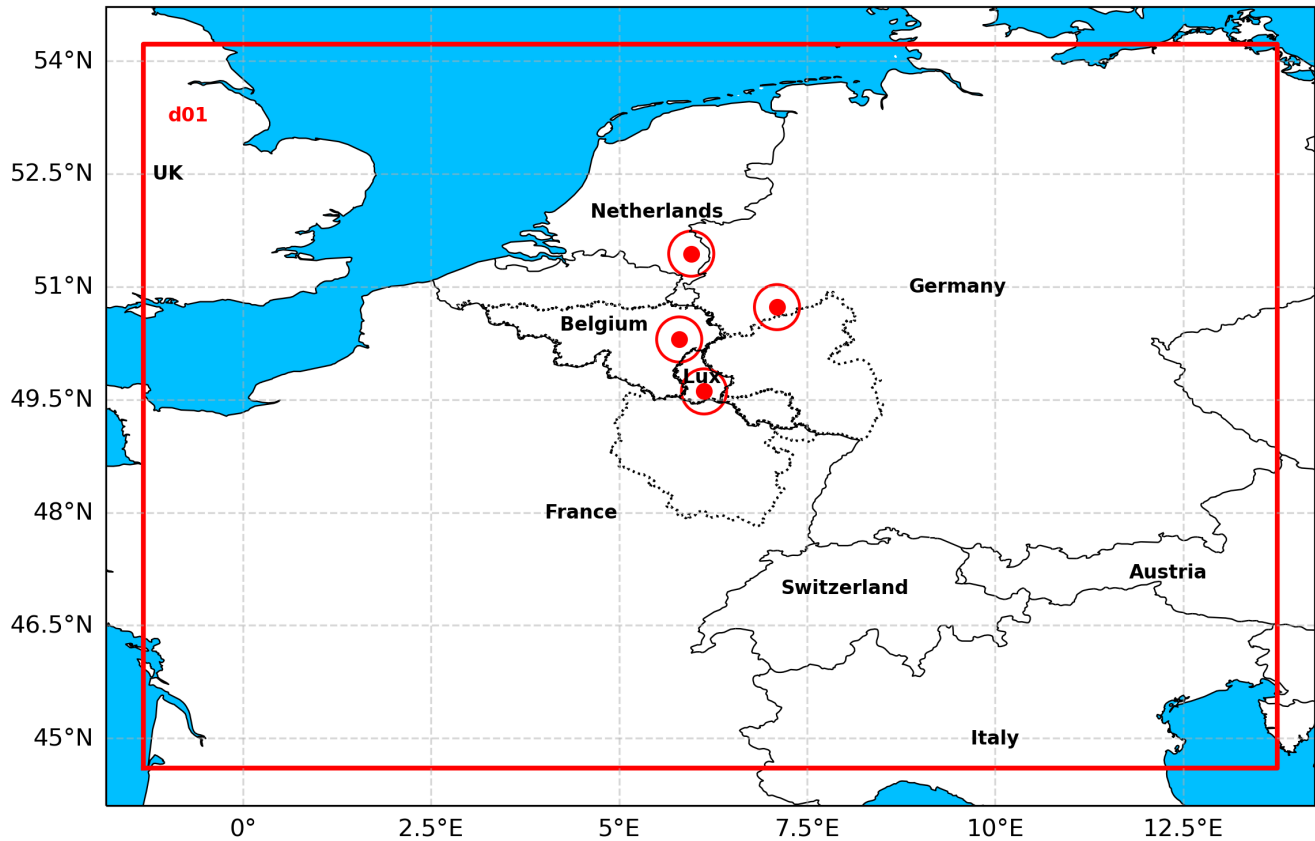


Figure 1. Map highlighting WRF Domain and areas affected by the 2021 European floods in Belgium, Germany, Luxembourg, and the Netherlands, marked with red dots and circles whereas the greater region is highlighted with dotted line

Table 2. The 10 highest rainfall totals from the Belvaux-Obercorn observation series, with return periods for the maximum cumulative rainfall in July 2021 [09.07–15.07], covering both the summer season [April–September] and the full hydrological year [12 months]. Source: LIST, 2021 (Luxembourg Institute of Science and Technology (LIST), 2021).

Summer (6 months)			Year (12 months)		
Year	Rainfall [mm]	Return Period	Year	Rainfall [mm]	Return Period
2021	134.2	>>100 years	1995	191.2	
1962	122.6		1994	164.1	
1977	104.0		1999	163.6	
2017	101.6		1968	150.3	
2000	100.6		2021	134.2	13 years
2016	99.6		1980	125.3	
2002	96.8		1962	122.6	
1958	95.6		2000	121.0	
1984	93.4		1990	120.0	
1986	91.6		1966	117.9	

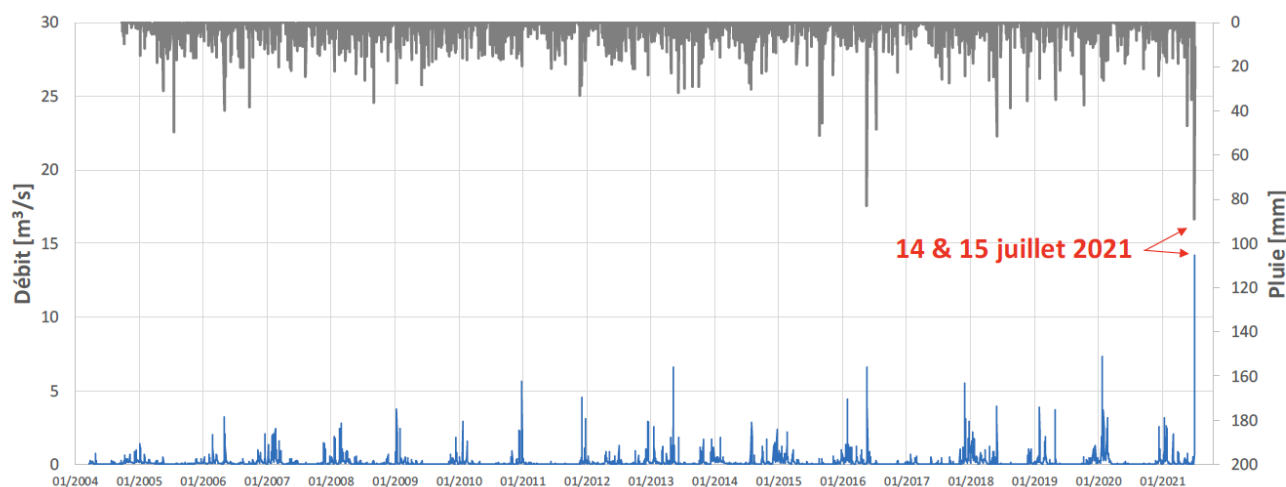


Figure 2. Bibeschbach watershed (Livange) – Time series [2004–2021] of precipitation in Livange (grey bars) and flow rates (blue line). Source: LIST, 2021 (Luxembourg Institute of Science and Technology (LIST), 2021).

Table 1. The 10 highest daily rainfall events from the Belvaux-Obercorn observation series, with return periods for the maximum daily rainfall recorded on July 14, 2021 (covering both the summer season [April–September] and the full hydrological year [12 months]). Source: LIST, 2021 (Luxembourg Institute of Science and Technology (LIST), 2021).

Summer (6-month)			Year (12-month)		
Year	Rainfall [mm]	Return Period	Year	Rainfall [mm]	Return Period
2021	68.1	92 years	1995	72.7	43 years
1976	59.5		2021	68.1	
2008	54.7		2000	66.8	
2015	54.6		1976	59.5	
2016	54.3		1994	58.6	
2013	54.2		1962	57.5	
2002	53.8		2008	54.7	
1959	52.3		2015	54.6	
1972	50.7		2016	54.3	
1956	46.2		2013	54.2	



The Weather Research and Forecasting (WRF) model is a cloud-resolving numerical weather prediction tool capable of simulating convective cells and heavy rainfall events leading to flash floods, as demonstrated in studies over Korea by Hong and Lee (2009). Although GNSS data were not assimilated, their study highlighted the importance of high-resolution modeling and accurate convective parameterization for capturing squall line formation and thunderstorm evolution, laying groundwork for future assimilation studies. The WRF Data Assimilation (WRF-DA) system, including the data assimilation module, incorporates observational data using techniques like 3D-Var to enhance short-term precipitation forecasts. In Italy, Torcasio et al. (2023) demonstrated that assimilating GNSS ZTD significantly improved both precipitable water vapor (PWV) and precipitation forecasts, especially during convective events. The study used a dense GNSS network and found that ZTD assimilation reduced forecast bias and enhanced spatial accuracy of rainfall predictions. Giannaros et al. (2020) assessed GNSS ZTD assimilation during high-impact rainfall events over Greece. Their results showed that ZTD assimilation led to better alignment with observed rainfall intensities and distributions, particularly for convective systems. The study used over 48 GNSS stations and found improvements in both forecast timing and magnitude. Laura Poletti et al. (2019) combined nowcasting techniques with GNSS ZTD assimilation in WRF to improve very short-range hydrological forecasts over northern Italy. Their hybrid approach enhanced rainfall field accuracy within the first 6 hours, which is critical for flash flood prediction. The study emphasized the synergy between radar-based nowcasting and GNSS-enhanced NWP models. In Bulgaria, Vladimirov et al. (2020) applied GNSS ZTD assimilation during a winter cyclone using the WRF-ARW model. The study found that ZTD data improved mesoscale precipitation forecasts, especially in complex terrain, by enhancing the model's representation of moisture fields and frontal dynamics.

Despite this growing body of work, most GNSS ZTD assimilation studies have focused on short, single-event case studies over regions with dense national GNSS networks, and no study to date has systematically quantified the added value of GNSS ZTD assimilation over Luxembourg and the Greater Region. The present study addresses this gap by performing a continuous, month-long 3D-VAR assimilation experiment covering the June–July 2021 flood period, in which conventional observations (CONV), GNSS ZTD, and their combination (CONV + ZTD) are assimilated separately and benchmarked against a no-assimilation control. A distinctive outcome of this work is that, although GNSS ZTD constrains only a comparatively thin, moisture-related slice of the atmospheric state and its direct influence is spatially localised around the station network, its assimilation nonetheless produces a measurable and consistent improvement in the model's ability to *detect* rainfall and to correct near-surface temperature bias, rather than in the raw magnitude of the forecast. In other words, the benefit of assimilation in this region manifests primarily through better event detection and bias reduction rather than through reductions in absolute error. This study is designed to answer the following questions: (i) Does assimilating GNSS ZTD and/or conventional observations measurably improve WRF precipitation and temperature forecasts over Luxembourg and the Greater Region during an extreme flood event? (ii) How do conventional and GNSS ZTD observations compare, and do they play complementary roles for precipitation versus temperature? (iii) Does combining both observation types (CONV + ZTD) yield a more balanced and stable forecast than either source alone? (iv) Given that the spatial footprint of the GNSS moisture signal is small, is its impact on regional-scale precipitation and temperature forecasts still significant when assessed over a full month of cycled assimilation?



1.1 Luxembourg and the Greater Region

The Greater Region features diverse landscapes, including the densely forested Ardennes massif, the rolling hills of the Oesling in northern Luxembourg, and the fertile lowlands of the Gutland in southern Luxembourg. The Ardennes massif has a mean altitude of about 400–500 meters. The Oesling, part of the Ardennes, averages around 450 meters. The Gutland, with gentler hills, has a mean altitude of approximately 200 meters (Lucius, 1948; Muller, 1980; Waterlot et al., 1973). The area's climatic conditions are characterized by a warm oceanic maritime climate with moderate to heavy rainfall throughout the year.

The Greater Region encompasses vital river systems, including the Moselle, Sauer, and Our, which are essential water sources and prone to seasonal flooding due to heavy rainfall. In Luxembourg, these rivers support agriculture and urban areas. In Belgium, the Semois and Ourthe rivers contribute to water supply and face similar flood risks. Germany's Moselle and Sauer rivers sustain local ecosystems and industry, with flooding challenges. In France, the Moselle and Meurthe rivers are critical for water resources, also experiencing periodic floods. Figure 3 shows the Greater Region with rivers and topography.

The climatic conditions prevailing in the Greater Region can be characterized as a warm oceanic maritime climate. This climate is influenced by maritime air masses, resulting in mild temperatures and relatively high levels of precipitation throughout the year. The temperature ranges from mild to moderate, with average annual temperatures typically ranging from 8 to 12 degrees Celsius. Precipitation is evenly distributed throughout the year, with annual rainfall ranging from 700 to 1,200 millimeters. The region experiences moderate to heavy rainfall, which contributes to soil fertility and the growth of lush forests and vegetation (Commission et al., 2018).

1.2 Weather Research and Forecasting (WRF)

The Weather Research and Forecasting (WRF) model is a next-generation mesoscale numerical weather prediction system, developed collaboratively by the National Center for Atmospheric Research (NCAR), the National Centers for Environmental Prediction (NCEP), the National Oceanic and Atmospheric Administration's Forecast Systems Laboratory (NOAA-FSL), and other research institutions (Skamarock et al., 2019)

It comprises two core model frameworks: the Advanced Research WRF (ARW), designed by NCAR using Eulerian mass coordinates for research applications, and the Nonhydrostatic Mesoscale Model (NMM), developed by NCEP for operational forecasting. The WRF model provides high-resolution data with a horizontal resolution ranging from 1 to 12 km and is widely used by meteorologists. WRF provides a versatile platform for research in weather, climate and disciplines in related categories, and plays an important role in practical weather forecasting and risk management. The flow chart for WRF and WRFDA can be seen in Figure 4. Figure 5 shows the interaction of physics parametrization schemes in WRF. Salient features of WRF configuration are shown in Table 4 and Table 3.

A single computational domain with a horizontal grid spacing of 12 km was adopted in this study. This choice reflects a deliberate balance between spatial detail and the computational demands of the experimental design. Because the central objective is to isolate the *added value of data assimilation*, the model was run continuously over a full month in a cycled configuration, and each of the four experiments (No DA, CONV, ZTD, and CONV + ZTD) was repeated over every assimilation



Table 3. WRF physical parameterizations for domain d01

Physics Option	Scheme
Microphysics (mp_physics = 8)	Thompson et al. Scheme (Thompson et al., 2008)
Longwave Radiation (ra_lw_physics = 1)	Rapid Radiative Transfer Model (RRTM) (Mlawer et al., 1997)
Shortwave Radiation (ra_sw_physics = 1)	Dudhia Scheme (Dudhia, 1989)
Surface Layer Physics (sf_sfclay_physics = 1)	Revised MM5 (Jiménez et al., 2012)
Land Surface Model (sf_surface_physics = 2)	Noah Land Surface Model (Tewari et al., 2004)
Planetary Boundary Layer (bl_pbl_physics = 1)	Yonsei University (YSU) Scheme (Hong et al., 2006)
Cumulus Parameterization (cu_physics = 3)	Grell-Freitas GF Scheme (Grell and Freitas, 2014)

Table 4. Spatial parameter of the WRF Model used in this study

Parameter	Description
Domain Location	Luxembourg and the Greater Region
Domain Size / Horizontal Grid Spacing	120 × 120 grid points, 12 km resolution
Vertical Levels	33
Static Data	MODIS Land Use (30") (Friedl and Sulla-Menashe, 2022) Soil Temperature (1°) Orography (1° - 30m) Green Fraction (MODIS) (Didan, 2021)
Meteorological initial/boundary condition	GFS (National Centers for Environmental Prediction (NCEP), 2025)
Output Interval	6 hr

Note: MODIS (Moderate Resolution Imaging Spectroradiometer) is a NASA satellite instrument providing land use and vegetation data for the WRF model. whereas GFS (Global Forecast System) is a global numerical weather prediction model developed by the National Centers for Environmental Prediction (NCEP), providing atmospheric initial and boundary conditions for WRF simulations.

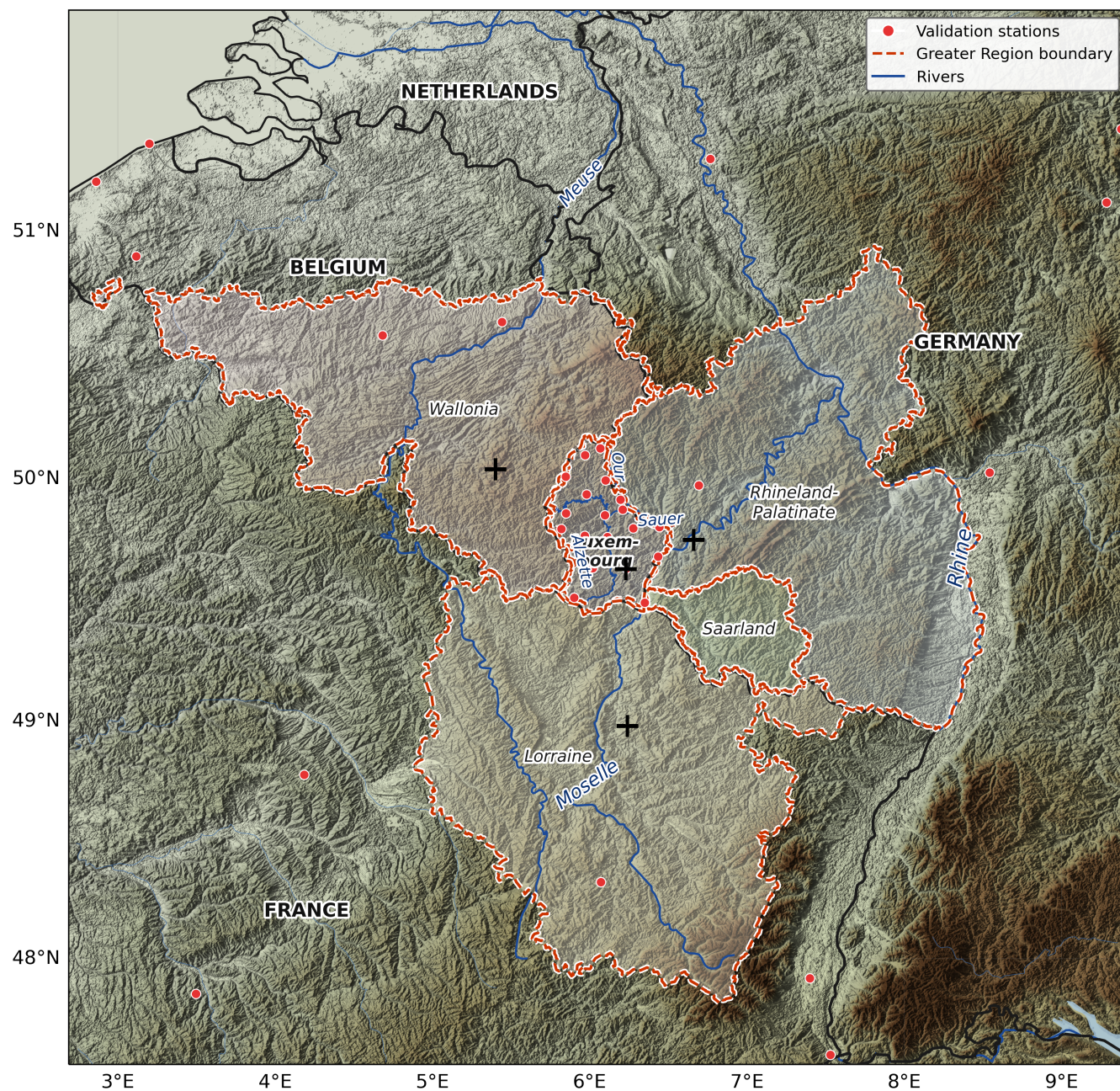


Figure 3. Topographic map of the study area showing major rivers (Rhine, Moselle, Alzette, Sûre, and Our), the greater region in dotted line and the locations of meteorological stations used for validation. The plus (+) signs represent the stations whose time series are plotted in Figures 9, 8, and 10 (WALF in Luxembourg, ARLO in Belgium, DILL in Germany, and THNV in France).

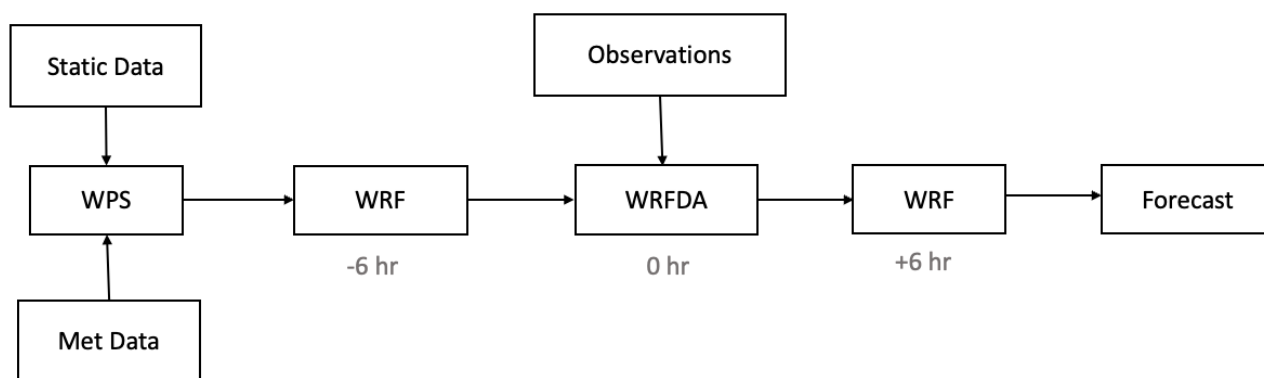


Figure 4. WRF Flow Chart

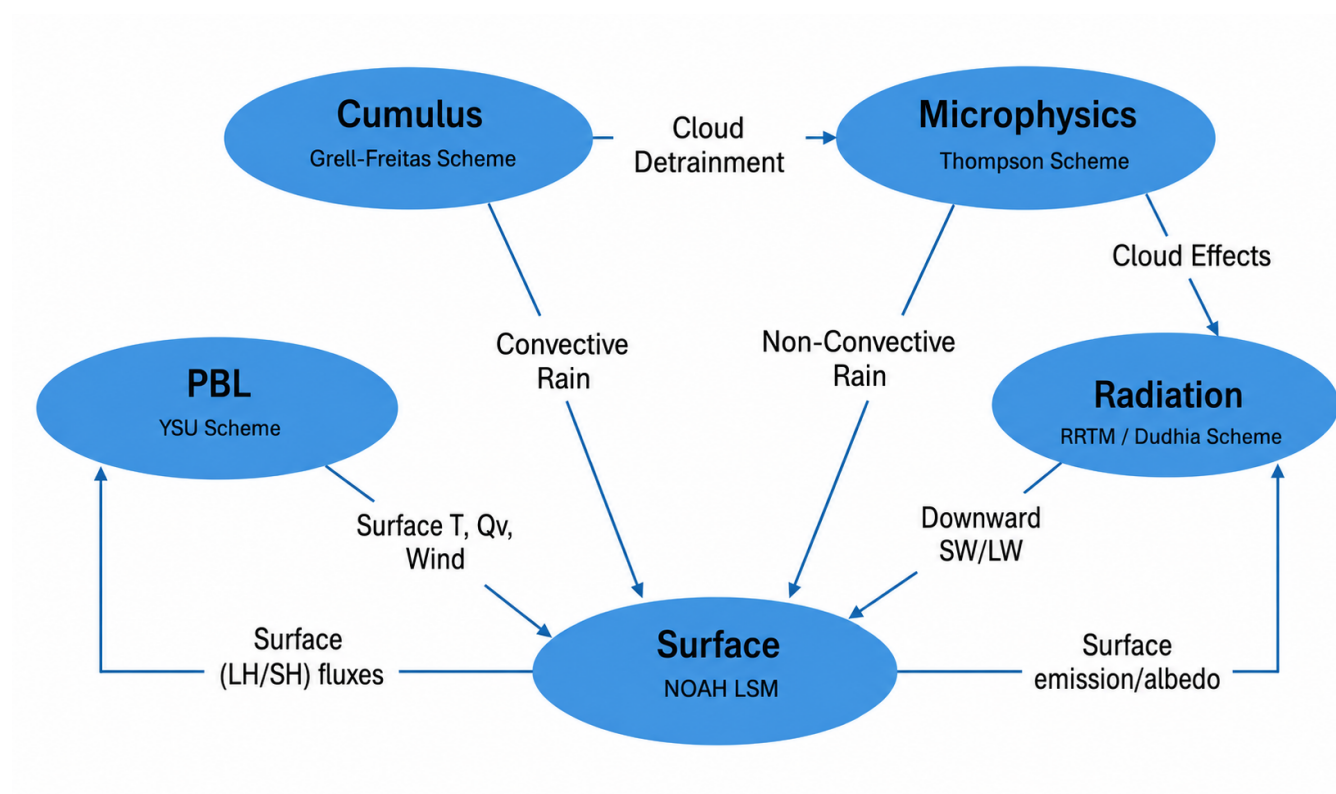


Figure 5. Interaction Between WRF selected Physics Parameterization Schemes



cycle. Performing month-long, four-fold cycled assimilation at convection-permitting resolution (≤ 4 km) would have been computationally prohibitive, whereas the 12 km configuration makes the full experimental matrix tractable while still resolving the synoptic and meso- β scale features that governed the July 2021 event. The domain is also large enough to encompass the entire Greater Region together with the surrounding GNSS network of 225 stations whose ZTD observations are assimilated, ensuring that the moisture information propagates within, rather than across, the lateral boundaries. Furthermore, the 12 km grid is consistent with the 0.5° resolution of the GFS initial and boundary conditions and with the Grell–Freitas cumulus parameterization employed here, which is appropriate for grid spacings at which convection is not explicitly resolved. As the analysis focuses on the *relative* improvement of each assimilation experiment with respect to a common baseline rather than on absolute convective-scale rainfall reproduction, the 12 km resolution is well suited to the aims of this work.

1.2.1 WRFDA Data Assimilation

In this study, the three-dimensional variational (3D-VAR) assimilation mode in the WRF Data Assimilation (WRFDA) system was employed for assimilating observational data. The core concept of 3D-VAR is to minimize a quadratic cost function, which quantifies the differences between the analysis field and both the observation and background fields. This objective function is mathematically expressed as Eq. (1) (Lorenc, 2003; Barker et al., 2004).

$$J(x) = (x - x_b)^T B^{-1} (x - x_b) + (H(x) - y)^T O^{-1} (H(x) - y) \quad (1)$$

where:

$J(x)$ is the cost function to be minimized in the 3D-Var data assimilation framework. It quantifies the total discrepancy between the analysis x and both the background field and the observations, x_b denotes the background field, B is the background error covariance matrix, H is the observation operator, which projects model variables into the observation space, y represents the observations, O is the observation error covariance matrix.

Four experiments were conducted over the full study period (20 June–20 July 2021) using an identical model configuration and differing only in the observations assimilated: (i) a control run with no data assimilation (No DA), initialised and driven solely by GFS; (ii) assimilation of conventional observations only (CONV); (iii) assimilation of GNSS ZTD only (ZTD); and (iv) assimilation of both observation types together (CONV + ZTD). The assimilation was carried out following a 6-hour rapid-update cycle (RUC) strategy. In this approach, observations were assimilated at the four synoptic times 00:00, 06:00, 12:00, and 18:00 UTC each day; at every cycle, WRFDA combined the observations with a short-range WRF background forecast to produce an updated analysis, which then served as the initial condition for the subsequent 6-hour forecast. Lateral boundary conditions were updated from GFS at each cycle. In this way the assimilation increments were propagated forward continuously throughout the month, allowing the model to progressively integrate the information content of the observations rather than treating each analysis in isolation. The No DA control was cycled in the same manner but without ingesting any observations, so that all differences between the experiments can be attributed to data assimilation alone.



The CV3 background error covariance option was used in WRFDA, which incorporates climatological background error statistics derived from a global NCEP/NCAR reanalysis dataset (Chen et al., 2016). This configuration represents a precomputed, static estimate of background error covariances based on long-term global forecasts and is commonly provided by NOAA as part of the operational WRFDA package. CV3 was selected deliberately because it is domain-independent and does not require the generation of a case-specific background error matrix (e.g. via the NMC method or an ensemble, as needed for the flow-dependent CV5 option). This provides a controlled, reproducible, and widely used baseline against which the impact of each observation type can be isolated and fairly compared across the four experiments, without introducing an additional degree of freedom from a locally tuned B matrix. It is nevertheless acknowledged that CV3, being climatological and homogeneous, is not the ideal choice for a precipitation-focused study, as it cannot represent the flow-dependent, anisotropic error structures associated with convective moisture fields. The regionally tuned CV5 option is expected to be more appropriate in this respect and is identified as a priority for future work (Section 4).

1.2.2 Data Extraction and Processing

To facilitate the extraction of meteorological variables from WRF model output, a custom Python-based automation script was developed. The workflow utilized the Geospatial Data Abstraction Library (GDAL) (GDAL/OGR contributors, 2025) to access NetCDF files and retrieve key atmospheric parameters, including temperature, precipitation, relative humidity, and Zenith Total Delay (ZTD). A systematic grid interpolation method was integrated into the code to match WRF model grid points with the geographic coordinates of selected observation stations.

For horizontal interpolation, the SciPy (Virtanen et al., 2020) Griddata function was used to estimate variable values at station coordinates, ensuring spatial consistency between WRF outputs and observational sites. The interpolation incorporated Inverse Distance Weighting (IDW) and linear methods. For vertical interpolation, when station heights differed from WRF terrain heights, values were estimated using layer-wise interpolation if the station was between vertical model layers, and extrapolation if below the lowest model level.

1.3 Data

The National Center for Environmental Prediction (NCEP) Global Forecast System (GFS) analysis and forecast data were used as initial and boundary conditions. The GFS dataset had a spatial resolution of $0.5^\circ \times 0.5^\circ$ and a temporal resolution of 6 hours. These data are stored in the Research Data Archive (RDA) at UCAR <https://rda.ucar.edu/>.

Conventional observational data, used for assimilation, including Surface Synoptic Observations (SYNOP), Radiosonde Temperature Profiles (TEMP), and Tropospheric Airborne Meteorological Data Reporting (TAMDAR) (Daniels et al., 2006), for the month of June and July 2021 were obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 reanalysis dataset (Hersbach et al., 2020). Meanwhile, Zenith Total Delay (ZTD) data was acquired from the Nevada Geodetic Laboratory (NGL) (Blewitt et al., 2018).



The precipitation data used for comparison in this study was obtained from the NASA Earthdata Global Precipitation Measurement (GPM) Integrated Multi-satellite Retrievals for GPM (IMERG) Final Run. This product delivers gauge-calibrated precipitation estimates with a spatial resolution of $0.1^\circ \times 0.1^\circ$ and a temporal resolution of 30 minutes (Huffman et al., 2023).

Radar-based quantitative precipitation estimates from the RADFLOOD21 product (Goudenhoofdt et al., 2023) were also utilized for validation purposes. This dataset provides precipitation fields with high spatial (1 km) and temporal (5-minute and hourly) resolution, derived from carefully processed weather radar measurements merged with rain gauge observations. The data, provided in HDF5 format, was processed to extract precipitation values over a 6-hour period, which were subsequently used for model validation.

The measured meteorological parameters of observed stations were collected from the AgriMeteo, SYNOP data from June 20 to July 20, 2021, outside Luxembourg but within our study area, were obtained from the NOAA Integrated Surface Database (ISD) (NOAA National Centers for Environmental Information, 2001)(NOAA National Centers for Environmental Information, 2001). The data have a temporal resolution of 1 hour. The locations of the observed stations used for validation, with elevation data, are shown in Figure 3. It is important to emphasise that these surface stations used for validation (the AgriMeteo network within Luxembourg and the NOAA ISD stations across the remainder of the study area) were *not* assimilated into the model. The conventional observations ingested by WRFDA were obtained from a separate source (ECMWF, see below), whereas the validation stations were deliberately withheld from the assimilation. They therefore constitute a fully independent set of observations against which the forecasts are verified, so that the reported performance is not artificially inflated by evaluating the model against data that had already been assimilated. A total of approximately 1,350 SYNOP stations, 2,303 TAMDAR points, 225 GNSS stations, and 20 TEMP stations were incorporated into the assimilation process. It should be noted that these numbers are subject to temporal variability, particularly for TEMP and TAMDAR datasets, as the availability of radiosonde launches and aircraft-based observations fluctuates over time.

1.3.1 Pre-Processing

Conventional data from ECMWF was provided in BUFR format, which was then converted to LITTLE_R format. LITTLE_R is an ASCII-based observation file format designed as an intermediate format to enable WRFDA to assimilate a wide range of observation types in a standardized manner. It is a report-based format and is also the format used by OBSPROC which is a WRFDA utility. The OBSPROC utility was employed to filter out unnecessary data beyond the model domain. Stations used for assimilation are shown in Figure 6.

To extract and process the NGL Zenith Total Delay (ZTD) data, compressed ZIP archives containing trop.gz files were systematically unpacked and parsed. These files contain yearly data with a temporal resolution of 5 minutes. Data corresponding to June and July 2021 were filtered at a 6-hour interval based on file metadata, and ZTD values were extracted and converted to meters from millimeters. The flow chart for the observed data pre-processing is shown in Figure 7.

The NGL ZTD estimates are derived from a precise-point-positioning (PPP) processing of the GNSS observations using the GipsyX software, and each estimate is accompanied by a formal uncertainty. Over the study period and network, this formal uncertainty was at the sub-centimetre level, with a median of approximately 1.7 mm and values ranging from about

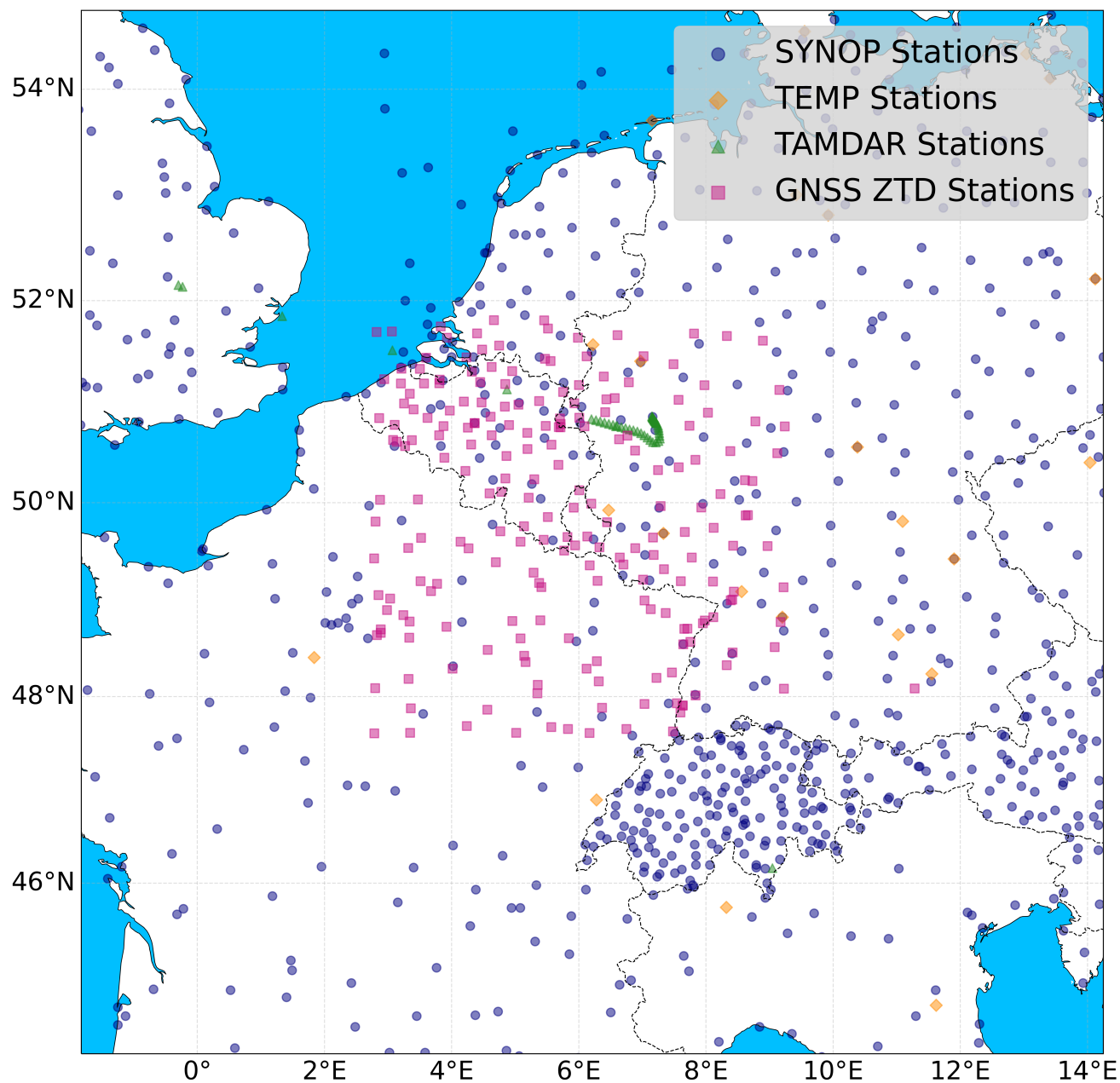


Figure 6. Stations locations for assimilation



1.3 to 4.3 mm, confirming the high quality and consistency of the ZTD observations used for assimilation. Individual epochs whose reported uncertainty was anomalously large were discarded during pre-processing. In the WRFDA cost function, a uniform observation error of 8 mm (0.8 cm) was assigned to all ZTD observations. This value is deliberately larger than the formal GNSS processing uncertainty because the observation error in data assimilation must additionally account for representativeness error and observation-operator (forward-model) error, including the mapping of the slant/zenith delay onto the model column and the sensitivity of the delay to the model humidity, temperature, and station-height representation. The chosen value of 8 mm lies within the accuracy range recommended for ZTD products used in numerical weather prediction under the E-GVAP standards (optimal 5 mm, target 10 mm) and is comparable to the ~ 7.6 mm ZTD accuracy reported for a similar WRFDA ZTD assimilation study over Greece (Giannaros et al., 2020).

To illustrate the temporal variability during the 2021 European floods, Figure 9 shows surface pressure, Figure 8 displays temperature, and Figure 10 presents zenith total delay (ZTD) from June 20 to July 20, 2021 (days 171–201). Due to space constraints, we plot one station per country: Luxembourg (WALF/6590), Belgium (ARLO/6476), Germany (DILL/10609), and France (THNV/7093). These reveal coordinated drops in pressure and rises in ZTD around mid-July, aligning with the flood event.

2 Accuracy Assessment Metrics

To evaluate the accuracy of numerical predictions, four statistical error metrics were employed: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Symmetric Mean Absolute Percentage Error (SMAPE), and Bias. Additionally, Probability of Detection (POD) and False Alarm Ratio (FAR) (Wilks, 2006) were used to assess precipitation detection performance. These metrics provide a quantitative measure of the deviation between model predictions and observed values, defined as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - y_i| \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2} \quad (3)$$

$$SMAPE = \frac{100\%}{n} \sum_{t=1}^n \frac{|\hat{y}_t - y_t|}{(|\hat{y}_t| + |y_t|)/2} \quad (4)$$

$$Bias = \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i) \quad (5)$$

$$POD = \frac{\text{hits}}{\text{hits} + \text{misses}} \quad (6)$$

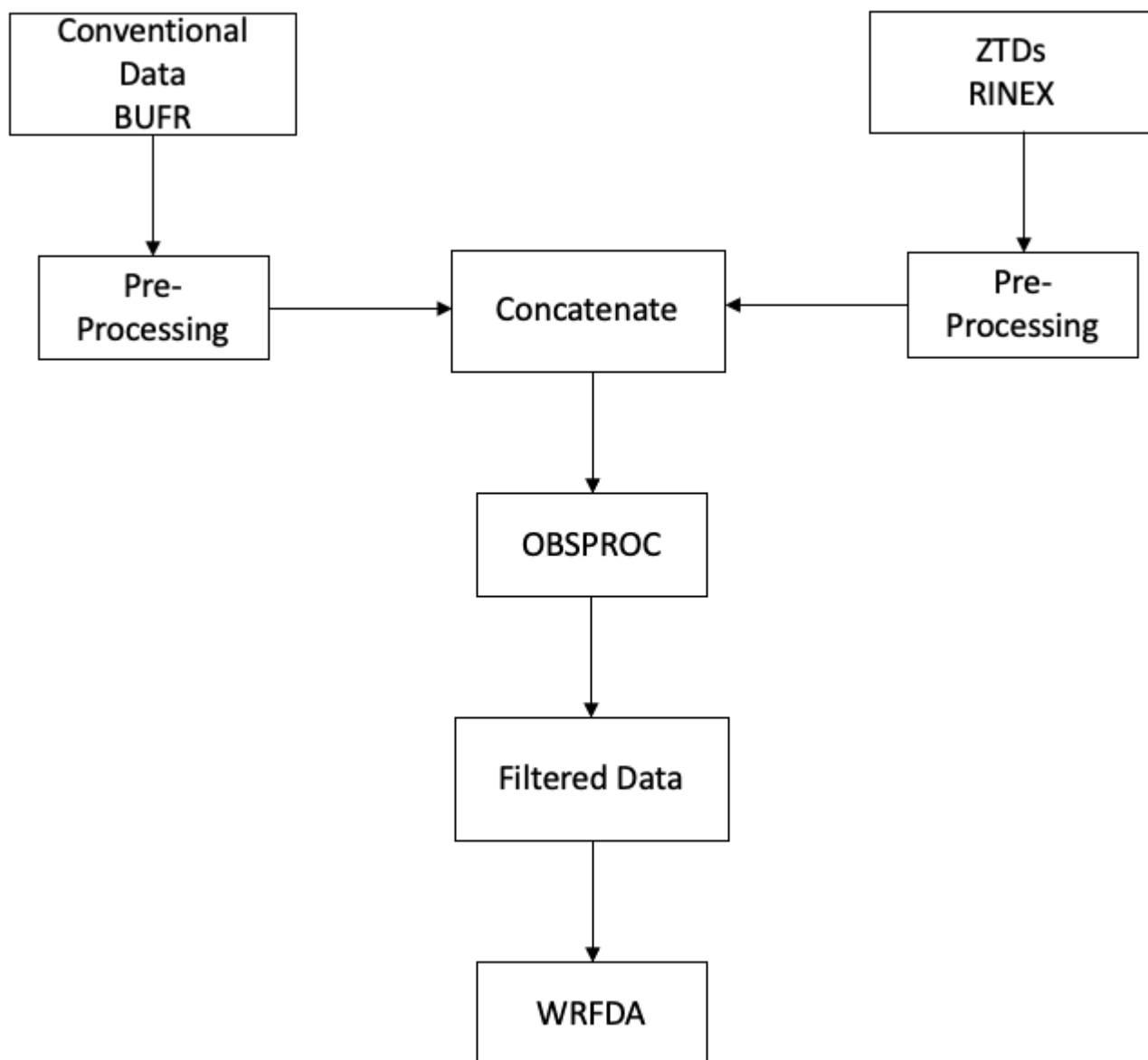


Figure 7. Pre-processing flow chart showing the integration of ECMWF BUFR and GNSS ZTD data, followed by filtering via OBSPROC for WRFDA assimilation.

$$FAR = \frac{\text{false alarms}}{\text{hits} + \text{false alarms}} \quad (7)$$

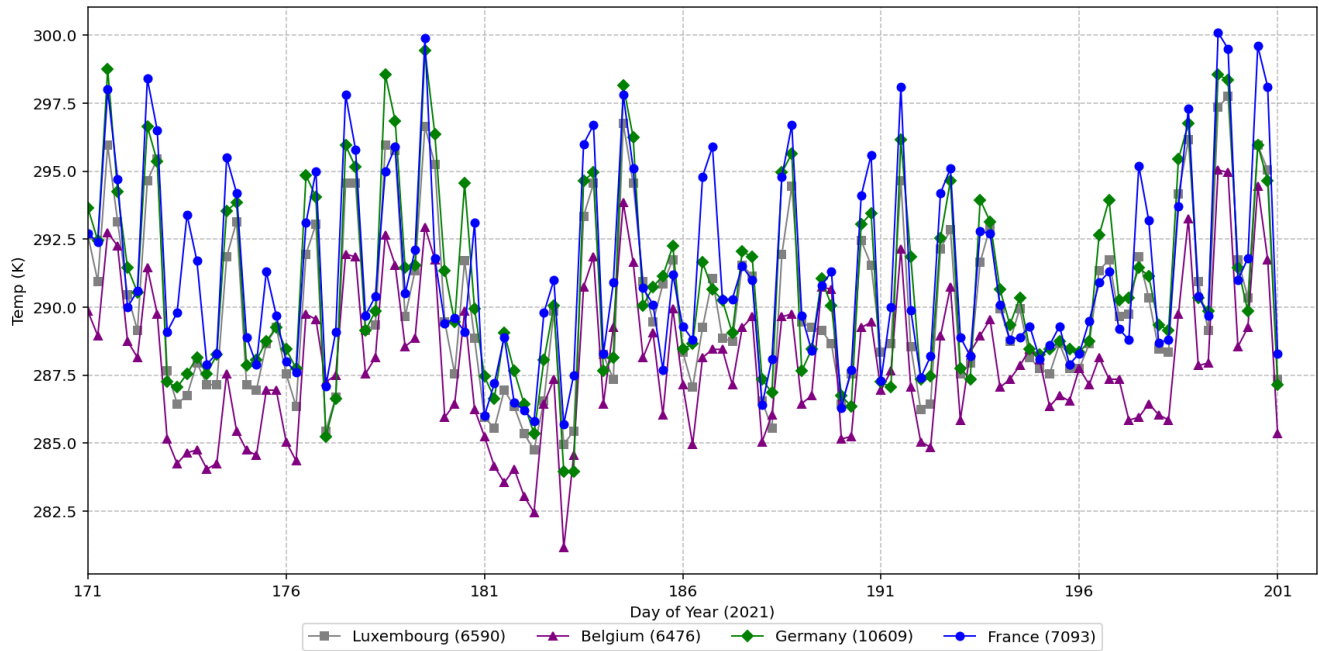


Figure 8. Time series of near-surface temperature (K) at representative stations (one per country) from 20 June to 20 July 2021, capturing thermal dynamics preceding the flood event. Stations temperatures are shown without altitude correction.

where n is the total number of samples, $\hat{y}_i$ denotes the model-predicted value, and y_i represents the observed value. For POD and FAR, a precipitation threshold of 0.1 mm is used to define "hits" (cases where both observed and predicted precipitation exceed the threshold), "misses" (observed events above the threshold not predicted), and "false alarms" (predicted events above the threshold not observed).

To ensure that the results are statistically robust and not driven by a single event, all of the metrics above were computed over the entire one-month study period (20 June–20 July 2021) rather than for isolated dates. Each metric aggregates every 6-hourly forecast cycle across all independent validation stations within the study area, so that n comprises several thousand matched model–observation pairs for both precipitation and temperature. This large sample, spanning the full range of quiescent and extreme-precipitation conditions during the period, means that the reported differences between the experiments reflect the sustained, month-long behaviour of the assimilation rather than event-specific fluctuations, and are therefore representative of the model's general performance over the region.

In addition to this monthly aggregation, the statistical significance of the Before-DA/After-DA differences was formally assessed at the level of the individual validation station. For each experiment (CONV, ZTD, and CONV + ZTD), the station-wise, month-integrated metric (Bias, MAE, RMSE, SMAPE, POD, or FAR) After DA was paired with the corresponding value Before DA at the same station ($n = 33$ independent stations), and the paired differences were tested with the non-parametric Wilcoxon signed-rank test, corroborated by a paired t -test. This station-level design tests whether the direction of change in-

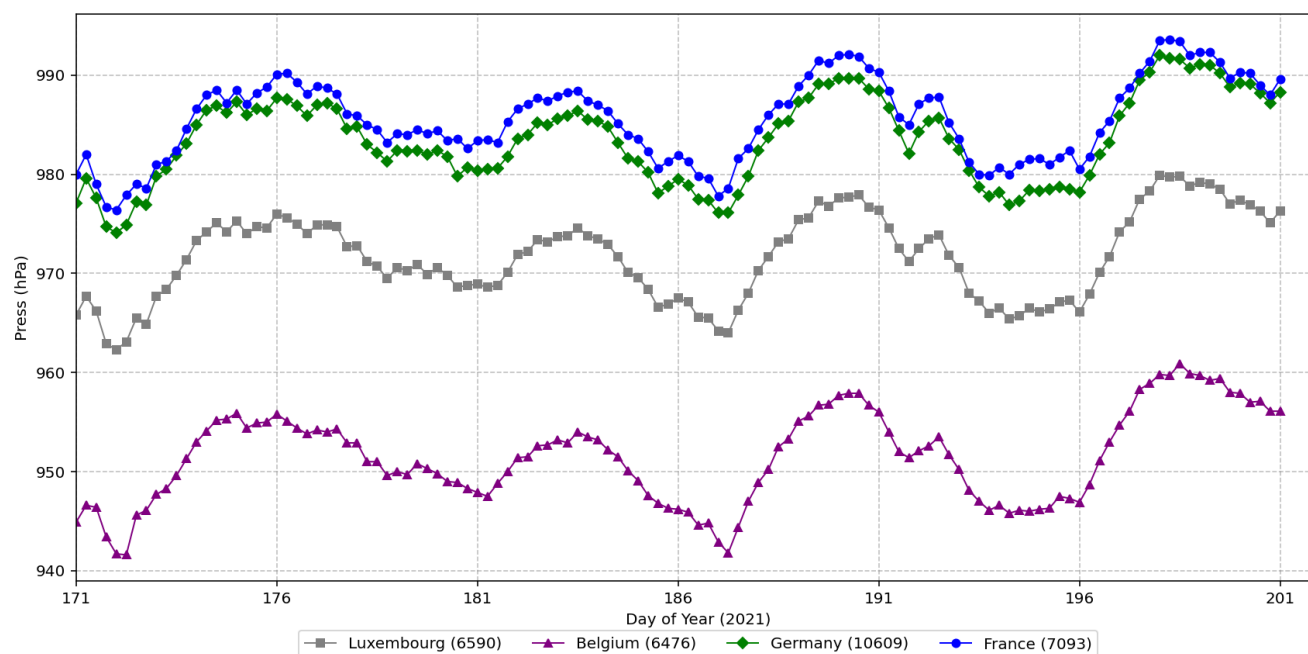


Figure 9. Time series of surface pressure (hPa) at representative stations (one per country) from 20 June to 20 July 2021, highlighting regional atmospheric variability preceding the flood event. Pressure values are shown without altitude correction.

duced by assimilation is consistent across the validation network, independently of the pooled-sample test described above. The improvements in Bias, POD, and FAR were statistically significant for all three DA experiments ($p < 0.001$, Wilcoxon signed-rank, $n = 33$), confirming that the detection and bias-correction gains reported below are systematic across stations rather than the result of a few strongly influenced sites. By contrast, the changes in the absolute-error metrics for precipitation (RMSE, MAE, SMAPE) were frequently not statistically significant (e.g. RMSE: $p = 0.62$ for ZTD and $p = 0.96$ for CONV + ZTD), whereas the corresponding temperature metrics were significant for all experiments ($p < 0.02$). This station-level test therefore provides independent statistical support for the central finding of this study: that data assimilation yields a robust, network-wide improvement in precipitation detection and bias, while its effect on precipitation error magnitude is not statistically distinguishable from no change.

3 Results and Discussions

To systematically evaluate the model performance, the results are structured in a comparative framework. First, the model outputs are compared against RADAR observations to assess spatial and temporal consistency. This is followed by a comparison between the model and GPM IMERG satellite estimates. Finally, all datasets, including ground-based observations, are used to perform a comprehensive verification. Statistical metrics are employed to quantify the accuracy and reliability of the model.

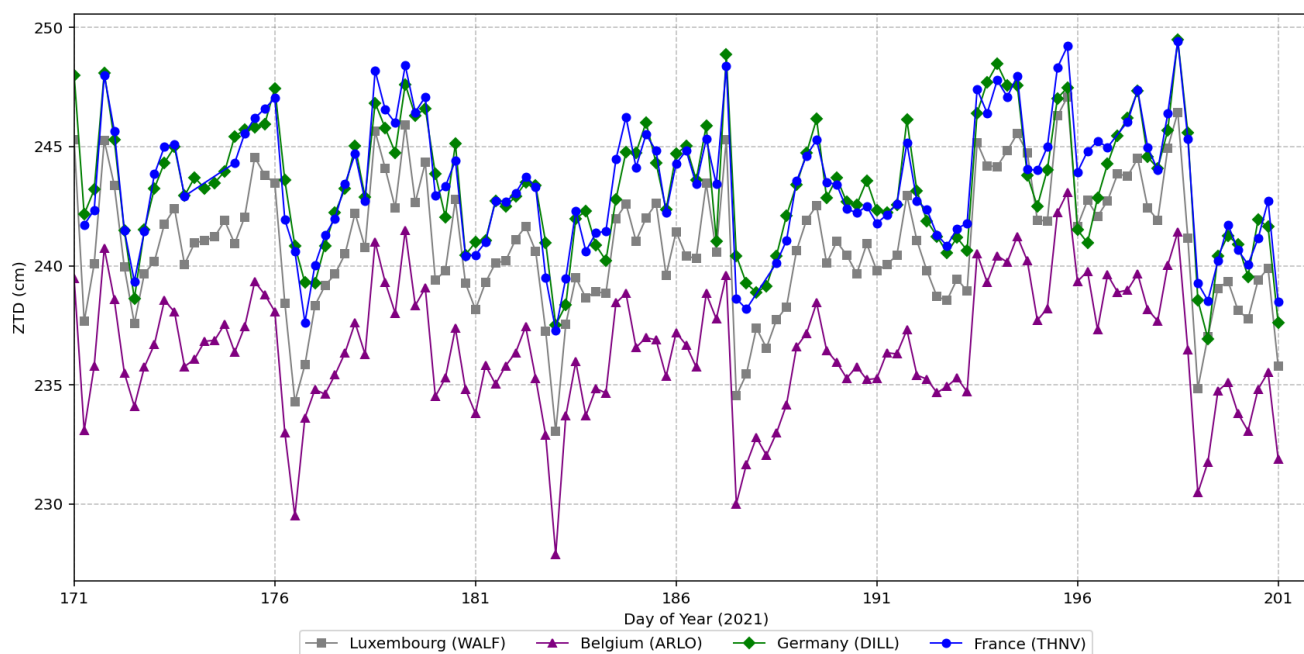


Figure 10. Time series of Zenith Total Delay (ZTD, cm) at GNSS stations (one per country) from 20 June to 20 July 2021, indicating atmospheric moisture variations preceding the 2021 European floods. ZTD values are shown without altitude correction.

3.1 Rainfall forecast results

To analyze the rainfall patterns and distribution in the study area, as well as the impact of assimilating different data types (conventional and ZTD data) on WRF model rainfall forecasts, we first constructed a model using only GFS data (Before DA).

280 We then incorporated conventional and NGL ZTD data through data assimilation (After DA). The model was run for a one-month period from June 20 to July 20, 2021. Rainfall data from RADAR, NASA GPM IMERG and Administration des services techniques de l'agriculture (ASTA) stations were used as a control group, while RADAR and NASA GPM IMERG data served exclusively for visual comparative analysis. Due to space constraints, instead of presenting the full monthly rainfall distribution, we illustrate a representative 6-hourly rainfall pattern for a single day (July 14-15, 2021) in the study area, comparing the model

285 forecasts before and after data assimilation which are shown in Figures 11 and 12. This date was selected due to the intensity and spatial extent of the precipitation event, which marked a critical phase of the 2021 flood episode.

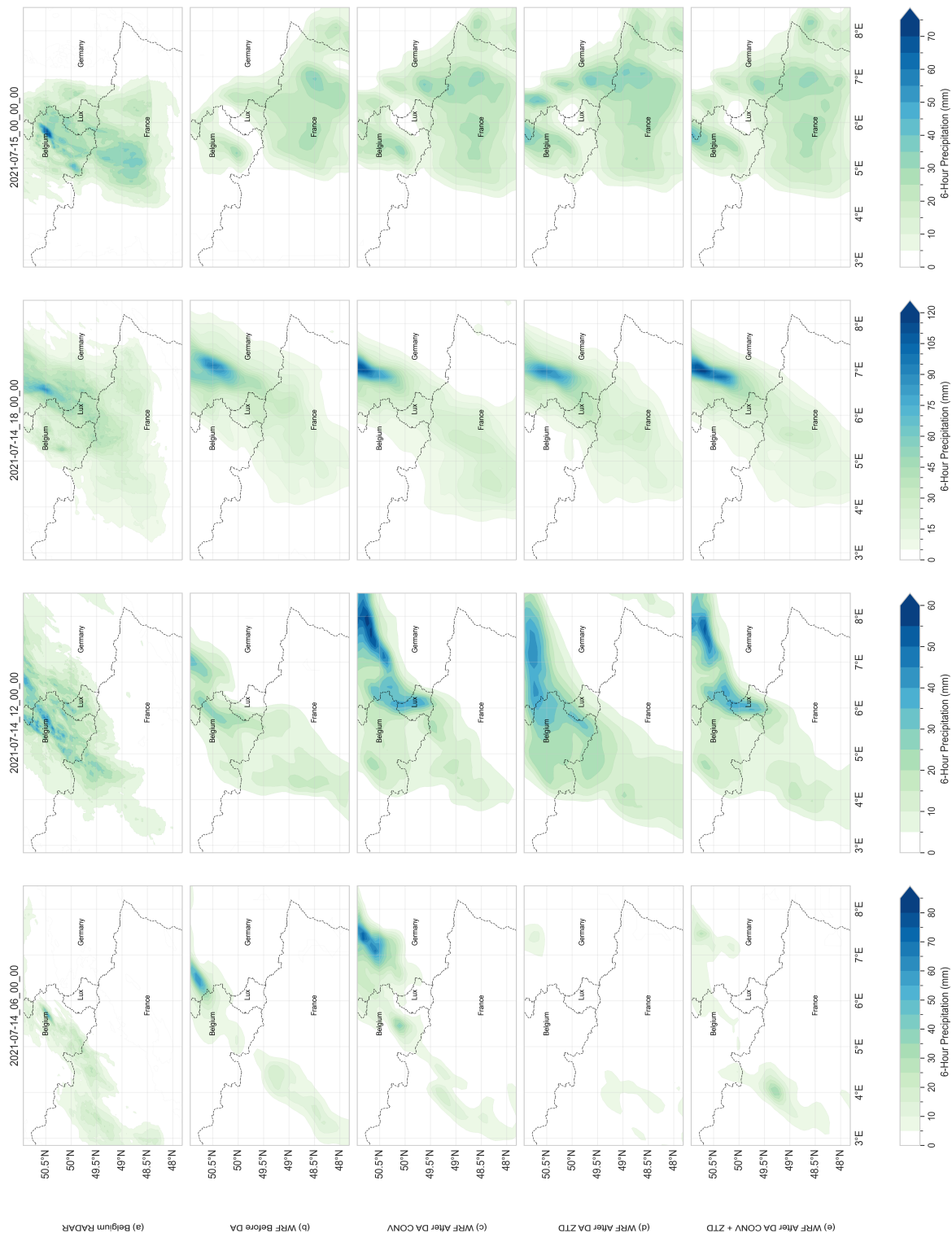


Figure 11. Spatial distribution of 6-hour accumulated precipitation (mm) over the Greater Region during July 14–15, 2021, at indicated UTC times. Panels: (a) Radar observations; (b) model simulation before data assimilation (WRF before DA); (c) WRF model simulation after DA with conventional observations (WRF-After DA CONV); (d) model simulation after DA with ZTD only (WRF-After DA ZTD) (e) model simulation after DA with conventional plus ZTD (WRF-After DA CONV + ZTD). The color scale maximum is set to the maximum value observed in the radar data, applied uniformly to all panels to facilitate direct comparison. This common practice ensures consistency in visualizing potential overestimation or underestimations in the model simulations relative to radar observations.



Figure 11 demonstrates that the model effectively captures the spatial and temporal evolution of rainfall over the Greater Region during July 14–15, 2021, compared to radar observations. The model before DA output (b) shows more concentrated heavy rainfall in Belgium and Germany, with intensities exceeding radar estimates, indicated by darker blue shades suggesting over 50 mm in 6 hours. After DA with conventional observations (WRF After DA CONV, c), rainfall intensity decreases and disperses, aligning better with radar patterns (a) that show gradual intensification from scattered rain at 06:00 to broader coverage by 00:00 on the 15th. With conventional plus ZTD assimilation (WRF After DA CONV+ZTD, e), the model further refines distribution, reducing overestimates and matching radar's eastward expansion by 18:00. Radar data (a) indicate heaviest rain (up to ~80 mm) starting in the north at 06:00 and spreading eastward. WRF-Before DA (b) overestimates with peaks over 80 mm in the northeast from 12:00. WRF After DA CONV (c) and WRF After DA CONV+ZTD (e) lower peaks (>60 mm) while improving spread across France and Luxembourg. Overall, DA enhances model agreement with radar estimates.

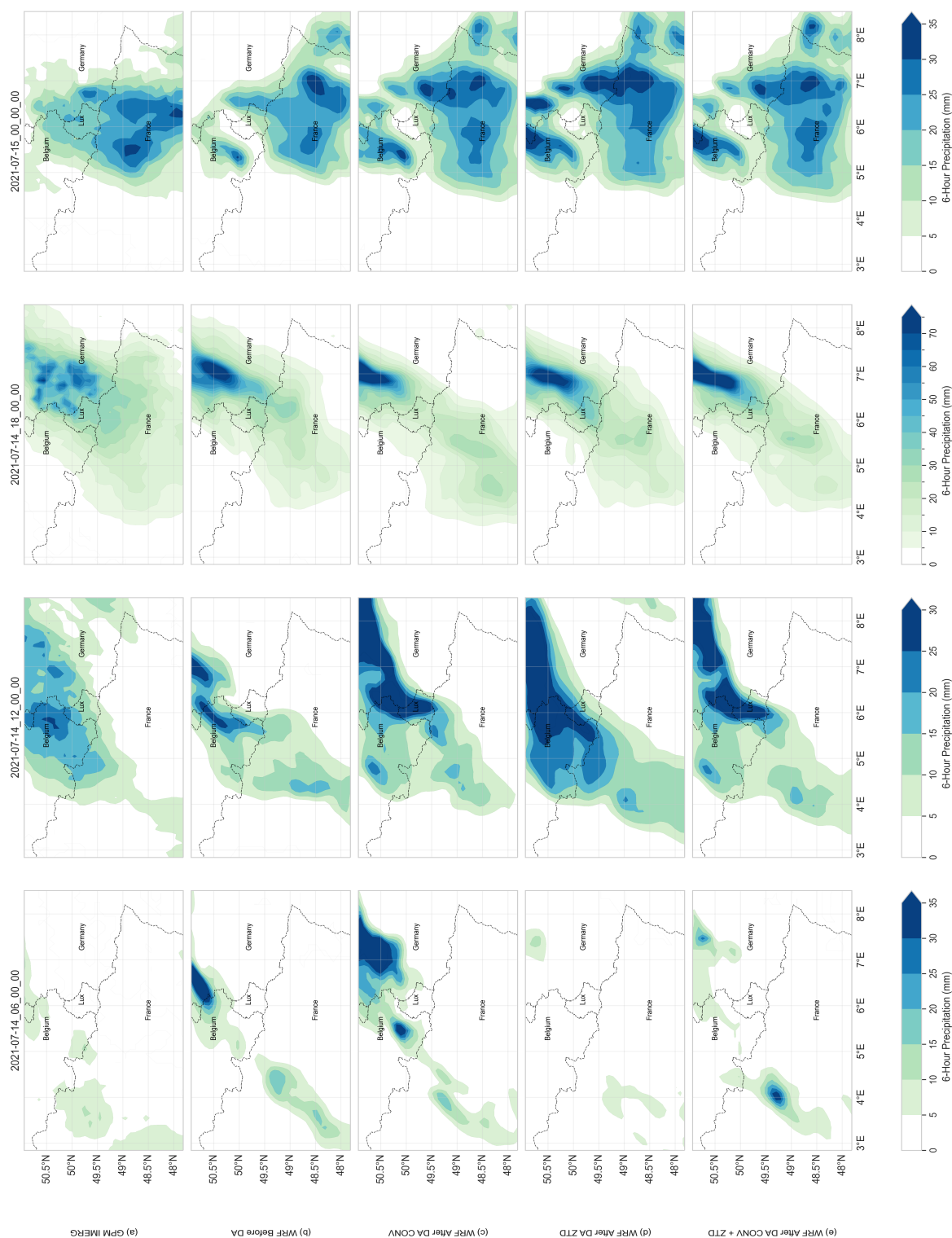


Figure 12. Spatial distribution of 6-hour accumulated precipitation (mm) over the Greater Region during July 14–15, 2021, at indicated UTC times (00:00, 06:00, 12:00, 18:00). Panels: (a) GPM IMERG satellite estimates; (b) model simulation before data assimilation (WRF before DA); (c) WRF model simulation after DA with conventional observations (WRF-After DA CONV); (d) model simulation after DA with ZTD only (WRF-After DA ZTD); (e) model simulation after DA with conventional plus ZTD (WRF-After DA CONV + ZTD). The color scale maximum varies per time step (e.g., 35 mm for 00:00), applied uniformly across panels to facilitate direct comparison. This practice ensures consistency in visualizing potential overestimation or underestimation in the model simulations relative to GPM observations.



Figure 12 demonstrates that the model output effectively captures the spatial and temporal evolution of rainfall over Greater Region during July 14–15, 2021. Before data assimilation (DA), the model output (b) shows more concentrated areas of heavy rain in Belgium and Germany across time steps, often exceeding satellite observations with darker blue intensities suggesting over 35mm in 6 hours. After DA (c), the rainfall is less intense and more dispersed, better aligning with the GPM IMERG patterns (a) that depict gradual intensification from scattered light rain at 06:00 to widespread heavy coverage by 00:00 on the 15th. In the GPM IMERG row (a), heaviest rain (up to ~30 mm) starts small in the north at 06:00 and expands eastward by 18:00. In the Before DA run (b), heavy rain appears tighter and stronger (over 35 mm) in the northeast from 12:00 onward. After DA (c), the model reduces northern overestimates but retains some peaks (>30 mm) while improving spread in France and Luxembourg. Overall, data assimilation enhances model agreement with satellite estimates in distribution and intensity progression.

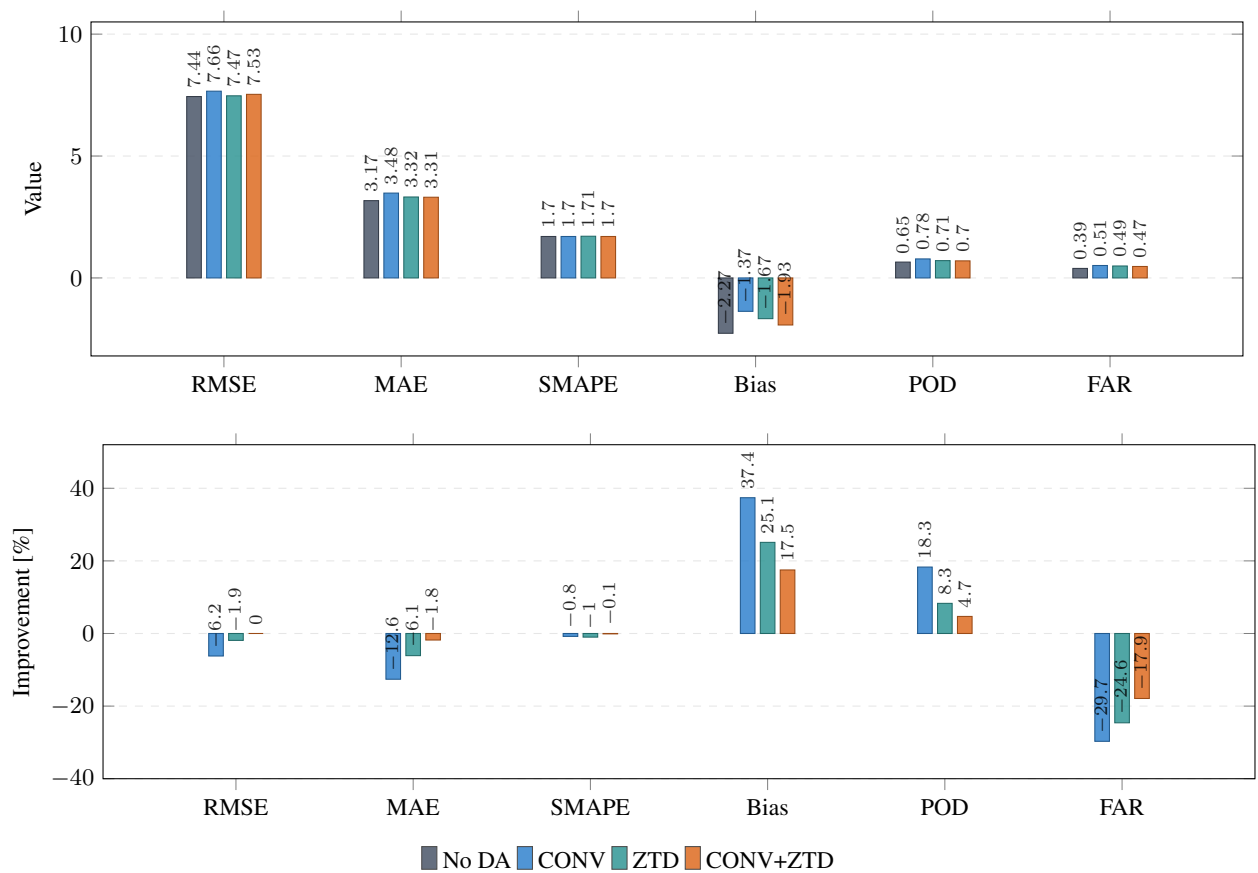


Figure 13. Precipitation metrics comparison: (top) overall actual metrics across case studies and (bottom) percentage improvement relative to the No DA baseline.

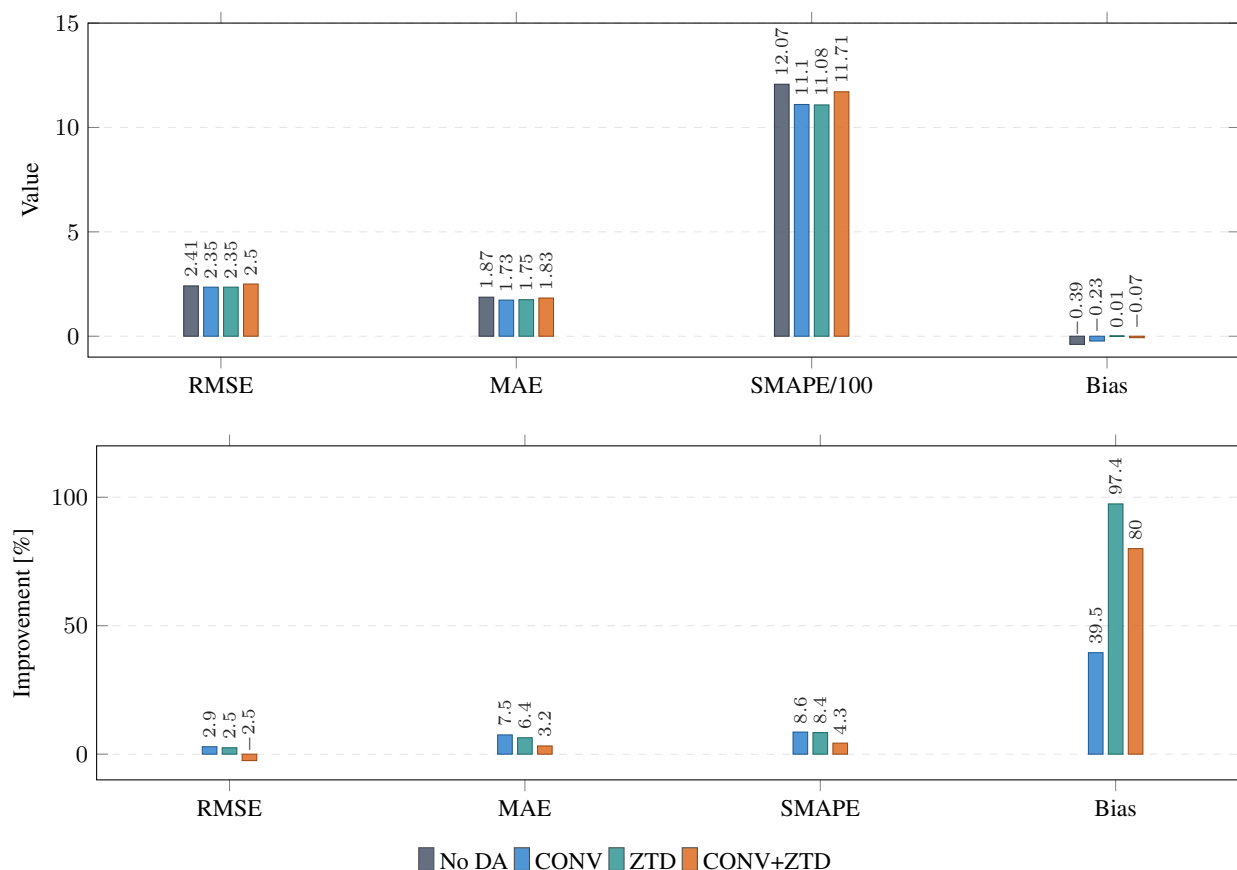


Figure 14. Temperature metrics comparison: (top) overall actual metrics across case studies and (bottom) percentage improvement relative to the No DA baseline.

Figures 13 and 14 summarise the quantitative performance of the four experiments for precipitation and temperature, respectively, with each metric aggregated over the entire study period and all independent validation stations. The main features of these results are discussed below.

It should be emphasised that the quantitative statistical metrics reported here were computed exclusively against the independent surface-station observations that were withheld from the assimilation; the radar and GPM IMERG datasets were used only for the visual and spatial comparison shown in Figures 11 and 12 and did not enter the statistical evaluation. The quantitative analysis revealed that DA improved the categorical skill of the precipitation forecasts. Specifically, assimilation of conventional data (CONV) yielded the highest Probability of Detection ($POD = 0.78$), improving hit rates by 18.3% compared to the No DA baseline, albeit with a higher False Alarm Ratio ($FAR = 0.51$). GNSS ZTD-only assimilation offered a more balanced behaviour ($POD = 0.71$, $FAR = 0.49$), while the combined CONV + ZTD configuration achieved a moderate POD gain (4.7%) and reduced bias by 17.5%. These bias, POD, and FAR improvements are statistically significant across the validation network



for all three experiments (paired Wilcoxon signed-rank test across $n = 33$ stations, $p < 0.001$; Sect. 2), whereas the concurrent changes in RMSE, MAE, and SMAPE are, in most cases, not statistically distinguishable from zero, confirming that the benefit of assimilation lies in categorical detection and bias correction rather than in absolute-error reduction.

For temperature forecasts, the CONV experiment achieved the lowest RMSE (2.35°C) and MAE (1.73°C), outperforming No DA (RMSE = 2.41°C , MAE = 1.87°C), with ZTD-only assimilation performing comparably (RMSE = 2.35°C , MAE = 1.75°C). ZTD-only assimilation showed the strongest bias correction, reducing the near-surface bias from -0.39°C to $+0.01^\circ\text{C}$ (+97.4%), indicating its effectiveness in improving moisture-sensitive thermal fields, while the CONV + ZTD configuration lowered the bias to -0.07°C .

Visual comparisons on July 14–15, 2021, demonstrated that DA reduced overestimation of rainfall intensities and improved eastward propagation patterns, especially in Belgium and Luxembourg. The CONV + ZTD configuration most closely matched radar-observed rainfall peaks and spatial spread.

While RMSE values for precipitation showed slight degradation post-assimilation (e.g., CONV RMSE = 7.66 mm vs. No DA = 7.44 mm), bias correction and spatial accuracy gains underscore the value of DA. These results affirm that multi-source assimilation enhances forecast realism, especially for convective and synoptic-scale events.

4 Conclusions and Outlook

This study evaluated the impact of assimilating conventional meteorological observations (CONV) and GNSS Zenith Total Delay (ZTD) data, individually and in combination, into the WRF model using the WRFDA 3D-VAR framework with CV3 global background error covariances. Four experiments (No DA, CONV, ZTD, and CONV + ZTD) were cycled continuously at a 6-hour interval over the full month of 20 June–20 July 2021, and were verified against independent surface stations, radar, and GPM IMERG data during the extreme July 2021 flood event in Luxembourg and the Greater Region. Returning to the questions posed in the Introduction, the following conclusions can be drawn.

First, data assimilation measurably improved both precipitation and temperature forecasts relative to the no-assimilation control. For precipitation, its principal benefit was in categorical skill: the CONV experiment delivered the largest gains in bias (+37.4%) and probability of detection (POD, +18.3%), although this improved detection came at the cost of a higher false alarm ratio in all DA configurations, reflecting the expected trade-off between increased detection and increased false alarms. For temperature, assimilation acted most strongly on the near-surface bias, which was reduced by up to 97.4%. Second, the two observation types played complementary roles: conventional observations were the more effective for precipitation detection, whereas GNSS ZTD was dominant in correcting temperature bias, consistent with its sensitivity to atmospheric moisture and temperature. Third, the combined CONV + ZTD configuration did not always maximise any single metric but provided the most balanced and stable improvements across both variables, making it the most robust choice overall. Fourth, and notably, even though the GNSS moisture signal constrains only a spatially limited portion of the atmosphere, its assimilation produced a consistent and non-negligible impact when assessed over a full month of cycling, confirming that the value of ZTD assimilation for this region lies in improved event detection and bias correction rather than in the reduction of absolute error magnitude.



Indeed, the absolute-error metrics (RMSE, MAE, SMAPE) for precipitation showed only minor changes, or slight degradation, indicating that assimilation improves *where* and *whether* rainfall occurs more than its precise intensity.

355 Taken together, these findings underscore the value of integrating conventional and GNSS-based observation networks for high-resolution weather prediction in the Greater Region, and demonstrate that even a modest, moisture-focused observation such as ZTD can contribute meaningfully to forecast quality during high-impact flood events.

Several avenues remain for future work. The most immediate is to replace the climatological CV3 background error covariance with a regionally tuned, flow-dependent option such as CV5, which is expected to represent the anisotropic moisture-error structures of convective events more faithfully and thereby to improve precipitation magnitude, not only detection. Extending the framework to convection-permitting resolution, assimilating additional GNSS products (e.g. slant delays or tropospheric
360 gradients), integrating real-time GNSS ZTD networks, and expanding the station coverage would further improve the temporal resolution and detection reliability required for operational flood forecasting in the Greater Region.

Code and data availability. The GFS analysis and forecast data used for the initial and boundary conditions are available from the UCAR Research Data Archive (<https://rda.ucar.edu/>). The GNSS ZTD observations were obtained from the Nevada Geodetic Laboratory, University of Nevada, Reno (<http://geodesy.unr.edu/>). The conventional observations (SYNOP, TEMP, and TAMDAR) were derived from the ECMWF ERA5 reanalysis, available through the Copernicus Climate Data Store (<https://cds.climate.copernicus.eu/>). The GPM IMERG Final Run precipitation product is available from NASA Earthdata (<https://disc.gsfc.nasa.gov/>). The RADFLOOD21 radar precipitation product is available at <https://doi.org/10.5281/zenodo.7740059>. The NOAA Integrated Surface Database (ISD) is available from the NOAA National Centers for Environmental Information (<https://www.ncei.noaa.gov/>), and the AgriMeteo station data are available at <https://www.agrimeteo.lu/>. The WRF and WRFDA modelling systems are open-source and available from NCAR (<https://www2.mmm.ucar.edu/wrf/users/>). The processing
370 and analysis scripts developed for this study are available from the corresponding author upon reasonable request.

Author contributions. H. Rehman: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Visualization, Writing – original draft. F. N. R. Teferle: Supervision, Funding acquisition, Writing – review and editing. A. Hunegnaw, R. M. Thundathil, J. Wickert, and F. Zus: Writing – review and editing. All authors have read and approved the final version of the manuscript.

Competing interests. The authors declare that they have no conflict of interest.

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References

- 385 Ali, K., Bajracharyar, R. M., and Raut, N.: Advances and challenges in flash flood risk assessment: a review, *Journal of Geography & Natural Disasters*, 07, <https://doi.org/10.4172/2167-0587.1000195>, 2017.
- Apel, H., Vorogushyn, S., and Merz, B.: Brief communication: Impact forecasting could substantially improve the emergency management of deadly floods: case study July 2021 floods in Germany, *Natural Hazards and Earth System Sciences*, 22, 3005 – 3014, <https://doi.org/10.5194/nhess-22-3005-2022>, 2022.
- 390 Barker, D. M., Huang, W., Guo, Y.-R., Bourgeois, A., and Xiao, Q.: A three-Dimensional variational data assimilation system for MM5: Implementation and initial results, *Monthly Weather Review*, 132, 897 – 914, [https://doi.org/10.1175/1520-0493\(2004\)132<0897:ATVDAS>2.0.CO;2](https://doi.org/10.1175/1520-0493(2004)132<0897:ATVDAS>2.0.CO;2), 2004.
- Bertola, M., Blöschl, G., Bohac, M., Borga, M., Castellarin, A., Chirico, G. B., Claps, P., Dallan, E., Danilovich, I., Ganora, D., Gorbachova, L., Ledvinka, O., Mavrova-Guirguinova, M., Montanari, A., Ovcharuk, V., Viglione, A., Volpi, E., Arheimer, B., Aronica, G. T., Bonacci,
395 O., Čanjevac, I., Csik, A., Frolova, N., Gnanadt, B., Gribovszki, Z., Gül, A., Günther, K., Guse, B., Hannaford, J., Harrigan, S., Kireeva, M., Kohnová, S., Komma, J., Kriauciuniene, J., Kronvang, B., Lawrence, D., Lüdtke, S., Mediero, L., Merz, B., Molnar, P., Murphy, C., Oskoruš, D., Osuch, M., Parajka, J., Pfister, L., Radevski, I., Sauquet, E., Schröter, K., Šraj, M., Szolgay, J., Turner, S., Valent, P., Veijalainen, N., Ward, P. J., Willems, P., and Zivkovic, N.: Megafloods in Europe can be anticipated from observations in hydrologically similar catchments, *Nature Geoscience*, 16, 982 – 988, <https://doi.org/10.1038/s41561-023-01300-5>, 2023.
- 400 Blewitt, G., Hammond, W. C., and Kreemer, C.: Harnessing the GPS Data Explosion for Interdisciplinary Science, *Eos*, 99, <https://doi.org/10.1029/2018EO104623>, 2018.
- Boin, A., Ekengren, M., and Rhinard, M.: Hiding in Plain Sight: Conceptualizing the Creeping Crisis, *Risk, Hazards and Crisis in Public Policy*, 11, 116–138, <https://doi.org/10.1002/rhc3.12193>, 2020.
- Chen, L., Wang, Z., Wang, Y., and Feng, J.: Preparation and properties of alkali activated metakaolin-based geopolymer, *Materials*, 9,
405 <https://doi.org/10.3390/ma9090767>, 2016.
- Commission, E., Centre, J. R., Cammalleri, C., Vogt, J., Micale, F., and Barbosa, P.: Climate change impacts and adaptation in Europe, focusing on extremes and adaptation until the 2030s : PESETA III : Task 9, Droughts : final sector report, Publications Office, <https://doi.org/doi/10.2760/282880>, 2018.
- Daniels, T. S., Moninger, W. R., and Mamrosh, R. D.: Tropospheric Airborne Meteorological Data Reporting (TAMDAR) Overview, Tech.
410 rep., NASA Langley Research Center, <https://ntrs.nasa.gov/api/citations/20080013600/downloads/20080013600.pdf>, presented at the 12th Conference on Aviation, Range, and Aerospace Meteorology, AMS Annual Meeting, 2006.
- Didan, K.: MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V061, <https://doi.org/10.5067/MODIS/MOD13Q1.061>, 2021.
- Duan, L., Liu, C., Xu, H., Pan, H., Liu, H., Yan, X., Liu, T., Yang, Z., Liu, G., Dai, X., Liu, X., and Lu, H.: Susceptibility Assessment of Flash Floods: A Bibliometrics Analysis and Review, *Remote Sensing*, 14, <https://doi.org/10.3390/rs14215432>, 2022.
- 415 Dudhia, J.: Numerical Study of Convection Observed during the Winter Monsoon Experiment Using a Mesoscale Two-Dimensional Model, *Journal of Atmospheric Sciences*, 46, 3077 – 3107, [https://doi.org/10.1175/1520-0469\(1989\)046<3077:NSOCOD>2.0.CO;2](https://doi.org/10.1175/1520-0469(1989)046<3077:NSOCOD>2.0.CO;2), 1989.
- EM-DAT: The Emergency Events Database, Tech. rep., <https://www.emdat.be/>, 2021.
- European Environment Agency (EEA): Climate change, impacts and vulnerability in Europe 2016, Tech. rep., 2017.



- Faranda, D., Bourdin, S., Ginesta, M., Krouma, M., Noyelle, R., Pons, F., Yiou, P., and Messori, G.: A climate-change attribution retrospective of some impactful weather extremes of 2021, *Weather and Climate Dynamics*, 3, 1311–1340, <https://doi.org/10.5194/wcd-3-1311-2022>, 2022.
- Ferreira, C. S. S., Potočki, K., Kapović-Solomun, M., and Kalantari, Z.: Nature-Based Solutions for Flood Mitigation and Resilience in Urban Areas, *Handbook of Environmental Chemistry*, 107, 59 – 78, https://doi.org/10.1007/698_2021_758, 2022.
- Fettweis, X. and Doutreloup, S.: Analyse météorologique de l'évènement pluvieux de Juillet 2021 et évolution climatique du bassin versant de la Vesdre, *StudioPaolaViganò &*, pp. 114–122, 2022.
- Friedl, M. A. and Sulla-Menashe, D.: MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500m SIN Grid V061, <https://doi.org/10.5067/MODIS/MCD12Q1.061>, 2022.
- GDAL/OGR contributors: GDAL/OGR Geospatial Data Abstraction software Library, Open Source Geospatial Foundation, <https://doi.org/10.5281/zenodo.5884351>, 2025.
- Giannaros, C., Kotroni, V., Lagouvardos, K., Giannaros, T. M., and Pikridas, C.: Assessing the impact of GNSS ZTD Data assimilation into the wrf modeling system during high-impact rainfall events over Greece, *Remote Sensing*, 12, <https://doi.org/10.3390/rs12030383>, 2020.
- Goudenhoofd, E., Journée, M., and Delobbe, L.: Observational rainfall data of the 2021 mid-July flood event in Belgium – Part 2. Radar product RADFLOOD21, <https://doi.org/10.5281/zenodo.7740059>, 2023.
- Grell, G. A. and Freitas, S. R.: A scale and aerosol aware stochastic convective parameterization for weather and air quality modeling, *Atmospheric Chemistry and Physics*, 14, 5233–5250, <https://doi.org/10.5194/acp-14-5233-2014>, 2014.
- Hapuarachchi, H. A., Wang, Q. J., and Pagano, T. C.: A review of advances in flash flood forecasting, *Hydrological Processes*, 25, 2771–2784, <https://doi.org/10.1002/HYP.8040>, 2011.
- Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., De Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R. J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., de Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., and Thépaut, J.-N.: The ERA5 global reanalysis, *Quarterly Journal of the Royal Meteorological Society*, 146, 1999–2049, <https://doi.org/https://doi.org/10.1002/qj.3803>, 2020.
- Hong, S. Y. and Lee, J. W.: Assessment of the WRF model in reproducing a flash-flood heavy rainfall event over Korea, *Atmospheric Research*, 93, 818–831, <https://doi.org/10.1016/J.ATMOSRES.2009.03.015>, 2009.
- Hong, S.-Y., Noh, Y., and Dudhia, J.: A New Vertical Diffusion Package with an Explicit Treatment of Entrainment Processes, *Monthly Weather Review*, 134, 2318 – 2341, <https://doi.org/10.1175/MWR3199.1>, 2006.
- Huffman, G., Stocker, E., Bolvin, D., Nelkin, E., and Tan, J.: GPM IMERG Final Precipitation L3 Half Hourly 0.1 degree x 0.1 degree V07, <https://doi.org/10.5067/GPM/IMERG/3B-HH/07>, accessed: March 06, 2025, 2023.
- IPCC: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, Tech. rep., Cambridge, United Kingdom and New York, NY, USA, <https://doi.org/10.1017/9781009157896>, 2021.
- Jiménez, P. A., Dudhia, J., González-Rouco, J. F., Navarro, J., Montávez, J. P., and García-Bustamante, E.: A Revised Scheme for the WRF Surface Layer Formulation, *Monthly Weather Review*, 140, 898 – 918, <https://doi.org/10.1175/MWR-D-11-00056.1>, 2012.
- Khayyam, U.: Floods: impacts on livelihood, economic status and poverty in the north-west region of Pakistan, *Natural Hazards*, 102, 1033–1056, <https://doi.org/10.1007/S11069-020-03944-7>, 2020.



- Koks, E. E., Van Ginkel, K. C. H., Van Marle, M. J. E., and Lemnitzer, A.: Brief communication: Critical infrastructure impacts of the 2021 mid-July western European flood event, *Natural Hazards and Earth System Sciences*, 22, 3831 – 3838, <https://doi.org/10.5194/nhess-22-3831-2022>, 2022.
- 460 Kreibich, H., Van Loon, A. F., Schröter, K., Ward, P. J., Mazzoleni, M., Sairam, N., Abeshu, G. W., Agafonova, S., AghaKouchak, A., Aksoy, H., Alvarez-Garretón, C., Aznar, B., Balkhi, L., Barendrecht, M. H., Biancamaria, S., Bos-Burgering, L., Bradley, C., Budiyo, Y., Buytaert, W., Capewell, L., Carlson, H., Cavus, Y., Couasnon, A., Coxon, G., Daliakopoulos, I., de Ruiter, M. C., Delus, C., Erfurt, M., Esposito, G., François, D., Frappart, F., Freer, J., Frolova, N., Gain, A. K., Grillakis, M., Grima, J. O., Guzmán, D. A., Huning, L. S., Ionita, M., Kharlamov, M., Khoi, D. N., Kieboom, N., Kireeva, M., Koutroulis, A., Lavado-Casimiro, W., Li, H.-Y., LLasat, M. C., Macdonald, D., Mård, J., Mathew-Richards, H., McKenzie, A., Mejia, A., Mendiola, E. M., Mens, M., Mobini, S., Mohor, G. S., Nagavciuc, V., Ngo-Duc, T., Thao Nguyen Huynh, T., Nhi, P. T. T., Petrucci, O., Nguyen, H. Q., Quintana-Seguí, P., Razavi, S., Ridolfi, E., Riegel, J., Sadik, M. S., Savelli, E., Sazonov, A., Sharma, S., Sörensen, J., Arguello Souza, F. A., Stahl, K., Steinhausen, M., Stoelzle, M., Szalińska, W., Tang, Q., Tian, F., Tokarczyk, T., Tovar, C., Tran, T. V. T., Van Huijgevoort, M. H. J., van Vliet, M. T. H., Vorogushyn, S., Wagener, T., Wang, Y., Wendt, D. E., Wickham, E., Yang, L., Zambrano-Bigiarini, M., Blöschl, G., and Di Baldassarre, G.: The challenge of
- 465 unprecedented floods and droughts in risk management, *Nature*, 608, 80 – 86, <https://doi.org/10.1038/s41586-022-04917-5>, 2022.
- 470 Kreienkamp, F., Philip, S., Tradowsky, J., Kew, S., Lorenz, P., and Arrighi, J.: Rapid attribution of heavy rainfall events leading to the severe flooding in Western Europe during July 2021, *Rapid attribution of heavy rainfall events leading to the severe flooding in Western Europe during July 2021*, 2021.
- Kuksina, L. and Golosov, V.: Flash floods: Formation, study and distribution, *E3S Web of Conferences*, 163, <https://doi.org/10.1051/E3SCONF/202016302005>, 2020.
- 475 Laura Poletti, M., Silvestro, F., Davolio, S., Pignone, F., and Rebora, N.: Using nowcasting technique and data assimilation in a meteorological model to improve very short range hydrological forecasts, *Hydrology and Earth System Sciences*, 23, 3823–3841, <https://doi.org/10.5194/HESS-23-3823-2019>, 2019.
- Lee, H. and Romero, J.: Summary for policymakers, *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, pp. 35–115, 2023.
- 480 Lorenc, A. C.: The potential of the ensemble Kalman filter for NWP - A comparison with 4D-Var, *Quarterly Journal of the Royal Meteorological Society*, 129, 3183 – 3203, <https://doi.org/10.1256/qj.02.132>, 2003.
- Lucius, M.: Erläuterungen zur Geologischen Karte Luxemburgs – Das Gutland, vol. V, *Service géologique du Luxembourg*, Luxembourg, 1948.
- 485 Ludwig, P., Ehmele, F., Franca, M., Mohr, S., Caldas-Alvarez, A., Daniell, J., Ehret, U., Feldmann, H., Hundhausen, M., Knippertz, P., Küpfer, K., Kunz, M., Mühr, B., Pinto, J., Quinting, J., Schäfer, A., Seidel, F., and Wisotzky, C.: A multi-disciplinary analysis of the exceptional flood event of July 2021 in central Europe - Part 2: Historical context and relation to climate change, *Natural Hazards and Earth System Sciences*, 23, 1287–1311, <https://doi.org/10.5194/nhess-23-1287-2023>, 2023.
- Luxembourg Institute of Science and Technology (LIST): Analyse Préliminaire des Inondations de Juillet 2021, Tech. rep., https://www.list.lu/fileadmin/files/news/2021/20210714_AnalysePreliminaireDesInondations.pdf, 2021.
- 490 Mathias, L.: Major flood event in the Mullerthal region on 1 June 2018: Event analysis and predictability, https://gouvernement.lu/fr/actualites/toutes_actualites/communiqués/2018/06-juin/12-bausch-kersch-mullerthal.html, 2019.



- Ministerium für nachhaltige Entwicklung und Infrastrukturen (MDDI) and Wasserwirtschaftsverwaltung Luxemburg: Hochwasserrisikomanagementplan für das Großherzogtum Luxemburg, Tech. rep., ARGE HWRM-PL GdL, LUXPLAN S.A, OBERMEYER, Luxembourg, 495 <https://mddi.gouvernement.lu/en/publications.html>, 2015.
- Mlawer, E. J., Taubman, S. J., Brown, P. D., Iacono, M. J., and Clough, S. A.: Radiative transfer for inhomogeneous atmospheres: RRTM, a validated correlated-k model for the longwave, *Journal of Geophysical Research: Atmospheres*, 102, 16 663–16 682, <https://doi.org/https://doi.org/10.1029/97JD00237>, 1997.
- Muller, A.: Luxembourg, in: *Géologie des Pays européens: France, Belgique, Luxembourg*, pp. 577–594, Dunod, Paris, 1980.
- 500 National Centers for Environmental Prediction (NCEP): NCEP GFS 0.25 Degree Global Forecast Grids Historical Archive, <https://www.ncei.noaa.gov/products/weather-climate-models/global-forecast>, <https://doi.org/10.5065/D65D8PWK>, accessed: March 17, 2025, 2025.
- NOAA National Centers for Environmental Information: Global Surface Hourly [SYNOP data from June 20–July 20, 2021], <https://www.ncei.noaa.gov/products/land-based-station/integrated-surface-database>, accessed: March 05, 2025, 2001.
- Pot, W., Scherpenisse, J., and 't Hart, P.: Robust governance for the long term and the heat of the moment: Temporal strategies for coping 505 with dual crises, *Public Administration*, 101, 221–235, <https://doi.org/10.1111/padm.12872>, 2023.
- Skamarock, W. C., Klemp, J. B., Dudhia, J., Gill, D. O., Liu, Z., Berner, J., Wang, W., Powers, J. G., Duda, M. G., Barker, D. M., and Huang, X.-Y.: A Description of the Advanced Research WRF Version 4, Tech. Note NCAR/TN-556+STR, National Center for Atmospheric Research, <https://doi.org/10.5065/1dfh-6p97>, 2019.
- Tewari, M., Chen, F., Wang, W., Dudhia, J., LeMone, M. A., Mitchell, K., Ek, M., Gayno, G., Wegiel, J., and Cuenca, R. H.: Implementation and Verification of the Unified Noah Land Surface Model in the WRF Model, in: 20th Conference on Weather Analysis and Forecasting / 16th Conference on Numerical Weather Prediction, American Meteorological Society, Seattle, WA, 2004.
- Thompson, G., Field, P. R., Rasmussen, R. M., and Hall, W. D.: Explicit Forecasts of Winter Precipitation Using an Improved Bulk Microphysics Scheme. Part II: Implementation of a New Snow Parameterization, *Monthly Weather Review*, 136, 5095 – 5115, <https://doi.org/10.1175/2008MWR2387.1>, 2008.
- 515 Tom, R. O., George, K. O., Joanes, A. O., and Haron, A.: Review of flood modelling and models in developing cities and informal settlements: A case of Nairobi city, *Journal of Hydrology: Regional Studies*, 43, 101 188, <https://doi.org/10.1016/J.EJRH.2022.101188>, 2022.
- Torcasio, R. C., Mascitelli, A., Realini, E., Barindelli, S., Tagliaferro, G., Puca, S., Dietrich, S., and Federico, S.: The impact of global navigation satellite system (GNSS) zenith total delay data assimilation on the short-term precipitable water vapor and precipitation forecast over Italy using the Weather Research and Forecasting (WRF) model, *Natural Hazards and Earth System Sciences*, 23, 3319–3336, 520 <https://doi.org/10.5194/nhess-23-3319-2023>, 2023.
- Tradowsky, J., Philip, S., Kreienkamp, F., Kew, S., Lorenz, P., Arrighi, J., Bettmann, T., Caluwaerts, S., Chan, S., De Cruz, L., de Vries, H., Demuth, N., Ferrone, A., Fischer, E., Fowler, H., Goergen, K., Heinrich, D., Henrichs, Y., Kaspar, F., Lenderink, G., Nilson, E., Otto, F., Ragone, F., Seneviratne, S., Singh, R., Skålevåg, A., Termonia, P., Thalheimer, L., van Aalst, M., Van den Bergh, J., Van de Vyver, H., Vannitsem, S., van Oldenborgh, G., Van Schaeybroeck, B., Vautard, R., Vonk, D., and Wanders, N.: Attribution of the heavy rainfall events 525 leading to severe flooding in Western Europe during July 2021, *Climatic Change*, 176, <https://doi.org/10.1007/s10584-023-03502-7>, 2023.
- United Nations Environment Programme: Adaptation Gap Report 2022: Too Little, Too Slow – Climate Adaptation Failure Puts World at Risk, Tech. rep., United Nations Environment Programme, Nairobi, Kenya, <https://www.unep.org/resources/adaptation-gap-report-2022>, 2022.
- Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J., 530 van der Walt, S. J., Brett, M., Wilson, J., Millman, K. J., Mayorov, N., Nelson, A. R. J., Jones, E., Kern, R., Larson, E., Carey, C. J., Polat,



Í., Feng, Y., Moore, E. W., VanderPlas, J., Laxalde, D., Perktold, J., Cimrman, R., Henriksen, I., Quintero, E. A., Harris, C. R., Archibald, A. M., Ribeiro, A. H., Pedregosa, F., van Mulbregt, P., and SciPy 1.0 Contributors: SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python, *Nature Methods*, 17, 261–272, <https://doi.org/10.1038/s41592-019-0686-2>, 2020.

535 Vladimirov, E., Dimitrova, R., and Dančovski, V.: Impact of Data Assimilation on Short-Term Precipitation Forecasts Using WRF-ARW Model, *Lecture Notes in Computer Science* (including subseries *Lecture Notes in Artificial Intelligence* and *Lecture Notes in Bioinformatics*), 11958 LNCS, 263–271, https://doi.org/10.1007/978-3-030-41032-2_30/COVER, 2020.

Waterlot, G., Beugnies, A., Bintz, J., Hary, A., and Muller, A.: *Ardenne – Luxembourg, Guides géologiques régionaux*, Masson, Paris, 1973.

Wilks, D. S.: *Statistical Methods in the Atmospheric Sciences*, vol. 91 of *International Geophysics Series*, Academic Press, 2nd edn., ISBN 9780127519654, 2006.