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# Impact of Iranian permanent GPS network precipitable water estimates on numerical weather prediction

**Ali Sam Khaniani[1]*, Majid Azadi[2], Zeinab Zakeri[3]**

[1] Civil Engineering Department, Babol Noshirvani University of Technology, Babol, Mazandaran, Iran

[2] Atmospheric Science and Meteorological Research Center, Tehran, Iran

[3] I.R. Iran Meteorological Organization, P.O. Box 13185-461, Tehran, Iran

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**ABSTRACT**

The aim of this study is to assess the impact of continuous and precise ground-based GPS water vapor estimates as a by-product of Iranian Permanent GPS Network (IPGN) geodetic data processing, together with conventional surface and upper air meteorological data on the short range prediction of rainfall and surface moisture fields, including 2 m relative humidity and Precipitable Water Vapor (PWV) over north of Iran. The Weather Research and Forecasting (WRF) model and its Four-Dimentional Variational Data Assimilation (4DVAR) system is used to determine the impact of data assimilation on simulation of three heavy rainfall cases that occurred over the northern part of Iran. All three rainfall cases considered in this study are associated with a shallow and cold high pressure located over Russia that extends towards the southern Caspian Sea. The results of numerical experiments showed that the assimilation of ground-based GPS PWV data, on average, improves simulation of precipitation, PWV and near surface relative humidity, even though the skill declines after 24-h simulation. It is found that inclusion of GPS PWV improved the predicted accumulated precipitation in day-1 of the model simulations for February and November cases up to 7 percent while there was almost no positive impact in September case. Results suggest that incorporation of observations in initial conditions of the WRF gives generally a slight improvement in 2 m relative humidity forecasts when compared with the control experiment without assimilation. Assimilation of GPS PWV in February and September cases reduces, on average, 0.8 mm the Mean Absolute Error (MAE) of the PWV model during 12-h forecast period. Overall, best results in terms of MAEs were achieved when GPS water vapor estimations were used along with conventional surface and upper air radiosonde data.

**KEYWORDS**

4DVAR assimilation
WRF
GPS PWV
surface observations
humidity precipitation

## 1. Introduction

The amounts and variability of water vapor as one of the most important greenhouse gases of the atmosphere has effective contributions on many atmospheric phenomena such as deep moist convection, rainfall process, flood and lightning (Bevis et al., 1992; Mazany et al., 2002). Atmospheric water vapor is highly variable at different temporal and spatial scales (Dai & Wang, 2002). Therefore, high-resolution measurement of this parameter is necessary to monitor the spatio-temporal variation of atmospheric water vapor and use of these information in Numerical Weather Prediction (NWP) models (Zhang et al., 2007).

Many techniques have been used to measure the atmospheric water vapor content. Radiosonde as a conventional tool observes the atmospheric water vapor

* Corresponding author
E-mail addresses: ali.sam@nit.ac.ir (A. Sam Khaniani); azadi68@hotmail.com (M. Azadi); z_zaaker@yahoo.com (Z. Zakeri)
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content. Due to the high cost of each launch, radiosondes often provide observations of water vapor twice a day only. Low temporal resolution and uneven spatial coverage of the radiosonde measurements is not ideal for monitoring the atmospheric water vapor variations at different temporal and spatial scales (Divakarla et al., 2006; Pramualsakdikul et al., 2007). Ground-based microwave radiometry can measure water vapor with high temporal resolution but this technique is useless during precipitation (Guldner & Spankuch, 1999). Satellite observations of water vapor have a good spatial coverage but they suffer from the low temporal resolution (Deeter, 2007).

The GPS remote sensing of atmospheric water vapor using ground-based GPS receivers was introduced in 1992 (Bevis et al., 1992). This technique operates in all weather conditions with high-temporal resolution (typically a few minutes) and long-term stability (Bevis et al., 1994; Duan et al.,, 1996; Rocken et al., 1997; Tregoning et al., 1998; Yunck et al., 2000). In addition, dense GPS receiver networks can be built at a low cost and it is one of the major benefits of GPS meteorology. Today, the analytical centers utilize advanced GNSS processing techniques such as Precise Point Positioning (PPP) and network solution to provide near real time and real time tropospheric products which are used in climate monitoring, water vapor tomography, Short-term, high resolution NWP forecasting nowcasting and many other applications (Guerova et al., 2016).

The atmospheric water vapor content can be expressed in terms of Precipitable Water Vapor (PWV). PWV is the depth of liquid water contained in a vertical column of the atmosphere, if the entire vapor in that column were compressed. Several studies have been conducted to validate the ground-based GPS PWV estimations. The reported Root Mean Squares (RMS) of GPS PWV change between 2 to 3.7 mm (Rocken et al., 1993; Ohtani and Naito 2000; Pottiaux & Warnant, 2002; Li et al., 2003; Dietrich et al., 2004; Van Baelen et al., 2005; Sibylle et al., 2010).

During recent years, the ground-based GPS estimates of PWV are applied on validating PWV measurements by other techniques (e.g., Prasad & Singh, 2009), investigating the diurnal variation of atmospheric water vapor (e.g., Dai et al., 2002; Wu et al., 2003), examining the water vapor changes during rainfalls (e.g., Liou and Huang 2000; Foster et al., 2003; Li & Deng, 2013; Choy et al., 2013), monitoring climate changes (e.g., Gradinarsky et al., 2002; Nilsson & Elgered, 2008; Ortiz de Galisteo et al., 2010). Besides the above-mentioned applications, the ground-based GPS meteorology provides a new data source for data assimilation (Gutman & Benjamin, 2001; Wang et al., 2009; Sharifi et al., 2016).

PWV is one of the key variables that indicates the precipitation potential in the atmosphere. Therefore, high-resolution measurements and assimilation of this parameter can play an important role on the precipitation forecasts of Numerical Weather Prediction (NWP) models (Mazany et al., 2002, Zhang et al., 2007). An accurate initial condition is one of the key factors in NWP to have a better numerical prediction of the atmosphere. Assimilation of observational data such as radiosonde, radar and GPS PWV estimates can improve the initial conditions (Falvey & Beavan 2002; Kalnay 2003; Govindankutty & Chandrasekar, 2011; Dong & Xue, 2012).

The variational data assimilation methods have the capacity of direct assimilation of many types of observations such as satellite radiance, radar reflectivity and GPS PWV that are not prognostic variables in forecast models. Using this type of data assimilation approaches, several researchers showed a positive impact on prediction of atmospheric fields (Lipton et al., 1995; Kalnay 2003; Fischer et al., 2006; Saito et al., 2007). It was found that the assimilation of water vapor estimates from ground-based GPS networks using three-dimensional and four-dimensional variational (3DVAR and 4DVAR) approaches has a positive impact on NWP of humidity and precipitation fields (Kuo et al., 1993; Kuo et al., 1996; Higgins, 2001; Falvey & Beavan 2002; Ha et al., 2003; Guerova et al., 2004; Guo et al., 2004; Iwabuchi et al., 2005; Zhang et al., 2007; Boniface et al., 2009; Bauer et al., 2011; Leiming et al., 2012).

The 4DVAR data assimilation method allows the ingest of high resolution multi-level data at their exact time of observation and utilizes a forecast model as a constraint to preserve the dynamic balance of the resulted analysis (Zhang et al, 2007; Huang et al., 2008). Up to now, the 4DVAR system has been developed and widely used in several operational centers such as European Centre for Medium-Range Weather Forecasts (ECMWF), Japan and Canada (Rabier et al., 2000; Honda et al., 2005; Gauthier et al., 2007). The aforementioned attempts and studies encouraged us to benefit from the ground-based GPS water vapor estimates by its 4DVAR assimilation into a mesoscale NWP model.

The National Cartographic Center (NCC) of Iran has established the Iranian Permanent GPS Network (IPGN) consisting of about more than 90 active stations to study the crustal deformation and also for navigation and surveying purposes (Jadidi et al., 2006). Most of the IPGN stations are distributed in the northern part of Iran. In addition, accurate prediction of precipitations is a challenging task in operational forecasting over the north of Iran. The present study is aimed to investigate the impact of 4DVAR assimilation of GPS PWV estimates together with the conventional observation types (e.g., surface meteorological data at synoptic stations and radiosonde profiles of humidity, temperature and wind) on the numerical simulation of moisture fields over the northern part of Iran using the Weather Research and Forecasting (WRF) model

(Skamarock et al., 2008).

We introduce the data used in this study in the following section, and then describe the estimation of PWV using GPS observations in Section 3. The description of the NWP model and its setting used in this study followed by assimilation methodology are then presented in Section 4. Afterwards, Section 5 gives the result of different numerical experiments in prediction of precipitation, PWV and surface relative humidity over the study area. Finally, the conclusions are drawn in the last section.

## 2. Methodology: Extending evaluation framework

Thermal shallow and cold high pressure system located over Russia and over the northern Caspian Sea is responsible for most of the heavy precipitations that occur in the southern coasts of Caspian Sea. The temperature difference between the warm water of Caspian Sea and relatively cold air above it, especially during the late summer and early autumn, in the shallow high pressure, causes an intense evaporation and thus air becomes saturated in the boundary layer. The overhead low pressure causes vertical motions and precipitations in the southern Caspian Sea. This relatively complicated mechanism along with complex topography in the northern Iran make the task of accurate rainfall prediction highly challenging. As such, timely and accurate prediction of heavy rainfalls in the region have much importance in operational forecasting. In this study, three precipitation events (1 February, 17 September and 24 November 2014) in the above-mentioned region are selected as case studies to examine the impact of assimilating the IPGN PWV estimates as well as local surface and upper air meteorological data in numerical simulation of moisture fields over the northern part of Iran.

The GPS PWV values with sub hourly temporal resolution derived from the geodetic processing of the GPS observations from 88 IPGN stations are used to improve the numerical prediction results. Figure 1 illustrates the distribution of GPS stations (black triangles) in the IPGN network along with the topographic information. As can be seen in Figure 1, most of the ground-based GPS stations are located in north and north-west of the country. Therefore, verification and comparison of the model outputs will be performed in this area only.

Synoptic data with 3-hour temporal resolution collected at more than 400 surface stations along with the vertical temperature and humidity profiles observed at four radiosonde stations located inside the model domain collected from the Islamic Republic of Iran Meteorological Organization (IRIMO) network are incorporated in the data assimilation process. The radiosondes are launched twice a day at 00 and 12 UTC. Green stars in Figure 1 show the location of the radiosonde stations. Daily rain gauge data collected from IRIMO network in the study area are used to validate the precipitation forecasts from the WRF model.

## 3. Estimation of PWV using GPS observations

The total atmospheric delay in the zenith direction can be estimated for each station during the data processing of GPS measurements. Total tropospheric zenith path delay (ZPD) of GPS signal consists of two components: the dry or hydrostatic delay (ZHD) which is related to the atmospheric dry air gases and the wet component (ZWD) that is contributed by the moisture contents of the atmosphere (Emardson et al., 2003).

$$\mathrm{ZPD}=\mathrm{ZHD}+\mathrm{ZWD} \tag{1}$$

Using the Saastamoinen model (Saastamoinen, 1972), the ZHD can be calculated as a function of surface pressure measurements ($P_0$) at GPS station, site latitude and height:

$$\mathrm{ZHD}=\frac{[(0.0022768\pm0.0000015)\mathrm{m.hPa}^{-1}]P_0}{1-0.00265\cos(2\varphi)-0.000285H} \tag{2}$$

where, $\varphi$ is the latitude and $H$ is the height from geoid in kilometers. The total zenith delay of the GPS signals is calculated during the processing of IPGN observations. The ZWD is achieved by reducing ZHD from the estimated total zenith delay.

The ZWD is a function of the water vapor and atmospheric temperature. Therefore, the PWV can be estimated when weighted average of the atmospheric temperature, $T_m$ is calculated (Davis et al., 1985). The GPS PWV over a station could be obtained via a dimensionless conversion factor (Π) which map ZWD into the PWV as follows (Bevis et al., 1994):

$$\mathrm{PWV}=\Pi.\mathrm{ZWD} \tag{3}$$

where

$$\Pi^{-1}=10^{-6}\rho_w\, R_v\left[\left({}^{k_3}/_{T_m}\right)+k_2+k_1\left({}^{M_w}/_{M_d}\right)\right] \tag{4}$$

Here, $M_w$(18.0152 gr mol$^{-1}$) and $M_d$(28.9644 gr mol$^{-1}$) are the molar mass of water vapor and dry air, respectively. The $\rho_w$=999.79 kg m$^{-3}$ denotes the density of liquid water and $R_v$=461.51 J K$^{-1}$ kg$^{-1}$ represents the specific gas constant of water vapor. The physical constants $k_1$(77.689±0.0094 (K hPa$^{-1}$)), $k_2$(71.295± 1.3 (K hPa$^{-1}$)),and $k_3$(3.75463±0.0076 (10$^5$K$^2$ hPa$^{-1}$)) are atmospheric refractivity constants given by Rüeger (2002).

The GPS observations processing strategy options are summarized in Table 1.

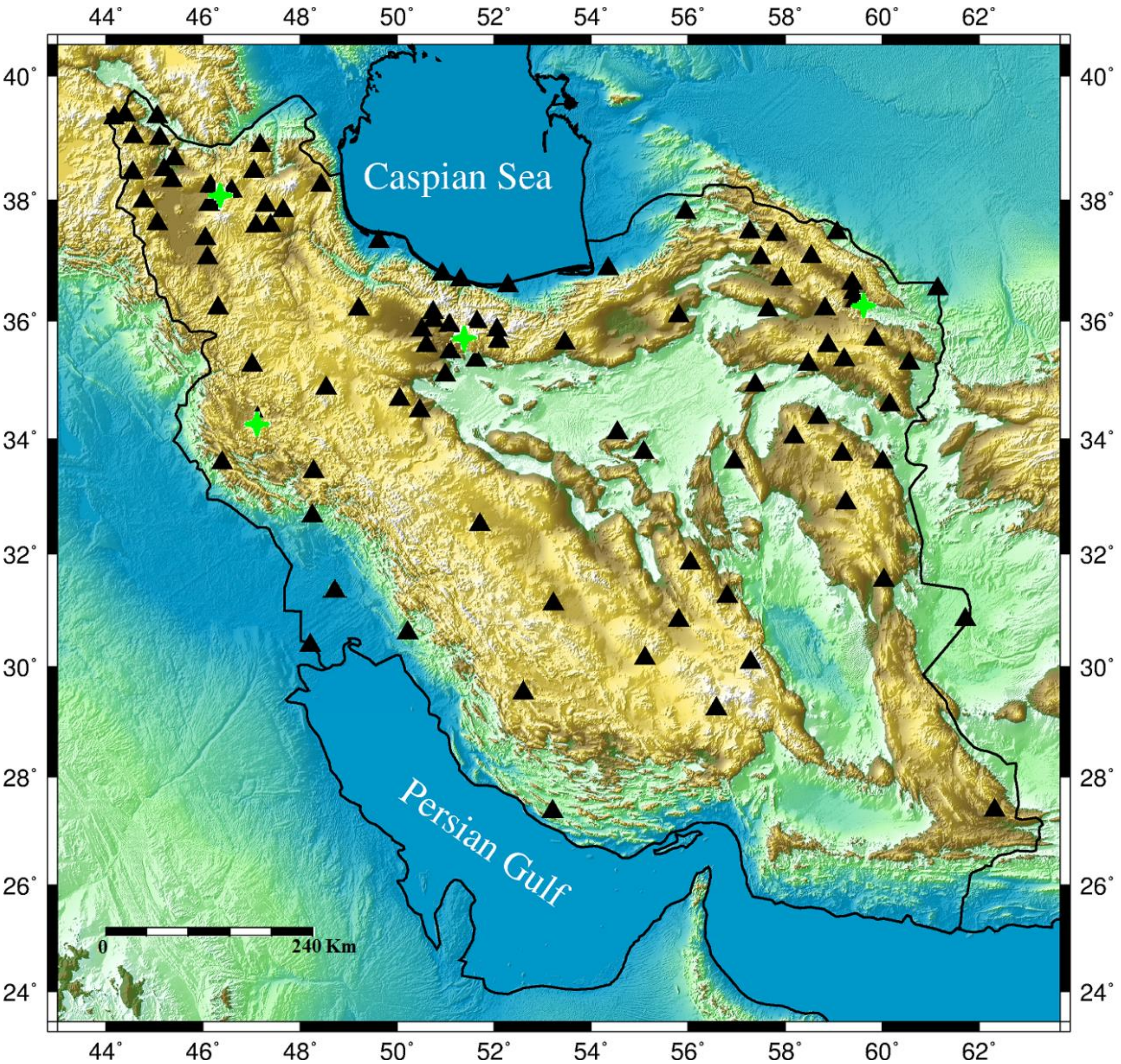


Figure 1. Distribution of IPGN stations (black triangles) together with topographic information over Iran. Green stars show the location of radiosonde stations in the IRIMO network

Table 1. Characteristics of GPS processing strategy used to compute the tropospheric parameters

| **Software** | **GAMIT** |
|---|---|
| Processing strategy | double difference (network solution) |
| Earth orientation parameters | IERS 2010 |
| Orbit and clocks products | IGS Final |
| Elevation cut-off angle | $7^{\circ}$ |
| Antenna calibration | IGS08.atx |
| Mapping function | Niell |
| Ocean tidal loading | yes |

## 4. Numerical model and assimilation methodology

In this section we describe the numerical experiments and the NWP model used to simulate three rainfall cases. Also, the data assimilation technique is briefly described here.

To investigate the observations impact in the short-range forecasts, for each rainfall case we performed three numerical experiments with alternative initial and boundary conditions. The initial and boundary conditions of the control experiment (CTRL), without assimilation, were interpolated from the $0.5^{\circ}\times0.5^{\circ}$ National Center for Environmental Prediction (NCEP) Global Forecast System (GFS) forecasts at 3-h intervals. In the second experiment called "CONV_4DVAR", the WRF-4DVAR system was used to assimilate the conventional surface and radiosonde observations collected from IRIMO network in the initial condition. In the third experiment, named as "GPSCONV_4DVAR", both GPS PWV from the IPGN network and conventional data were assimilated. The observations were assimilated every 1-hour, beginning at 1800 UTC one day before the rainfall event. The assimilation time window was 6 hours, so the optimal initial condition was obtained at 1200 UTC and the model was integrated 54 hours ahead.

In the current study, we used WRF version 3.6.1 mesoscale model (Skamarock et al., 2008) and WRFDA data assimilation system (Barker et al., 2012) for the assimilation process. The WRF simulations were conducted in a single domain (Figure 2), with 21-km horizontal resolution (142×130 grid points in east-west and north-south directions) and 41 vertical levels. The model physics options were selected based on earlier experience and include the WRF Single-Moment 3-class (WSM3) simple ice scheme (Hong et al., 2004) for microphysics, Rapid Radiation Transfer Model (RRTM) for longwave radiation (Mlawer et al., 1997) and Dudhia (1989) for shortwave radiation, MM5 Monin-Obukhov surface layer scheme (Monin & Obukhov, 1954), the Unified Noah land-surface model (Chen & Dudhia, 2001), the YSU scheme (Hong et al., 2006) for the planetary boundary layer turbulence and Kain-Fritsch (new Eta) (Kain, 2004) mass flux scheme for cumulus convection. The choice of model setup and parameterizations is based on our previous experience using WRF for forecasting weather conditions in Iran.

The 4DVAR assimilation applied for the incorporation of observational data (Skamarock et al., 2008) provides the optimal initial condition that minimizes a cost function defined as the squared distance between model values and observations within a certain assimilation window. The 4DVAR cost function is given by (Ide et al., 1997):

$$J(x_0)=J_b+J_o$$
$$=\frac{1}{2}\left(x_0- x_b\right)^T\mathbf{B}^{-1}\left(x_0- x_b\right)+\frac{1}{2}\sum_{i=0}^{n}\left[y_i-\mathbf{H}(x_i)\right]^T R_i^{-1}\left[y_i-\mathbf{H}(x_i)\right] \quad (5)$$
$$x_{i+1}=\mathbf{M}_i x_i \quad (i=0,\ldots,n) \quad (6)$$

where $x_0$ and $x_b$ are the analytical and forecast background vectors, respectively. $y_i$ represents the vector of observations at time i within the assimilation window and the forecast model **M** predicts the vector $x_i$. The matrix **B** is the background error covariance matrix and **O** is the covariance matrix of the observational error. **H** denotes the observation operator which maps model state vector into observation space. The control variables of the cost function are the amplitudes of Empirical Orthogonal Functions (EOFs) of stream function, unbalanced velocity potential, unbalanced part of temperature, pseudo relative humidity, and unbalanced surface pressure (Barker et al., 2004).

GPS PWV is not a prognostic variable and the observation operator uses a model state to estimate the value of PWV at the same time and location of the IPGN observations. The observation operator of the GPS PWV used in WRF data assimilation system is expressed as follows (Iwabuchi et al., 2005):

$$\mathrm{PWV}=\sum_{k=1}^{k=nk}\rho_k\, q_k dz_k \quad (7)$$

where, $\rho$ ($^{kg}/_{m^3}$) is the air density, $q$($^{kg}/_{kg}$) is specific humidity and $dz$(m) is the height of the vertical model grid.

## 5. Results

Three heavy rainfall cases (1 February, 17 September and 24 November, 2014) over the north of Iran were selected to investigate the influence of 4DVAR assimilation of observations on the model prediction of precipitation, surface relative humidity and water vapor fields. The simulations were conducted with different initial conditions as introduced in Section 4. Table 2 shows the percentage of each observation type used in the assimilation process for three rainfall cases.

For verifying the process, the model predicted precipitation, relative humidity and PWV were compared with their corresponding values collected from the IRIMO and IPGN networks. The area between $35^{\circ}$ and $40^{\circ}$N latitude of the country (northern Iran) was selected for the validation process and is shown as a rectangle with the model domain in Figure 2.

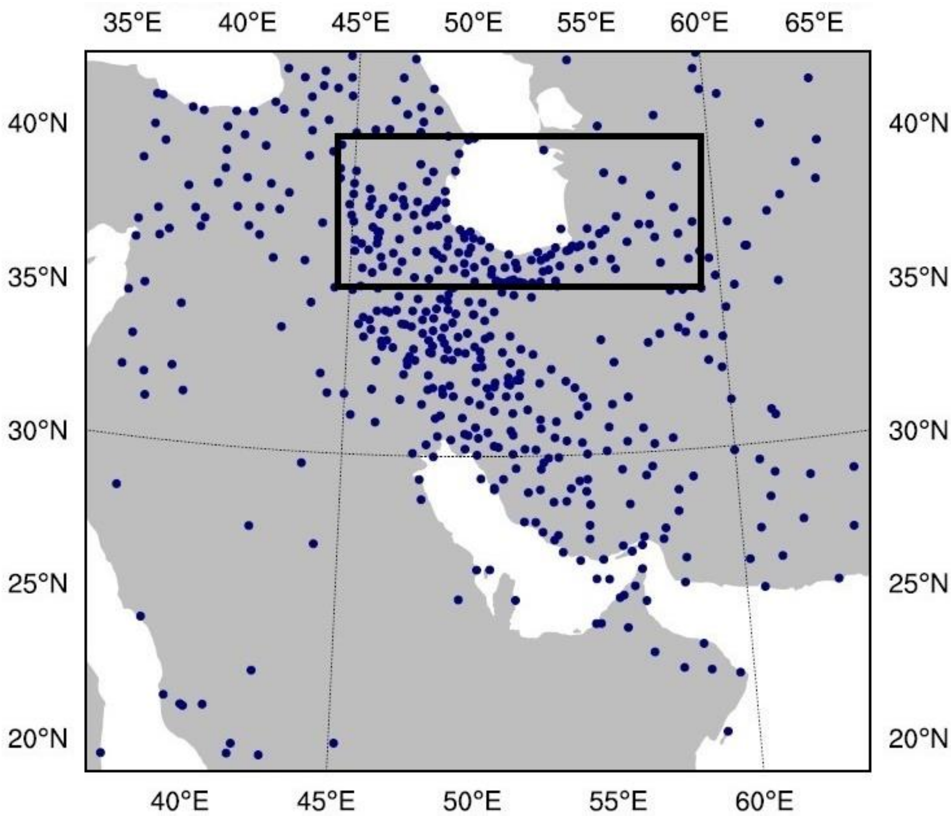


Figure 2. The distribution of synoptic observations on the model domain used in numerical experiments. Stations which located in the inner rectangle were selected for the validation process

Table 2. The number and percentage of all the types of observations assimilated in the numerical experiments

| | Case-1 | | Case-2 | | Case-3 | |
|---|---|---|---|---|---|---|
| **Observation type** | **Number** | **Percentage** | **Number** | **Percentage** | **Number** | **Percentage** |
| Conventional (synoptic and upper air) data | 3399 | 85% | 3184 | 84% | 3388 | 855 |
| GPS PWV | 595 | 15% | 598 | 16% | 598 | 15% |
| Total | 3994 | 100% | 3782 | 100% | 3986 | 100% |

**5.1 Precipitation**

The observations collected from surface rain gauges were used to assess the impact of 4DVAR assimilation on the model's rainfall forecast. The location of rain gauges is depicted in the inner rectangle of Figure 2. For each of three precipitation cases and experiments, the Mean Absolute Errors (MAEs) of the 24-h accumulated model predicted rainfall for day-1 and day-2 of simulations initialized at 1200 UTC 31 January for Case-1, 1200 UTC 16 September for Case-2 and 1200 UTC 31 November 2014 for Case-3 are given in Table 3. The mean absolute is the absolute error averaged over all stations used in verification. As can be seen in Table 3, it is clear that the assimilation of observation into the model reduced the accumulated precipitation forecast error for all three cases at the first day of simulations.

During the first day of forecast in Case-1, incorporation of observation in the experiments CONV_4DVAR and GPSCONV_4DVAR decreased the rainfall simulation error by 2 and 8 percent respectively, compared to CTRL. Similarly, considering the MAE values in Case-3, the CONV_4DVAR and GPSCONV_4DVAR experiments reduced the error on the first day of model simulations by 2 and 9 compared to the forecast with no data assimilation. Accordingly, it is inferred that the inclusion of GPS PWV estimates into assimilation process for both Case-1 and Case-3, further decreases the precipitation forecast error at day-1 by 7 percent.

Table 3. MAE of the 24-hour accumulated precipitation (in mm) simulated in different numerical experiments. For the Case-1,-2 and -3, the WRF was initialized at 1200 UTC 31 January, 1200 UTC 16 September and 1200 UTC 23 November 2014, respectively

| **Experiments** | **Case-1: 1 February 2014** | | **Case-2: 17 September 2014** | | **Case-3: 24 November 2014** | |
|---|---|---|---|---|---|---|
| | Day-1 | Day-2 | Day-1 | Day-2 | Day-1 | Day-2 |
| **CTRL** | 4.22 | 3.20 | 1.87 | 1.57 | 5.23 | 4.18 |
| **CONV_4DVAR** | 4.14 | 3.27 | 1.79 | 1.70 | 5.12 | 4.13 |
| **GPSCONV_4DVAR** | 3.88 | 3.29 | 1.81 | 1.58 | 4.75 | 4.22 |

From Table 3 it is seen that, using conventional data in CONV_4DVAR, assimilation experiment reduced the MAE of accumulated precipitation for the first day of simulations in Case-2 but the addition of GPS PWV data did not make indicative improvement in the model simulated precipitation. Moreover, during day-2, assimilation of observations has no significant impact on the WRF rainfall predictions in either of the cases considered here. Overall, the error values in Table 3, indicate that 4DVAR assimilation of the estimated PWV from IPGN network along with meteorological data can improve the precipitation forecast.

### 5.2 Surface relative humidity

Assimilation of surface and upper air meteorological observations along with GPS PWV estimates which represent the moisture distribution over the study area can improve the prediction of humidity fields (Gutman et al., 2001; Iwabuchi et al., 2005). Using surface relative humidity observations collected from 130 synoptic stations of IRIMO network and the corresponding WRF predicted values at the same locations; the model performance was evaluated in three different numerical experiments and rainfall cases. In each case, 6 hourly MAEs for 2 m relative humidity were computed and are depicted in Figure 3.

For Case-1, the GPSCONV_4DVAR experiment showed the lowest forecast error for relative humidity during the whole simulation period when compared to the other two experiments. Also, the positive impact of GPS PWV data on 2 m relative humidity only lasts for 24-h (Figure 3a) and the error reduction, gradually decreased by the end of the forecast. From Figure 3b it is seen that incorporation of observation has a positive impact during the first 24-hr forecast of CONV_4DVAR experiment in Case-2. However, in Case-3, assimilation experiments in comparison with the CTRL had almost no positive impact on simulation of 2 m relative humidity (Figure 3c). Overall, the assimilation experiments compared to CTRL have, on average, higher impact on near surface moisture simulation.

### 5.3 Precipitable water vapor

To further elaborate the impact of data assimilation, one can assess the model simulations of PWV. Therefore, the comparison made between ground-based GPS PWV estimates from the IPGN geodetic processing as a reference and corresponding model derived values of PWV in all experiments. Figure 4 depicts the temporal variation of MAEs of the WRF simulated PWV (mm) with 6-h intervals in different numerical experiments for rainfall Case-1 (Figure 4a), Case-2 (Figure 4b) and Case-3 (Figure 4c). In order to compute the MAEs, we used all 60 GPS stations located in the inner rectangle of Figure 2.

It is seen that in all rainfall cases (Figure 4a, b and c), the assimilation of conventional data in CONVDA_4DVAR experiment has almost no positive impact on the prediction of PWV fields. As compared with the CTRL, the inclusion of ground-based GPS water vapor data improved the GPSCONV_4DVAR forecasts of PWV in Case-1 and 2, but not in Case-3. As such, the assimilation of GPS data, during 12-h forecast length in Case-2, reduces the MAE of the model PWV from 2.5 to 2 mm. In Case-1 and -2, after the end of 4DVAR assimilation window, during 12-h forecast of PWV, the GPSCONV_4DVAR reduces the MAEs, on average up to 0.8 mm.

## 6. Summary and conclusions

Using observations from synoptic and upper air stations of IRIMO network and GPS water vapor estimates prepared from IPGN, this study investigated the impact of 4DVAR data assimilation method on the model forecast of rainfall and moisture fields including PWV and 2 m relative humidity during precipitations over northern Iran.

Three numerical experiments were carried out for simulation of aforementioned fields for three rainfall cases (1 February, 17 September and 24 November 2014) in the study area. The CTRL experiment was conducted without data assimilation and served as a benchmark for examining the assimilation experiments. In the second experiment named CONV_4DVAR, surface and upper air data collected from IRIMO network were inserted in the initial conditions of the WRF. The third experiment named asGPSCONV_4DVAR assimilated GPS PWV data together with the conventional data provided by IRIMO. The WRF-4DVAR system with total assimilation window of 6-h was used to assimilate the data in a single domain of model with 21-km horizontal resolution.

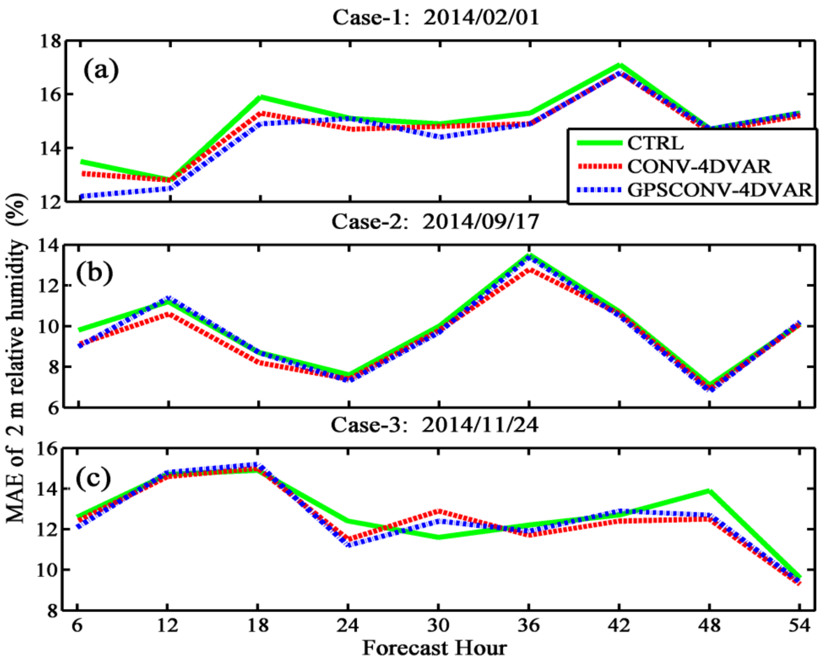


Figure 3. Time series of MAEs of model predicted 2 m relative humidity (%) with 6-h intervals during the simulation period from experiments CTRL, CONV_4DVAR and GPSCONV_4DVAR for case (a) 20140201, (b) 20140917, and (c) 20141124

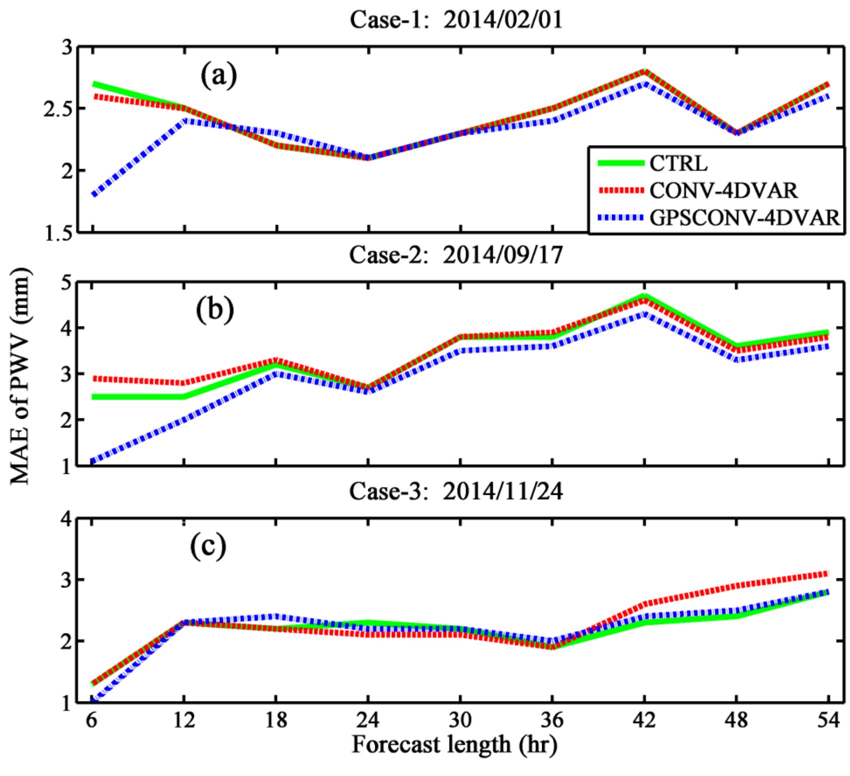


Figure 4. Time series of MAEs of model predicted PWV (mm) with 6-h intervals during the simulation period from experiments CTRL, CONV_4DVAR and GPSCONV_4DVAR for case (a) 20140201, (b) 20140917, and (c) 20141124

Comparison of error values calculated in different numerical experiments showed that the combination of meteorological observations and GPS PWV data in assimilation process has in general more positive impact on WRF prediction of rainfall and moisture fields compared to other experiments. The simulation of accumulated precipitation showed that, in particular, the impact of data assimilation is positive albeit confined to the day-1 of the forecast and the improvements declines after 24-h simulations. The spread of observational information within the 4DVAR assimilation window was very effective on day-1 of forecasts which are closer to the end of assimilation, and the simulations from the global forecast system prevail after the first day of forecast. Generally, the assimilation process using conventional IRIMO data reduced the MAE of accumulated precipitation forecast in first day of simulations by 2 percent for all three rainfall cases. In Case-1 and Case-3 adding the GPS PWV data from IPGN network into the WRF-4DVAR system further decreased the accumulated rainfall simulation error in day-1 of forecast by 7 percent and in Case-2, the impact of this data type was insignificant.

Moreover, investigation of model predictions of 2 m relative humidity as a near surface moisture field, indicated that assimilation experiments compared to the CTRL, on average, improved the model simulations in term of MAEs. Although, in case November, the improvement in prediction of 2 m relative humidity was almost insignificant.

Comparison between the model simulated PWV and corresponding ground-based GPS PWV values indicated that the experiment in which GPS water vapor estimations are assimilated, showed better performance in predicting the PWV. Incorporation of GPS data in 4DAVR process caused, on average, about 0.8 mm error reduction in 12-h forecast of PWV and the impact of GPS water vapor estimates was minor in PWV simulations of Case-3. Generally, the comparison results showed that the inclusion of local water vapor observations prepared from IPGN into the model leads to a slight reduction in the errors of moisture field predictions. Moreover, the best simulation results in term of MAE were obtained when both GPS data and conventional meteorological observations were used in experiment GPSCONV_4DVAR.

In this study, we focused on evaluating the impact of WRF 4DVAR-system on short-term predictions and the results were presented using three rainfall cases. To get more encouraging and general results using data assimilation techniques, more rainfall cases with different synoptic patterns are needed to be considered in future works. In order to achieve more improvements in numerical weather prediction, one of the key factors in effective data assimilation is the availability, coverage and quality of the observational data (Bauer et al., 2010). Considering the areal extent of Iran, it seems that for better representation of water vapor field in data assimilation process, the number of GPS stations should be increased across the country. Moreover, assimilation of unconventional data such as satellite radiance and radar data using WRF-4DVAR system is suggested.

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