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4DVAR assimilation of GNSS zenith path delays and precipitable water into a numerical weather prediction model WRF

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Abstract. The GNSS data assimilation is currently widely discussed in the literature with respect to the various applications in meteorology and numerical weather models. Data assimilation combines atmospheric measurements with knowledge of atmospheric behavior as codified in computer models. With this approach, the 'best' estimate of current conditions consistent with both information sources is produced. Some approaches allow assimilating also the non-prognostic variables, including remote sensing data from radar or GNSS (Global Navigation Satellite System). These techniques are named variational data assimilation schemes and are based on a minimization of the cost function, which contains the differences between the model state (background) and the observations.

This paper shows the results of assimilation of GNSS data into numerical weather prediction (NWP) model WRF (Weather Research and Forecasting). The WRF model offers two different variational approaches: 3DVAR and 4DVAR, both available through WRF Data Assimilation (WRFDA) package. The WRFDA assimilation procedure was modified to correct for bias and observation errors. We assimilated the Zenith Troposphere Delay (ZTD), Precipitable Water (PW), radiosonde (RS) and surface synoptic observations (SYNOP) using 4DVAR assimilation scheme. Three experiments have been performed: 1) assimilation of PW and ZTD for May and June of 2013, 2) assimilation of: PW alone; PW, with RS and SYNOP; ZTD alone; and finally ZTD, with RS and SYNOP for 5-23 May, 2013, and 3) assimilation of PW or ZTD during severe weather events in June 2013. Once the initial conditions were established, the forecast was run for 48 hours.

The obtained WRF predictions are validated against surface meteorological measurements, including air temperature, humidity, wind speed, and rainfall rate. Results from the first experiment (May and June, 2013) show that the assimilation of GNSS data (both ZTD and PW) have positive impact on the rain and humidity forecast. However, the assimilation of ZTD is more successful, and brings substantial reduction of errors in rain forecast by 8%, and a 20% improvement in bias of humidity forecast, but it has a slight negative impact on temperature bias and wind speed. Second experiment (5-23 May, 2013) reveals that the PW or ZTD assimilation leads to a similar reduction of errors as in the first experiment, moreover, adding SYNOP and RS observations to the assimilation does not improve the humidity or rain forecasts (in the 48h forecast) but reduces errors in the wind speed and temperature. Furthermore, short term predictions (up to 24h) of rain and humidity are better when SYNOP and RS observations are assimilated. The impact of assimilation of ZTD and PW in severe weather

cases is mixed, one out of three investigated cases shows positive impact of GNSS data, whereas other two neutral or negative.

1 Introduction

The data assimilation in weather forecasts is one of the key component in all prediction systems as it is an initial value problem and the quality of the initial field has large impact on the forecasts. Currently, the leading weather agencies assimilate operationally few dozens of observation data types such as: radiosonde (RS) profiles, radiances from satellite observations, SYNOPs, GPS refractivities from radio occultations, pilot reports and many others (Barker et al., 2004). With an advent of European Cooperation in Science & Technology (COST) actions 716 (1999-2004), 1206 (2013-2017), as well as the project funded in the 5th framework program Targeting Optimal Use of GPS Humidity Measurements in Meteorology" (TOUGH), the adoption of the ground based Global Navigation Satellite Systems (GNSS) observations to the operational forecasts by most of the weather services in Europe become a fact. In this study the term GNSS covers all navigation systems used world-wide, whereas the term Global Positioning System (GPS) is related to only one source of observations – the US based GPS. There are many publications related to either 1) performance of large scale weather forecast systems augmented with many observations including GNSS, 2) added value of GNSS observations in nowcasting services, or 3) case-based studies showing impact of GNSS data in particular cases. The following three approaches are discussed below.

A very comprehensive study done by (Poli et al., 2007) on the global forecast model Arpage using 4 dimensional variational assimilation (4DVAR) shows that the impact of GPS Zenith Troposphere Delay (ZTD) on forecasts is different in winter (improving pressure), spring (reducing surface humidity Root Mean Square Error) and summer (positive impact on wind, geopotential and precipitation, negative on humidity). A similar, very detailed study was done by (Bennitt and Jupp, 2012), where Authors discussed the operational assimilation of GPS ZTD in MetOffice into North Atlantic and European 12 and 24 km model in spring, summer and autumn. The results were mixed: for all cases the introduction of GPS ZTD increased the humidity bias, however the improvements of clouds forecasts were observed. Authors also identify no clear benefit of 4DVAR against 3DVAR. (Lindskog et al., 2017) in their Nordic country study of GNSS ZTD impact on forecasts, confirmed that the forecasts are sensitive to thinning distance. Shorter distance between stations (below 100km) leads to a larger humidity bias in the lower troposphere, which may explain the humidity bias in the (Bennitt and Jupp, 2012) solution. (Lindskog et al., 2017) showed that the humidity forecast is better when the GNSS ZTD is assimilated with other meteorological observations such as Advanced Microwave Sounding Unit (AMSU) or Infrared Atmospheric Sounding Interferometer (IASI) radiances. Authors also showed that the adopted bias correction strategy and GNSS ZTD estimation procedure have marginal impact on the forecasts. All studies run in large weather forecasting systems suggests that the assimilation of GNSS ZTD, either 3D or 4DVAR, on average has mostly neutral impact on the forecast if the system is already saturated with meteorological observations.

Another branch of weather models are those used in nowcasting, such as the (legacy) Rapid Update Cycle RUC 20 km and RUC 40km (Benjamin et al., 2002) or currently operational Rapid Refresh (RAP) (Benjamin et al., 2016) that are targeting short 12h and 24h predictions for decision making and safety operations with a large number of observations assimilated every hour. One of the first experiments using GPS Precipitable Water (PW) in nowcasting service in USA (RUC model 60km) (Smith et al, 2000), showed 1% improvement of the relative humidity forecast in the bottom part of the atmosphere. However, in specific cases related to active frontal weather, the improvement was much larger: 14% in moistening and 24% in drying stage of the advection. The increased spatial resolution to 20km of RUC20 (Smith et al., 2007) shows stronger improvements in humidity field and Convective Available Potential Energy CAPE than with RUC40. The 850 hPa relative humidity (RH) forecasts improve more in the night time, and in the colder season than that in the warmer season. Current RAP model, running on 13km grid, continuously assimilates GPS PW every hour from 300 stations across US (Benjamin et al., 2016). It shows that there is clear benefit in using GPS observations, especially for short term (nowcasting) predictions.

The third type of studies that are appearing in the literature are case-based, showing the impact of GNSS on particular weather event. One of the first to test the impact of GPS based ZTD observations in Europe were Cucurull et al., (2004). Authors used NCAR / Penn State Mesoscale Model 5 (MM5) model ZTD 3DVAR assimilation for a case of snow storm in 14-15 December 2001 over western Mediterranean Sea. They found that there are reductions of RMSE wind by 1.7%, temperature by 4.1% and surface humidity by 17.8%. Authors also noted that the forecasts work better if the ground based automatic weather stations were used in the same assimilation run. Another example of an early stage case-based research is the assimilation of GPS PW by Nakamura et al., (2004) with 4DVAR scheme into mesoscale JMA model for summer intensive rain cases. The assimilation of GPS data improved the precipitation location, but the statistics did not show large improvement. One of the first GPS 4DVAR ZTD study in US was by De Pondeca and Zou, (2001), who run assimilation of GPS observations in MM5 together with the wind profiler data and radio acoustic sounding system (RASS) virtual temperature. Five 12h experiments for California's December frontal system passage were performed. It was found that the ZTD assimilation corrects the underestimation of accumulated rain by 33.15% and 25.08% for 6h and 12h respectively. Adding the wind profiler improves the forecast by 88.26% and 32.53% and adding further RASS observations increases the performance to 93.21% and 50.58%, respectively. In a more recent study by Boniface et al., (2009), the GPS ZTD was assimilated (3DVAR) for 280 stations over 15 days into high-resolution (2.5km) AROME model. The results were positive for poorly predicted precipitation and neutral for well predicted one. More recently, Tilev-Tanriover and Kahraman, (2014) studied the impact of the GPS PW assimilation in the Weather Research and Forecasting (WRF) model in a 2 days case of intense snowfall forecasts in the central Anatolia. Authors performed 3 experiments: base run, cold start and cycling all with PW 3DVAR operator. Results show that the cycling assimilation mode decreases the temperature and humidity biases, whereas the cold start performs worse than the control run. Saito et al., (2016) studied the impact of ensemble prediction that did not produce enough precipitation. They found that even downscaling from 10km to 2km, still do not improve locations of precipitation's cores. Finally, the 4DVAR PW assimilation into a non-hydrostatic model improved the location of

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scattered intensive rain. In summary, most of the literature reported substantial increase in the quality of the forecast of humidity, rain location and sometimes also the rain accumulated total amount. Less significant improvement was achieved for wind speed and temperature. All studies that used additional observations, especially these resolving vertical structure of the water vapor and temperature, complemented GNSS observations and improved the forecast even more.

The literature review shows that the impact of the GNSS ZTD/PW assimilation depends on the number of already assimilated observations and applied preprocessing (Bennitt and Jupp, 2012; Lindskog et al., 2017; Poli et al., 2007) as well as on the type of weather conditions. The main aim of this paper is to quantify the impact of the GNSS data, both ZTD and PW, gathered operationally in Poland, in weather forecasting. The study is based on the WRF model with high spatial resolution of 4 km x 4 km supported with the WRF Data Assimilation (WRFDA) package. We show the importance of the GNSS data assimilation for cases of various meteorological conditions observed in May and June 2013, which is a benchmark period for COST Action ES1206. To our best knowledge, no GNSS ZTD/PW assimilation experiment was carried out in Poland yet. Moreover, we found only one publication (Tilev-Tanriover and Kahraman, 2014) dealing with the assimilation of GPS ZTD and PW into the very popular WRF model using the WRFDA package. We present a study showing the impact of GNSS ZTD and PW observations on the forecasts for a longer time period - two months (May 2013 – calm weather conditions and June 2013 – active stormy weather), followed by quantifying improvements of adding RS and SYNOP data into the assimilation system already run with GNSS observations and finally we verified impact of GNSS observations on prediction for specific cases.

The paper has following structure: after introduction section short overview of used data and methodology is presented in sections 2 and 3, respectively. These sections are followed by experiments setup description and results (section 4). The paper is closed with a conclusion section 5.

2 Data

The GNSS PW/ZTD data are assimilated into NWP WRF model. The chosen period is covering May and June 2013, with special focus on May, 5-23, 2013 and three shorter cases: a) May, 29-31, 2013, b) June, 17-19, 2013 and c) June, 24-26, 2013. The period is chosen in accordance to the COST Action ES1206 GNSS meteorology benchmark (Douša et al., 2016).

2.1 WRF model

In this study the WRF model is used, it is numerical weather prediction system designated for simulation of multiscale, spatial and temporal atmosphere flows. The WRF configuration (Kryza et al., 2013) is based on two nested model domains. The first domain covers the European area with 12km x 12 km grid spacing. The second, nested domain covers Poland and Central Europe with 4km x 4km grid spacing (Fig. 1).

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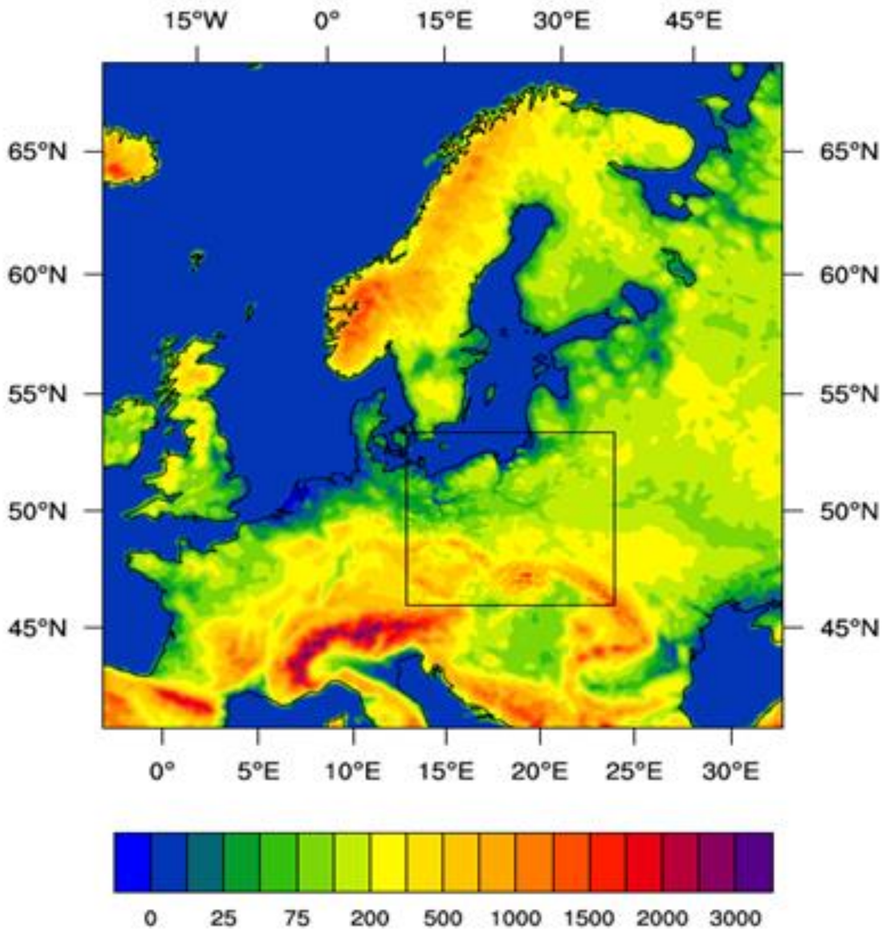

Fig. 1 The WRF model configuration (the inner square represents the nested domain with 4 km x 4 km resolution). Colors denote the orography of the terrain (m a.s.l.).

Initial and boundary conditions are taken from the National Center for Environmental Prediction Final Analysis, Operational Model Global Tropospheric Analyses (NCEP FNL) database (National Centers for Environmental Prediction, 2000). The data are available with 1° x 1° horizontal and 6h temporal resolution and with 26 vertical levels from 1000 to 10 hPa. The WRF model for Poland is calculated and provided by the Department of Climatology and Atmosphere Protection of the University of Wroclaw. The details of the WRF configuration are presented in Table 1.

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2.2 GNSS data

The GNSS data are calculated by the GNSS and Meteo working group from Institute of Geodesy and Geoinformatics, Wroclaw University of Environmental and Life Sciences (www.igig.up.wroc.pl/igg). The PW and ZTD values are calculated at 106 stations of the European Position Determination System Active Geodetic Network (ASG-EUPOS, www.asgeupos.pl) in Poland and adjacent areas (Fig. 2).

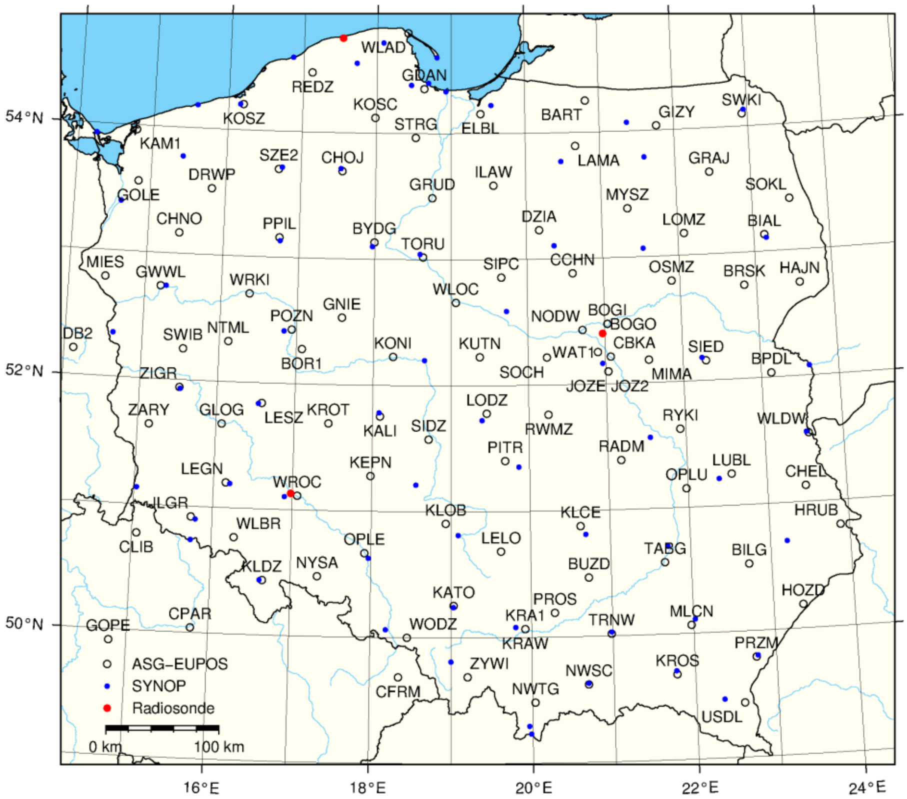

Fig. 2. Location of the GNSS, SYNOP and Radiosonde stations in Poland

The GNSS parameters are calculated from GPS data only, using the Bernese GNSS Software version 5.0 (Dach et al., 2007). The parameters (coordinates and troposphere) are estimated in a near-real time (NRT) regime, 30 min after each full hour, without the gradients estimation. The dry troposphere a-priori model is taken from Saastamoinen, (1972) mapped with Dry Niell MF (Niell, 2000) and the ZTD relative constraining of 3 mm is applied. International GNSS Service (IGS) ultra-rapid orbits, clocks and Earth rotation parameters are used. These parameters are now altered to fit more recent version of Bernese (5.2) (Dach et al., 2015; Dymarska et al., 2017), but this study uses NRT data, originally processed in 2013. Fifteen of the stations are a part of the EUREF Permanent Network (EPN) and provide the tropospheric parameters with the accuracy required by NWP data assimilation (Dymarska et al., 2017), i.e. the standard deviation between GNSS ZTD and

WRF ZTD is 10 mm and the standard deviation between radiosonde ZTD and WRF ZTD is 14 mm. In the inter-comparison study using multiple techniques (Wilgan et al., 2015), the discrepancy between GNSS observations and radiosonde was found to be 10 mm. According to the EGVAP requirements (Met Office, 2012), this accuracy of the GNSS data is sufficient for the assimilation in NWP models.

2.3 Model evaluation

The WRF model runs are compared with surface meteorological measurements of air temperature, relative humidity, wind speed and precipitation. The measurements are available every hour at 66 SYNOP stations, evenly distributed over the area of Poland, operated by the Institute of Meteorology and Water Management – National Research Institute. Model evaluation is performed only for the nested domain. Four error metrics are calculated to assess the forecast performance:

- Mean error (ME), which describes the model tendency of overestimation (ME >0) or underestimation (ME<0) of the given meteorological parameter. The ME (bias) is calculated as a mean difference between the modelled and observed values for all stations (domain wide). The units are the same as for the analyzed meteorological parameters.
- Root mean squared error (RMSE), which takes only non-negative values. The RMSE (scatter) is calculated as a root of the squared differences between the modelled and observed values for all stations. The units are the same as for the analyzed meteorological parameters.
- Pearson correlation coefficient (corr), which takes values from -1 to +1, and the expected value is 1. Corr is unitless.
- Index of agreement (IOA), developed by (Willmott, 1981) as a standardized measure of the degree of model prediction error. IOA varies between 0 and 1, and 1 indicates a perfect match.

The model evaluation is done for each simulation considering entire period and for different lead times. For rainfall forecasts, binary evaluation is also presented using performance diagrams (Roebber, 2009), separately for five different precipitation intensity thresholds.

3 Methodology

The variational assimilation is based on the Bayesian probability theory and it states that the model analysis is inferred from two probabilities: background and observations. These can also be expressed as a minimization of a cost function, with two major components: background B and observations O error covariance (De Pondeca and Zou, 2001) in the 4DVAR implementation:

$$J(x_o) = (x_o - x_B)^T B^{-1} (x_o - x_B) + \sum_n^N \sum_{r=ni}^{r=nf} \left[H^n(x_{t_r}) - y_{t_r}^n\right]^T O_{t_r}^{n^{-1}} \left[H^n(x_{t_r}) - y_{t_r}^n\right], \quad (1)$$

where x_{t_r}, x_B, x_o are model state vector at the time t_r, background vector and model initial conditions, respectively. In the most general case, there are N kinds of observations $y^n_{t_r}$ defined at discrete times t_r from $t_{ni}$to t_{nf}, where the assimilation window spans from the lowest to the highest t_r. The $H^n(x_{t_r})$ is a forward operator that transforms parameters from the model space to the observations space for $n-th$ type of observation. The 3DVAR differs to 4DVAR by taking $t_r$equal to observation time and analysis time. Minimization of the equation (1) requires also finding adjoint (ADJ) and tangent linear (TLM) operators, each related to the observation type and forward operator $H^n(x_{t_r})$. For more details, the readers are referred to e.g. Barker et al., (2004) or Huang et al., (2009).

3.1 GPSPW operator

The WRFDA system employed in this study hosts variational (VAR) 3D/4D as well as hybrid variational-ensemble algorithms (Barker et al., 2012). Currently, the system supports the assimilation of: surface, radiosonde, aircraft, wind profile observations as well as atmospheric motion vectors, radar reflectivities, spectrometric, GPS radio occultation and GPS ground-based data. The latter is linked directly to the GPSPW operator (The National Center for Atmospheric Research and WRF Model Users' Page, 2017). The operator defines the forward, tangent linear and adjoint of H for the 4DVAR and 3DVAR case for both ZTD and PW. The operator also defines the observation covariance O; in here diagonal matrix is assumed, with no correlation between observations, which requires spatial and temporal thinning (Bennitt et al., 2017; Bennitt and Jupp, 2012). The ZTD forward operator H reads as follows (Vedel and Huang, 2004) with further corrections made by Y.-R. Guo (from da_transform_xtoztd module of GPSPW) :

$$ZTD(i,j) = ZHD(i,j) + \sum_{k=kts}^{k=kte}\left(\frac{wdk_1 p(i,j,k)q(i,j,k)}{t(i,j,k)} + \frac{wdk_3 p(i,j,k)q(i,j,k)}{t^2(i,j,k)}\right)\frac{\Delta h}{a_{ew}}, \quad (2)$$

where i, j, k are indices of model nodes, p is a pressure, q is specific humidity, t is temperature, Δh is a height difference between two consecutive model layers, $a_{ew} = 0.622$ is a constant, $wdk_1 = 2.21\ 10^{-7}, wdk_3 = 3.73\ 10^{-3}$ are compressibility constants, ZHD is a Zenith Hydrostatic Delay computed according to the (Saastamoinen, 1972) explicitly given in Eq. 6.

The PW forward operator is formed similarly to the ZTD operator (following da_integrat_dz module of GPSPW operator):

$$PW(i,j) = \sum_{k=kts}^{k=kte}(\rho(i,j,k)q(i,j,k)\Delta h), \quad (3)$$

where ρ is an air density.

3.1 GNSS data preprocessing

Two kinds of GNSS data are accepted by WRFDA package: ZTD and PW. In order to prepare the GNSS estimates for GPSPW, a preprocessing is required. The ZTD data is processed according to the following steps:

1. Calculation of the GNSS ZTD using Bernese software for all the stations.
2. Assimilation of the GNSS ZTD obtained in step 1) using the 3DVAR scheme.

3. Calculation of 'background' corrections from WRF model to reduce the systematic error between WRF and GNSS data and subtracting the corrections from the GNSS ZTD obtained in the step 1)

In the first step, we adjust the formal errors of GNSS ZTD by multiplying them by a factor of 10.5 mm, which is the standard deviation of differences between WRF ZTD and GNSS ZTD according to Dymarska et al., (2017). Next, we remove the observations, which errors exceed 20 mm, which is the standard procedure in GNSS data assimilation (Bennitt and Jupp, 2012).

In the second step, the GNSS data is assimilated in the 3DVAR procedure in order to calculate the corrections that come from the 'background', which is the WRF model. The corrected ZTDs are calculated as:

$$ZTD_{corr} = ZTD_{GNSS} - (O - B + dZTD) \quad (4)$$

where ZTD_{GNSS} is ZTD obtained in step 1), O is 'observation' ZTD (in this case same as ZTD_{GNSS}), B is 'background' ZTD, i.e. the model ZTD, and $dZTD$ is the correction that comes from the assimilation.

The PW data is processed in a similar way:

1. Calculation of the GNSS PW from GNSS data.
2. Assimilation of the GNSS PW obtained in the step 1) using the 3DVAR scheme
3. Calculation of 'background' corrections and subtracting them from the GNSS PW obtained in the step 1)

From GNSS processing, we can only estimate ZTDs. The PWs in step 1) are calculated in a standard way from GNSS and WRF data as:

$$PW = Q \cdot (ZTD_{GNSS} - ZHD_{WRF}) \quad (5)$$

where ZHD_{WRF} is the hydrostatic delay calculated using Saastamoinen, (1972) formula from pressure from WRF model p_{WRF}, height h and latitude φ of a GNSS station:

$$ZHD = \frac{0.0022767 p_{WRF}}{1 - 0.00266\cos(2\varphi) - 0.00000029\, h} \quad (6)$$

The proportionality factor Q is calculated as:

$$Q = \frac{10^6}{R_w(k_3/T_m + k_2')} \quad (7)$$

where R_w= *461.525* [J /(K kg)] is the gas constant of a wet air, k_2'=*22.9726* [K/hPa] and k_3 =*375463* [K^2/hPa] are the 'best average' refractivity constants from (Rueger, 2002) and T_m is the mean temperature calculated from T_{WRF} as:

$$T_m = 70.2 + 0.72 \cdot T_{WRF} \quad (8)$$

After calculation of GNSS PW, the processing in steps 2) end 3) is analogical to GNSS ZTD.

4 Case studies

All cases presented in this study are selected from the period of May – June, 2013 and location (Central Europe) covering the benchmark campaign of COST Action ES1206 (Douša et al., 2016). Following experiments are considered: 1) assimilation of ZTD or PW for whole May and June 2013, 2) assimilation of ZTD or PW and ZTD or PW with support of RS and

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SYNOP for 5-23 May, 2013, 3) case studies a, b and c, showing impact of assimilation of ZTD or PW in severe weather cases which took place during May and June 2013.

According to synoptic analysis presented in (Douša et al., 2016), the beginning of May 2013 was characterized with cyclonic field over 500hPa, which in turn resulted in precipitation and convection development, moving from west to east. The mid-May weather in the region was developing under the influence of upper level cyclone (500hPa) that brought the cold advection from west. Towards the end of May, series of Atlantic cyclones approached Europe. The end of the month brought a stop to the advection of cold air by upper east ridge, which pushed the cyclones more to the south and brought humid and warm air to the central Europe. In June, three flooding events were recorded in Czech Republic, which were associated with baroclinic instability developing over area of interest, with a first one (June, 1-3) event unexpected and of disastrous nature while two latter (June, 9-11; June, 23-26) less severe and better predicted. As in this work, we use Poland as a study region, thus, there is a time shift between the events recorded in Czech Republic (described by Douša et al., 2016) and Poland and also the precipitation effects were not as disastrous.

The first severe weather case study (case a) was observed in May, 29 -31, 2013. The weather event is related to an unusual, low-pressure regions: 1) developing over Hungary and moving towards Czechia, 2) developing over the Moldavia and moving towards east of Poland. In these two lows, in the presence of stratified clouds, the cumulonimbus clouds develop and form a supercell. It brought intensive rain and hail, however the precise location of such supercells is not easy to predict (www.meteo.pl).

The second analyzed case (case b) occurred in June, 17 – 18, 2013 and is related to two weather systems: 1) high pressure system with a center in Belarus affecting northern part of Poland, 2) low pressure system over the Bay of Biscay. The cold weather is observed in the north (20^{o} C) and hot and humid in the south (above 30^{o} C). The thermic contrasts and warm unstable air result in occurrence of convective cells located southeast to the region. These cells merged in the late afternoon and formed a supercell storm that moved southward to the Moravy region (www.meteo.pl).

The third case analyzed was June, 24 – 25, 2013. The weather in Europe was driven by high pressure system located over the Atlantic Ocean, as well as large and shallow trough extending to the north to Norway from a weak low centered over the northern part of the Adriatic Sea (with the atmospheric pressure of around 1010 hPa). Secondary cyclogenesis is organized over central Poland in the form of thermal asymmetric low pressure system. A quasi-stationary anabatic cold front spread along this trough changing very slowly its position and bringing cold air from the north (in the western part of Poland), and warm, humid and unstable air masses from the south (in the eastern part of Poland). These conditions are prone to develop strong precipitation, thunderstorms and hail in the central Poland (www.meteo.pl).

4.1 Assimilation of GNSS observations

The full period of two months is used as a first approach to validate the impact of PW or ZTD data on weather forecasts. The verification is based on a 66 SYNOP stations evenly distributed evenly across Poland (Fig. 2). Table 2 summarizes model forecast performance using: ME, RMSE, corr and IOA. The statistics are calculated for lead times from 1 to 48h for the following parameters: rain intensity (rain), wind speed (wspd), relative humidity (rh2) and temperature (T2).

The overall accuracy of the rain forecast in the long run (48h) is low, i.e. the base run prediction correlate with the observations in less than 10%, while the same parameter for wind speed attains 55%, whereas corr for relative humidity is 88% and for temperature 95%. As the assimilation changes the initial conditions of parameters directly linked with the adjoint operator (a transpose of forward operator), the impact while using ZTD should be visible in: pressure p (Eq. 2) (and thus also wind speed), specific humidity q (and thus relative humidity) and temperature t. Whereas PW should have impact mostly on specific humidity q (Eq. 3) and thus on rh2 parameter. Rain as a parameter linked with physical parameterization and many parameters such as humidity, vertical and horizontal motion, temperature profile is also sensitive to the GNSS data assimilation.

If the rainfall forecasts are analyzed more closely using the binary verification with data stratification according to rainfall intensity (Fig. 3), it is clear that the PW run is very similar to the base run, regardless the rainfall intensity. The ZTD assimilation leads to overall decrease of the probability of detection.

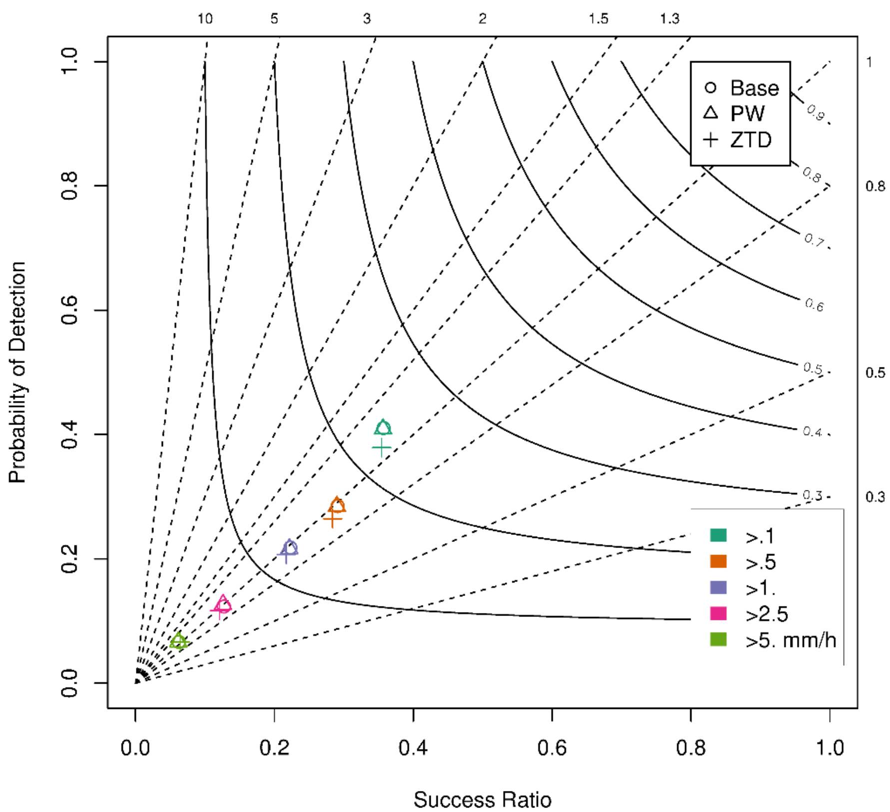

Fig. 3 Performance diagram for assimilation of ZTD and PW for May and June 2013

The results confirm that the assimilation of PW over the whole period of two months affects the forecasts only slightly: there is no improvement for hourly rainfall, but the assimilation reduces the relative humidity scatter and has negative or neutral impact on the rain ME and RMSE, neutral impact on wind speed and negative or neutral on temperature. Similarly, there is no gain for rainfall forecasts if ZTD is assimilated for the entire period, but there is 20% improvement in ME reduction of humidity observations, while it has negative impact on temperature bias and all parameters related to the wind speed. This negative impact could be linked to the representation of ZHD as a parameter related only to ground based observations of temperature and pressure (Eq. 2), whereas in reality the ZHD is an integral of pressure and temperature across the whole troposphere (Vedel and Huang, 2004).

4.2 Assimilation of GNSS, RS and SYNOP observations

In the second experiment, we focus on a short time span covering May with moderate precipitation and standard cyclonic weather, as oppose to the June with the occurrence of major severe weather events (analyzed in 4.3). This experiment is prepared to assess the impact of using RS and SYNOP together with GNSS data in 4DVAR assimilation. The MEs for base run forecasts in May (Table 3) are lower than for May and June, e.g. rain ME is approx. -0.5 whereas May and June is approx. -0.7, May relative humidity ME is approx. -0.9% and May and June is approx. -2.9%. Wind speed errors are similar or slightly higher in May than in May and June (May: ME=0.,108, RMSE=1.643; May and June: ME = 0.108, RMSE=1.594) similar statement is correct for temperature errors (May: ME=-0.447, RMSE=2.413; May and June: ME =-0.153, RMSE=2.310). The overall correlation between observations and forecasts is in range from 10% to over 20% for rain, 52% for wspd, 79% for rh2 and 90% for T2, which is a few percent lower than in May and June run.

Table 3 shows that the assimilation of either PW or ZTD has a positive impact on rain forecast scatter by 4%, however increases the rain forecast bias by 9% (maximal increase). The relative humidity forecast bias is reduced with assimilation by at least 75% and RMSE is reduced by minimum 2%. Surprisingly, adding more observations i.e. SYNOP and RS data does not improve rain or relative humidity forecast in case of ZTD assimilation, but rather decreases the forecast's quality. It slightly improves the wind speed forecast RMSE, and has a marginally positive impact on the T2 forecast, however overall quality of this parameter forecast is better in the base run. The highest reduction of both ME and RMSE is visible in the relative humidity using PW, RS and SYNOP information, the ME reduced from -0.907 to -0.140 and RMSE from 11.755 to 11.505 with an increase of correlation coefficient and index of agreement. It has also a slight negative impact on temperature and wind speed forecast.

As two forecasted parameters are improved: relative humidity and rain (see Table 3), we investigate the lead time differences between base run and four assimilation setups namely: PW, PW+SYNOP+RS, ZTD, ZTD+SYNOP+RS (Fig. 3).

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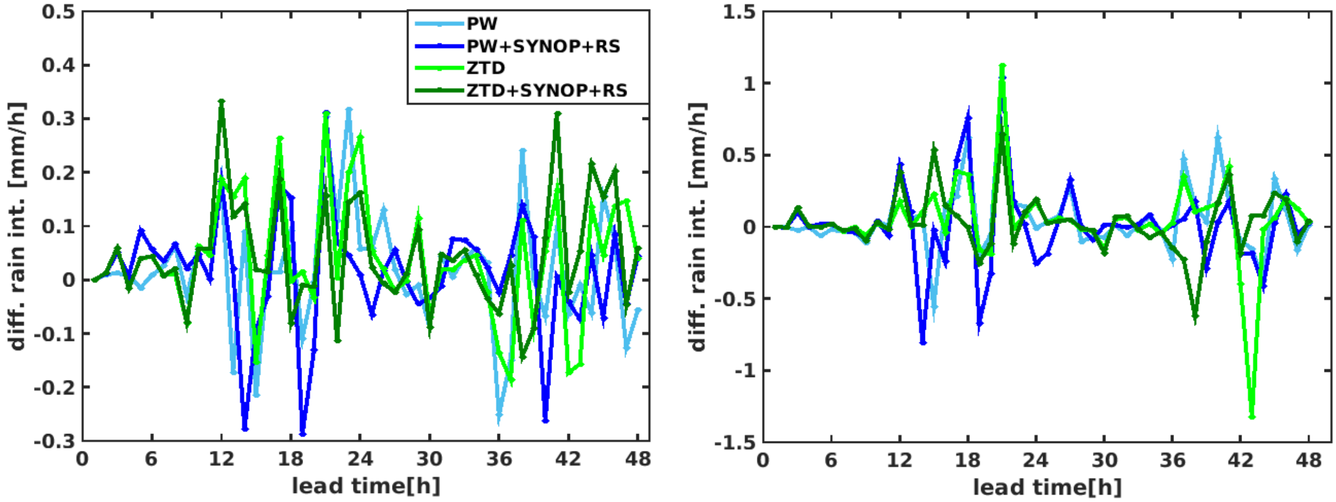

Fig. 4 Performance of rain intensity forecast w.r.t. lead time (positive – improvement with respect to the base run, negative – deterioration with respect to the base run); left panel: ME, right panel: RMSE.

The Fig. 4 ME (left panel) of rain forecast varies significantly during 48 hours, especially in the lead time 10 to 25h and 35 to 48h and is relatively stable between 1 to 9h and 26 to 34h., In the scattered section of figure 4, the ZTD+SYNOP+RS solution seems most of the time positive, while it is negative in the first 9h of forecast. In the first 9 hours of forecast PW+SYNOP+RS reduces the forecast bias. PW and ZTD alone are rarely observed to improve ME of rain forecast. The RMSE pictured on the right panel of Figure 4 shows similar to ME scattered and compacted sections, however there is clear positive impact of assimilating GNSS observations, especially ZTD+SYNOP+RS in short run (until 25h) and PW in long run 35 to 48h. Overall, the RS and SYNOP data helps to improve RMSE of rain forecast.

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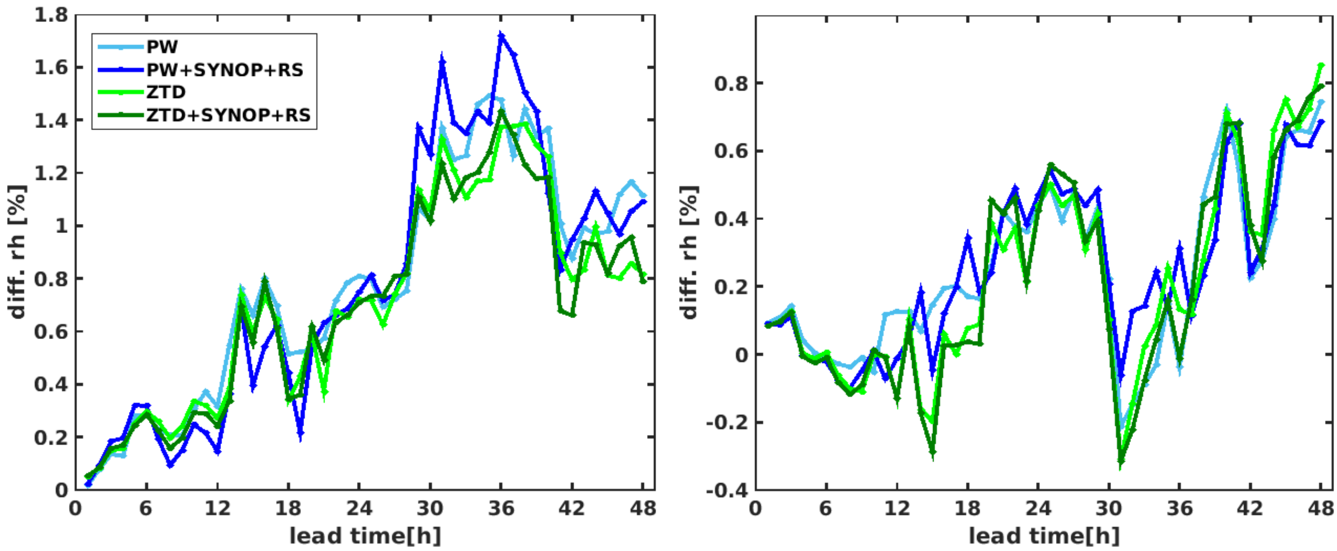

Fig. 5 Performance of rh2 forecast w.r.t. lead time. Left panel: ME, right panel: RMSE.

Less variation between the four scenarios is observed for relative humidity errors (Fig. 5). Both, ME and RMSE are reduced while assimilating each data type, with an exception of lead time 15h, and 31h when RMSE increases (more when ZTD is used, less when PW is used). Moreover, the highest reduction of ME is noticed past 30h of lead time for PW+SYNOP+RS scenario, but other scenarios are also showing positive impact. It is also worth to mention that the rh2 forecast RMSE is reduced after 12h lead time whereas bias is constantly reduced starting form the first hour of forecast.

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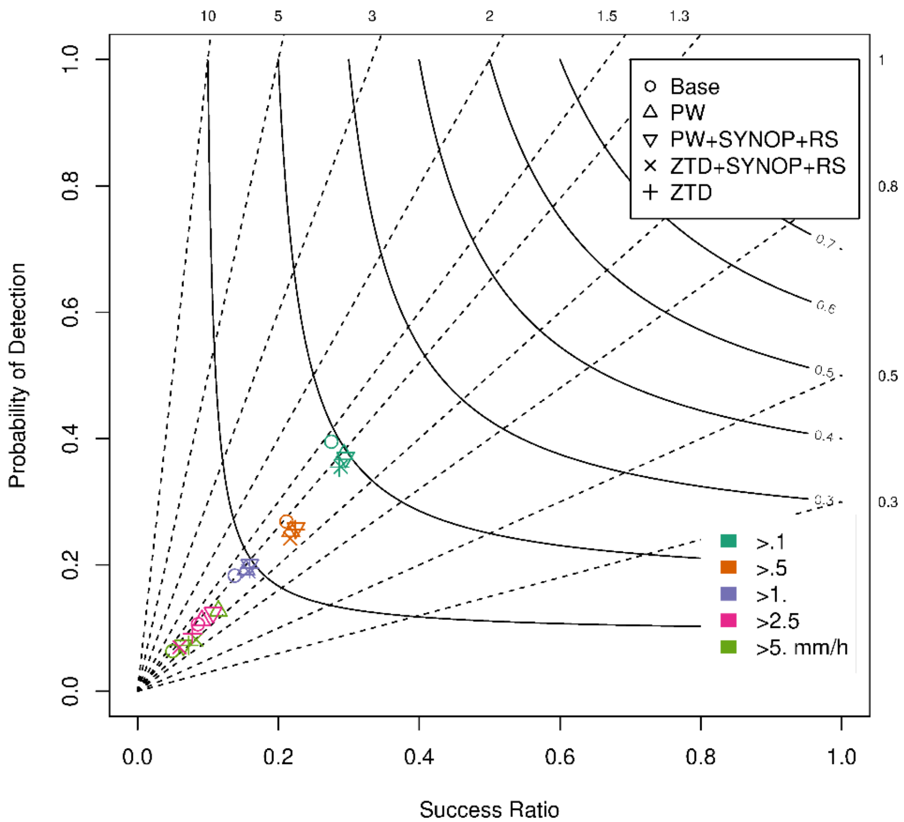

Fig. 6 Performance diagram for assimilation of PW, PW+SYNOP+RS, ZTD+SYNOP+RS, ZTD for May 2013

The impact of data assimilation on rainfall forecasts changes with rainfall intensity (Fig. 6). For the rainfall intensity above 0.1 mm/h, there are small improvements for all the model runs, if compared to the base run in terms of Success Ratio, but the Probability of Detection is smaller. The positive impact of data assimilation is much stronger for higher rainfall intensities. For the thresholds exceeding 1.0 mm/h, both Probability of Detection and Success Ratio are improved if compared to the base run. The improvement is especially large for PW data assimilation and threshold >5.0 mm/h.

4.3 Severe weather cases

The final test is performed using selected 3 cases (Table 4) with strong instabilities and supercell storms. The overall impact of GNSS data in all cases is similar: if there is any reduction in uncertainty it is visible mostly in rain and relative humidity forecast, with a small negative or neutral impact on the wind speed and temperature forecasts.

Mixed results are observed for case a). Rain forecast shows better performance if compared to base run. Humidity forecast (rh2) is improved in terms of RMSE and corr, when PW is assimilated, but ME is slightly worse than in the base run. On contrary, the assimilation of ZTD brings reduction in rh2 ME by 36% while decreasing other forecast quality measures (RMSE, corr, IOA).

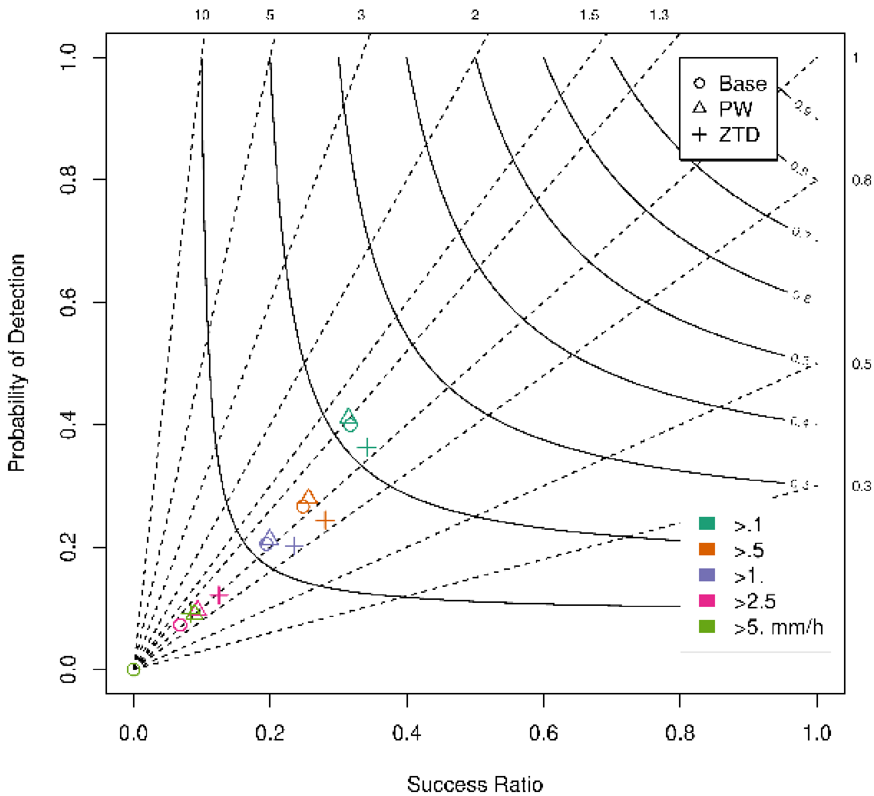

Fig. 7 Performance diagram for assimilation of PW, ZTD for case a)

However, Fig. 7 shows the positive impact of assimilating of PW in a rainfall rate above 0.5 mm/h, and ZTD above 2.5 mm/h. Similarly difficult to interpret results are showed for case b). The assimilation of PW has some positive effect on rainfall, e.g. in terms of ME or RMSE, but negative impact on all other verified parameters: wspd, rh2 (except ME) and t2. Whereas, the ZTD assimilation has very small positive impact on RMSE, corr and IOA of rain intensity forecast, but negative on ME (increase by 2%). Relative humidity MEs are reduced by assimilation of PW by 2% and up to 43% while ZTD is used, all other measures are better for base run. In the local type of rain in SE Poland, as in this case, it is impossible to present statistically sound results for 5 rainfall classes.

Third case also shows small but positive impact of ZTD and, especially PW data assimilation on rainfall forecasts. ME (for PW run only) and RMSE are decreased, and corr and IOA are higher if compared to base run. In the same case also the rh2 ME and RMSE are reduced while using PW assimilation by 4% and 2% respectively, whereas the ZTD assimilation is increasing humidity ME by 1% and reducing RMSE by 1%.

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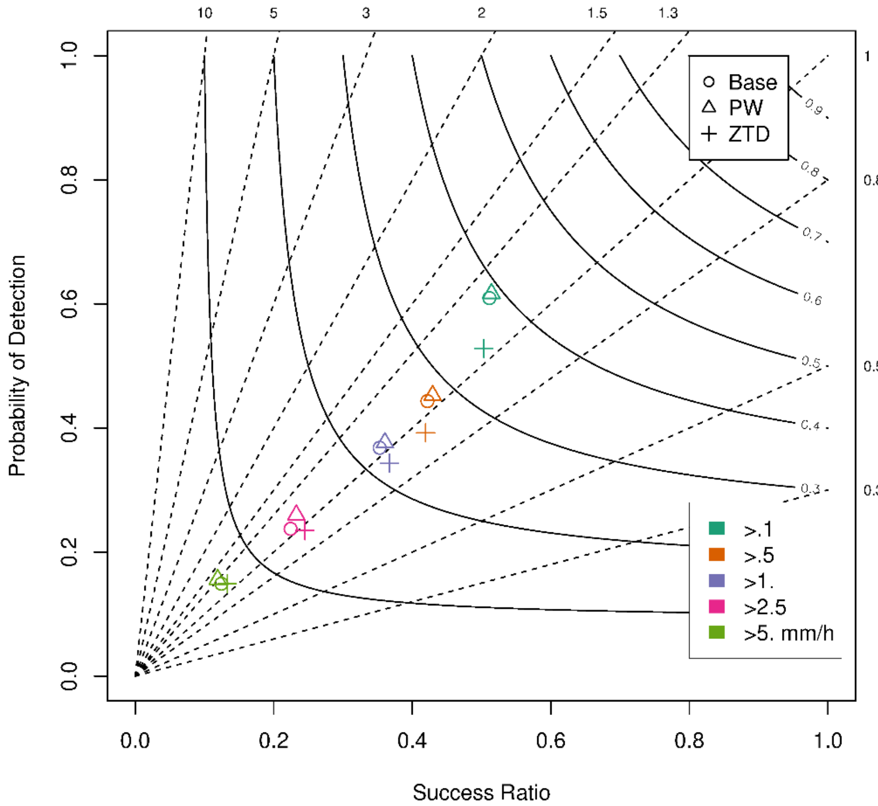

Fig. 8 Performance diagram for assimilation of PW, ZTD for case c)

In the performance diagram in Fig. 8, the rain rate forecasts are improved with PW w.r.t. the base forecast, but worse when ZTD is assimilated. This effect is visible for all rain rates lower than 1mm/h and this discrepancy disappears for rain rates in the 2.5 mm/h class, where both ZTD and PW have positive impact, whereas no impact is noticed for rainfall rates above 5 mm/h.

5 Summary and conclusions

In this study we have analyzed 2 months (May and June 2013) of 4DVAR assimilation of GNSS ground-based observations in WRF model, from over a 100 stations in Poland. Two major approaches were investigated using GPSPW operator: assimilation of PW and ZTD. For shorter time period of 21 days in May additional data were assimilated, namely: RS and SYNOP observations across Poland. Moreover, three different case studies related to severe weather occurrence were investigated. All were linked to a supercell development and intense rain.

May and June case results showed that the assimilation of GNSS data (both ZTD and PW) had positive impact on the humidity forecasts. The assimilation of PW over whole period of two months slightly reduced correlation of daily rainfall rates, reduced relative humidity scatter and had negative or neutral impact on the rain ME and RMSE, neutral impact on wind speed and negative or neutral on temperature. Assimilation of ZTD reduced the ME for humidity by 20%, while it had negative impact on rain, temperature and wind speed bias. However, the binary analysis of rain rate in five intensity classes revealed that the forecasts with assimilation of PW improves forecasts scores in high intensity rain above 2.5 mm/h.

More detailed study focused on May, 5-23, with non-severe weather events showed that the assimilation of either PW or ZTD had positive impact on rain forecast and relative humidity forecast. It improved rain rate RMSE by 4% and had negative impact on bias (9% increase). The relative humidity forecast bias was reduced with assimilation by at least 75% and RMSE was reduced by minimum 2%. Adding SYNOP stations and radiosonde did not bring any further improvements in forecasting humidity or rain but reduced the errors in wind speed and temperature data. Furthermore, the analysis of lead time w.r.t. the errors revealed that two periods of varied positive and negative impact is visible in ME and RMSE statistics. The binary analysis show positive impact of GNSS data assimilation especially for rain rates above 2.5 mm/h.

In the analyzed severe rain cases, the assimilation of GNSS in case a) and c) brings reduction of ME and RMSE. In case b), with more local rain event in the southeast Poland, the assimilation is not improving solution. Binary rain rate forecast performance analysis shows that the intensive rain is better predicted once GNSS data are assimilated. Further research, based on larger number of cases, is required to investigate what are the reasons of different impact of GNSS data on model forecast. We suspect that the ZTDs or PWs calculated from the WRF model with GNSS data assimilated would be improved w.r.t. the WRF model without assimilation. Although, this research was not covered by this study, as the improvement in forecasts of meteorological parameters is much more difficult to gain than of tropospheric parameters with GNSS data assimilation.

Author contribution

Witold Rohm - provided leadership as project PI, wrote the manuscript, prepared art works and tables, coordinated research.

Jakub Guzikowski – run the WRF simulations and assimilation.

Karina Wilgan – prepared the GNSS data and the bias corrections, wrote the GNSS preprocessing section and reviewed the manuscript.

Maciej Kryza – performed the verification of the simulations, wrote the model evaluation section and reviewed the manuscript.

Competing interests

Authors confirm no conflict of interest

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Data

GNSS data used in this study are available from the Institute of Geodesy and Geoinformatics data base MaGDA, access could be granted to any individual after mailing to jan.sierny@igig.up.wroc.pl. Meteorological data were provided by the Institute of Meteorology and Water Management – National Research Institute. National Centers for Environmental Prediction/National Weather Service/NOAA/U.S. Department of Commerce, 2000: NCEP FNL Operational Model Global Tropospheric Analyses as boundary and initial conditions for the model run.

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Table 1. The WRF configuration used in the experiment

Parameters	**Domain 1**	**Domain 2**
spatial resolution	12 km x 12 km	4 km x 4 km
vertical levels	48	48
microphysics	Thompson	-
cumulus	Kain-Fritsch	-
longwave radiation	RRTMG	RRTMG
shortwave radiation	Dudhia	Dudhia
surface layer	MM5	MM5
planetary boundary layer	Yonsei University scheme	Yonsei University scheme

Table 2. Impact of assimilation of PW and ZTD using 4DVAR operators, validated against SYNOP observations, for June and May. Colors decode improvement (green), deterioration (red) or no impact (yellow), of forecast with the use of GNSS data.

run	**rain**				**wspd**				**rh2**				**T2**			
	me	**rmse**	**corr**	**IOA**	**me**	**rmse**	**corr**	**IOA**	**me**	**rmse**	**corr**	**IOA**	**me**	**rmse**	**corr**	**IOA**
Base May and June	-0.713	2.573	0.098	0.363	0.108	1.594	0.552	0.735	-2.862	11.365	0.803	0.889	-0.153	2.310	0.911	0.953
PW	-0.713	2.601	0.094	0.359	0.107	1.591	0.552	0.735	-2.869	11.359	0.803	0.889	-0.157	2.312	0.911	0.953
ZTD	-0.739	2.616	0.093	0.357	0.126	1.605	0.543	0.729	-2.179	11.151	0.805	0.893	-0.274	2.296	0.913	0.954

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Table 3. Impact of assimilation of PW, ZTD, RS and SYNOP using 4DVAR operators, validated against SYNOP observations, for May, 5-23, 2013. Colors decode improvement (green), deterioration (red) or no impact (yellow), of forecast with the use of GNSS data.

run	rain				wspd				rh2				T2			
	me	rmse	corr	IOA	me	rmse	corr	IOA	me	rmse	corr	IOA	me	rmse	corr	IOA
Base May	-0.518	1.977	0.116	0.382	0.108	1.643	0.523	0.713	-0.907	11.755	0.793	0.888	-0.447	2.413	0.903	0.948
PW	-0.536	1.904	0.202	0.457	0.129	1.647	0.519	0.711	-0.134	11.516	0.802	0.893	-0.590	2.409	0.906	0.948
ZTD	-0.558	1.930	0.166	0.426	0.119	1.641	0.518	0.710	-0.202	11.540	0.801	0.893	-0.593	2.413	0.906	0.948
PW+ SYNOP+RS	-0.526	1.976	0.137	0.401	0.108	1.647	0.512	0.706	-0.140	11.505	0.802	0.894	-0.591	2.421	0.905	0.948
ZTD+SYNOP+RS	-0.567	1.951	0.122	0.388	0.115	1.637	0.518	0.711	-0.214	11.546	0.801	0.893	-0.589	2.417	0,905	0,948

Table 4. Impact of assimilation of PW, ZTD, RS and SYNOP using 4DVAR operators, validated against SYNOP observations, for selected cases (case a) May, 29-31, 2013; (case b) June, 17-19, 2013; (case c) June, 24 -26, 2013. Colors decode improvement (green), deterioration (red) or no impact (yellow), of forecast with the use of GNSS data.

run	rain				wspd				rh2				T2			
	me	rmse	corr	IOA	me	rmse	corr	IOA	me	rmse	corr	IOA	me	rmse	corr	IOA
Base (case a)	-1.129	3.320	0.017	0.325	0.200	2.010	0.493	0.691	-4.516	11.554	0.769	0.859	0.049	2.251	0.889	0.940
PW (case a)	-1.077	3.282	0.056	0.360	0.202	2.006	0.494	0.692	-4.525	11.512	0.771	0.860	0.050	2.247	0.889	0.940
ZTD (case a)	-1.084	3.332	0.084	0.375	0.291	2.131	0.443	0.657	-2.875	11.930	0.724	0.844	-0.075	2.274	0.882	0.937
Base (case b)	-1.981	4.578	-0.079	0.330	0.283	1.394	0.448	0.665	-1.451	11.459	0.782	0.881	-0.194	2.346	0.913	0.950
PW (case b)	-1.965	4.580	-0.069	0.330	0.285	1.399	0.446	0.664	-1.416	11.525	0.780	0.880	-0.210	2.362	0.912	0.949
ZTD (case b)	-1.980	4.578	-0.045	0.330	0.309	1.408	0.421	0.65	-0.824	11.517	0.779	0.880	-0.295	2.366	0.912	0.949
Base (case c)	-0.801	3.282	0.162	0.434	-0.092	1.959	0.524	0.717	-3.070	10.756	0.726	0.835	-0.114	2.333	0.851	0.921
PW (case c)	-0.793	3.217	0.172	0.450	-0.115	1.946	0.526	0.719	-2.955	10.546	0.735	0.841	-0.146	2.314	0.853	0.922

ZTD (case c)	-0.915	3.204	0.169	0.449	-0.112	1.915	0.523	0.716	-3.074	10.681	0.730	0.838	-0.258	2.332	0.848	0.919