VARBC for GNSS ZTD in AROME-HU

Patrik Benáček, Máté Mile

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1 Introduction

The source code of Variational Bias Correction (VarBC) scheme has been backphased from P. Poli's modifications of cy40t1 for GNSS ZTD observations by X. Yan at 2014. A modset of this VarBC ZTD was prepared for *cy38t1_bf03* and first tests were run to verify the correctness of the VarBC approach. In 2017, more ZTD observations from E-GVAP networks (SGO1-Satellite Geodetic Observatory and TU of Budapest; GOP1-Geodetic Observatory Pecny; WUEL-Wroclaw University of Environmental and Life Science) were collected and tested in the AROME DA system using additional predictors (1, 3, 4) implemented to the VarBC scheme (Mile and Duygu 2017). The aim of this study is study to revise passive data assimilation for GNSS ZTD, evaluate effect of air-mass/surface predictors on a bias correction and investigate a possible setting of VarBC for GNSS ZTD observations.

This study is separated into two parts. Firstly, we prepare a dataset based on passive DA experiments and evaluate the observation bias of GNSS ZTD in the AROME/HU model. Secondly, we compare different bias correction approaches based on offline regression models to examine a predictor selection, VarBC cycling strategy and VarBC adaptivity.

2 Method

The application of VarBC for GNSS ZTD is studied based on a passive data assimilation (DA) experiment during 30-day period from 2017060100 to 2017063021 using 3-hour AROME analysis cycle. The passive DA is achieved by increasing the observation error (more details in below). The study is based on trusted GNSS stations only put on whitelist during the training period in May 2017 (Mile and Duygu 2017). The whitelist criteria used in AROME/Hungary are described in detail by Poli et al. (2007).

2.1 Passive assimilation of ZTD

Passive assimilation of measurements is usually set by *fail(EXPERIMENTAL)* in *mf_blacklist.b*. Although this option works correctly for satellites, its application for conventional observations (AMDAR, TEMP, SYNOP including GNSS stations) have problems in terms of the observation status association. Regarding the time schedule, we achieved the passive assimilation of GNSS ZTD in DA system by increasing the ZTD observation error via GNSS whitelist. This assures using GNSS data in DA system without impact to analysis. [1] For this purpose, the *PREPGPSSOL* programme was modified in order to increase the observation error (up to 1000 mm) for all the whitelisted stations: */home/guest/pack/cy38t1_gnssztd_DYG_varbc_passive.06.INTEL.x.pack/bin/PREGPSSOL*

2.2 The ZTD observation bias

Observation biases (systematic errors) are expected in GNSS ZTD measurements due to several reasons like the mapping function which projects delay information to zenith direction and also the conversion of excess length of the satellite signal to time-delay estimation, etc (Sanchez Arriola et al. 2016). However, the following two most important should be also highlighted:

1. difference in altitude between GNSS stations and model orography,
2. an atmospheric contribution to the ZTD above the model top.

We detect the observation bias as a time-average of observation (o_i) minus model-background (b_i) differences (OMG):

$$BIAS = \frac{1}{n}\sum_{i=1}^{n} o_i - b_i$$

This estimation of observation bias is statistically meaningful assuming unbiased model background and OMG values with Gaussian distribution (see Fig.1). However, the former assumption is not assured because of systematic errors in the model background and an observation operator $H()$. But in case of GNSS ZTD other bias-free reference would be difficult to utilize.

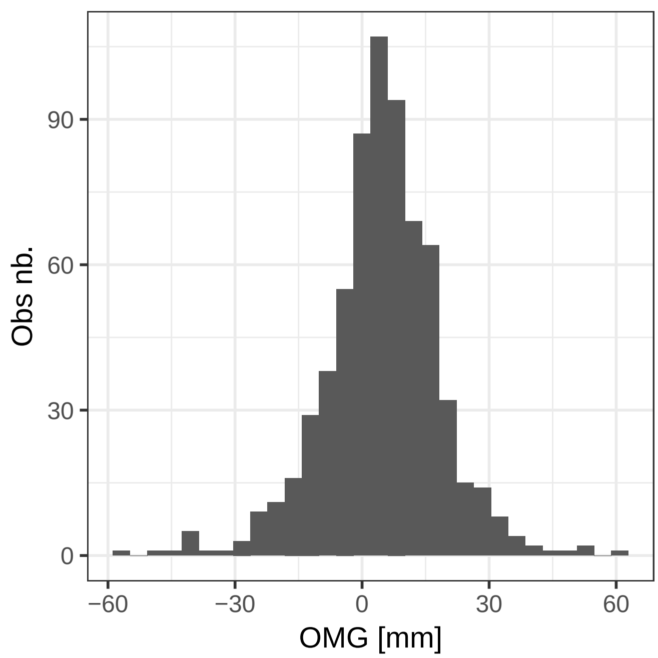

Figure 1: Distribution of OMG values for all GNSS stations.

[1] This approach offers a future solution for an operational implementation of ZTD into AROME DA. Including all GNSS stations on whitelist and increasing the observation error for untrusted data only allows to have the quality of all GNSS stations at hand (in ECMA ODB database). Moreover, bias parameters of all GNSS stations are included in VarBC file. Thus every untrusted GNSS station can be assimilated immediately in AROME analysis (as active) without necessity of a training period.

The ZTD observation bias is detected in AROME/Hungary about 4.6 mm and the observation error is about 14.4 mm. In fact, both values are overestimated because of the NWP model error contribution. Fig.2 presents ZTD biases with regards to particular GNSS stations and analysis times.[2]. The daily variability of observation bias is probably related with a daily variation of the humidity NWP model bias in the boundary layer. Note that the bias increases early morning (3-9 UTC) than it culminates around noon (9-15 UTC) and starts increasing in the evening (18-21 UTC). It is also evident (on the top figure) that each GNSS stations has specific bias value so the regression coefficients should be estimated separately in VarBC scheme.

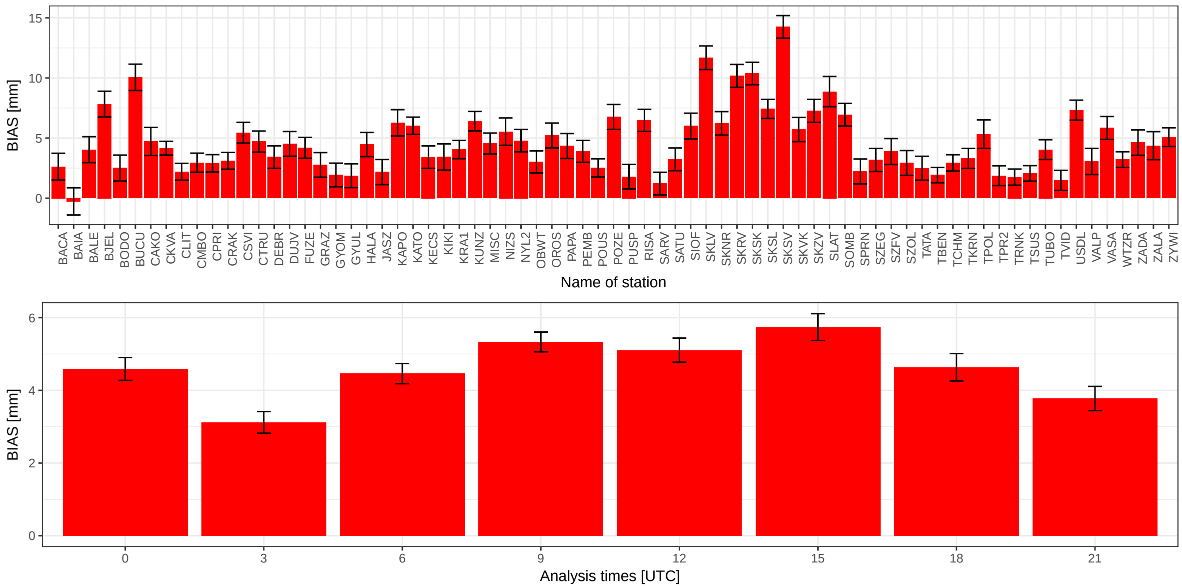

Figure 2: Observation bias with regards to GNSS stations (top) and analysis times (bottom).

[2] There is also expected a bias dependency on network providers (different quality of data processing) but this is beyond a scope of this study.

3 The VarBC application for GNSS ZTD

3.1 New predictors in VarBC for ZTD

Impact of additional air-mass and surface predictors on top of a constant bias (bias-offset) in a bias correction model is examined for GNSS ZTD data. This study is based on an offline multiple-linear regression (MLR) scheme estimating regression coefficients by the least-squared method. The aim of this study is to evaluate a benefit of additional predictors in VarBC scheme. The following predictors are investigated in MLR:

- p_0 – constant
- p_1 – $1000 - 300$ hPa layer thickness
- p_2 – $200 - 50$ hPa layer thickness
- p_3 – skin temperature
- p_4 – total column water vapor
- p_5 – $10 - 2$ hPa layer thickness
- p_6 – $50 - 5$ hPa layer thickness
- p_7 – model orography
- p_8 – altitude of station
- p_9 – model orography error

Before including these predictors into MLR, we examine *spread*, *normality* and *collinearity* of these predictors.

Spread of predictors

The spread indicates variability of predictors during the time-period. Normalized predictors are usually used in VarBC when mean and standard deviation of predictors is pre-calculated in the global model ARPEGE (see routine *arpifs/module/varbc_pred.F90*). If a predictor value is higher than one, this indicates higher contribution of the NWP model (AROME) errors to predictor with respect to ARPEGE. Note that the higher contribution of model errors is detected for stratospheric layer thicknesses (i.e. predictors p_5 and p_6) due to a sparse model vertical resolution in AROME (see Fig.3). Therefore these predictors p_5 and p_6 are rejected from MLR.

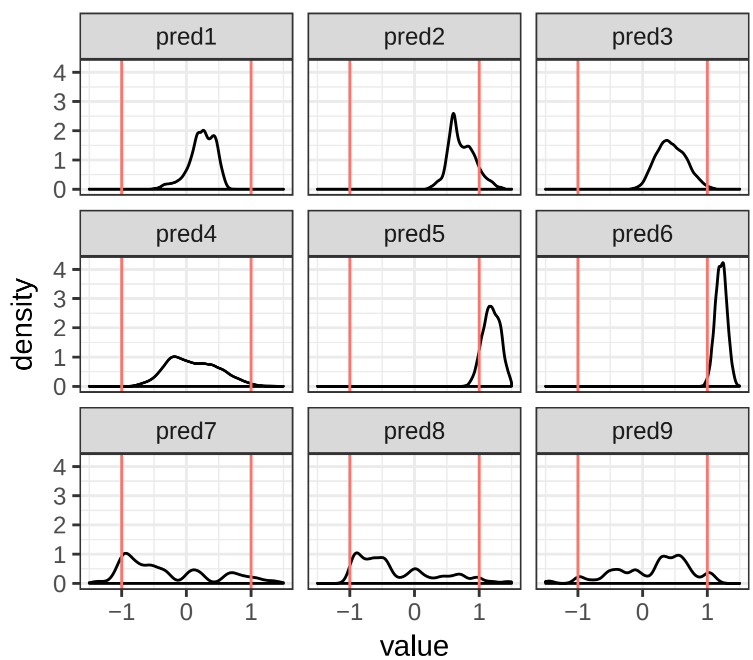

Figure 3: Density function of normalized predictors during a one-month tested period.

Table 1: Summary of MLR model.

Predictor	Coefficient	Std. Error	p-value
pred0	-2.52	0.77	0.001
pred2	4.66	0.78	0.000
pred3	10.45	0.75	0.000
pred4	-7.58	0.40	0.000
pred9	-0.71	0.15	0.000
		R-squared:	0.044

Normality and collinearity of predictors

The normality of predictors (i.e. the examined data sample follows a normally distributed population) is determined by using the Shapiro-Wilks test and boxplot visualization (not shown). We do not prove normal distribution of predictors and thus the non-parametric Spearman correlation coefficient is used for evaluation of a collinearity among the predictors (see Fig.4). Correlation coefficients higher than 0.6 indicate strong collinearity between predictors i.e. one of these predictors should be removed from MLR. Note that significant collinearities are detected between model orography and altitude of station (p_7 and p_8), stratospheric predictors (p_5 and p_6) and skin temperature and low-tropospheric layer thickness (p_3 and p_1). In summary, the predictors p_1, p_5 and p_7 are rejected from MLR.

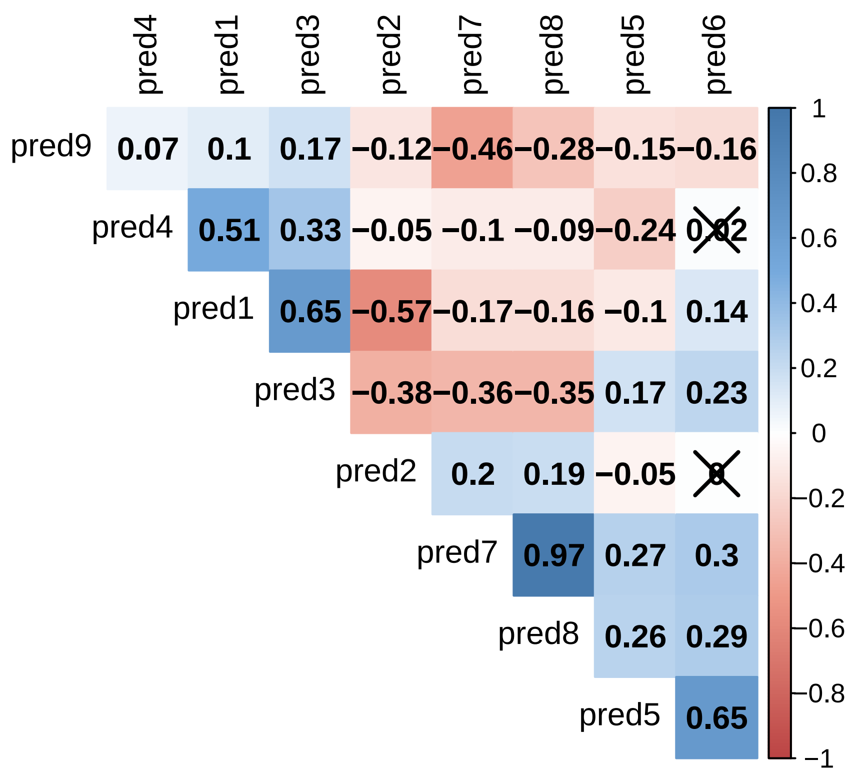

Figure 4: Correlation matrix for selected VarBC predictors.

Step-backward elimination method

The remaining predictors p_2, p_3, p_4, p_8 and p_9 are reduced by the step-backward elimination method (Hebbali 2017). This method select a subset of predictors that do the best at having the smallest AIC (i.e. the smallest relative information lost). In Table 1 is presented a summary of MLR model based on one-month experimental period. Note that the predictors 0 (intercept), 2, 3, 4, and 9 are significant in MLR ($p < 0.01$). The model is able to predict about 4.4% of variance ($R^2 = 0.044$).

Table 2: Evaluation of NOCOR, MLR and CONST models.

variable	training	validation
bias.NOCOR	4.7	4.4
bias.CONST	0.0	-0.3
bias.MLR	0.0	-0.3
std.NOCOR	14.5	14.3
std.CONST	14.5	14.3
std.MLR	14.2	14.0

Evaluation of new predictors

Impact of additional predictors on the ZTD bias correction is evaluated based on these experiments:

1. NOCOR – no bias correction,
2. CONST – using bias-offset p_0,
3. MLR – using additional predictors p_0, p_2, p_3, p_4, p_9.

We estimate regression coefficients based on the measurements from all GNSS stations. This is distinct from the VarBC scheme where the regression coefficients are calculated for each GNSS stations separately. However, gathering all stations in one group provides better sample for evaluation of the MLR predictors. The experiments are evaluated on a one-month period (06/2017) when 60%/40% of dataset is used for the models' training/validation.

Table 2 presents the BIAS and STDE scores of OMG differences for training/validation period before bias correction (NOCOR) and after using MLR and CONST bias correction. Note that both correction schemes reduce most of the observation bias (4.4 mm) in validation period close to zero value. Using additional predictors on the top of constant bias correction in MLR decreases the standard error of OMG from 14.3 to 14.0 mm.

3.2 VarBC cycling strategy

The cycling strategy of regression coefficients in VarBC scheme is examined based on CONST model. There are two approaches how the bias-offset parameters can be updated in VarBC scheme, namely 3-hour and 24-hour cycling. While 3-hour cycling represents a daily-mean observation bias, the 24-hour cycling represents also daily-variation of the observation bias detected in Fig.2. This study is based on the following experiments:

1. NOCOR – no bias correction,
2. CONST03 – regression coefficients separately for each UTC, represents 3-hour cycling,
3. CONST24 – common regression coefficients for all UTC; represents 24-hour cycling.

Table 3 presents BIAS and STDE scores of uncorrected OMG (NOCOR) and corrected OMG values using CONST03 and CONST24 models. Note that both models correct the observation bias 4.7 mm up to 0.2 – 0.3 mm. Higher standard error of OMG is detected using CONST24 which is caused by overfitting the bias model during training period.

It seems that the 3-hour cycling strategy provides bias correction that is more representative across the analysis cycle. However, it should be noted that the offline regression models are based on a data sample shuffled randomly for both training and validation period. Therefore it would be desirable to confirm this results by the adaptive VarBC scheme in a full data assimlation cycle.

3.3 VarBC adaptivity

The VarBC scheme is implemented in variational analysis i.e. regression coefficients (bias parameters) are updated during minimization with respect to the model background and available observations. The

Table 3: A table of overall scores for NOCOR, CONST03 and CONST24 methods based on training/validation period.

variable	training	validation
bias.NOCOR	4.5	4.7
bias.CONST03	0.0	0.2
bias.CONST24	0.0	0.3
std.NOCOR	14.4	14.4
std.CONST03	14.2	14.3
std.CONST24	13.7	14.8

Table 4: Default VarBC setting for GNSS ZTD in the AROME/Hungary.

Parameter	Settings
$N_{bg_{min}}$	60
N_{obs}	1
n_{days}	30
k_{an}	0
N_{bg}	60

background constraint of bias parameters is determined by background bias parameter error covariance matrix which is simplified by diagonal elements:

$$\sigma^2_{\beta_b} = \frac{\sigma^2_o}{N_{bg}}$$

where σ_o is the error variance of observations and N_{bg} is a stiffness parameter (positive integer) for the VarBC scheme. This parameter determines adaptivity of bias parameters in analysis cycle. In AROME/Hungary, the stiffness parameter for GNSS ZTD observations is set as:

$$N_{bg} = MAX(nbg, N_{bg_{min}})$$

$$nbg = n_{days} \cdot N_{obs} \cdot k_{an}$$

where $N_{bg_{min}}$ is a minimum stiffness parameter used as a safety mechanism (default to 60), N_{obs} is number of ZTD observations per each GNSS station at analysis time (based on whitelist criteria equal 1), n_{days} is minimum number of days for background constraint (default to 30) corresponding to a reduction of half observation bias and k_{an} is number of analysis per a day. The default VarBC setting for GNSS ZTD in AROME/Hungary is summarized in Table 4.

Considering eight analysis times in AROME/HU DA system, the VarBC is able to reduce half of the ZTD observation bias in $60/8 = 7.5$ days and the entire observation bias is reduced in about 15 days. In the VarBC routine (*arpifs/module/varbc_sfcobs.F90*), k_{an} is read from $N4DMIN$ variable which is not initialized properly in AROME/Hungary system (probably general problem in most regional models). Considering that $N_{bg} = 60$ for all time, the default VarBC settings might not be flexible enough for the ZTD bias correction. This hypothesis is verify in the following passive DA experiments:

1. **DEF** – default settings ($N_{bg} = 60$) described in Table 4,
2. **EXP** – VarBC modset corresponding to 10-day spin-up period ($n_{days} = 5$, $k_{an} = 8$, $Nbg_{min} = 10$, $N_{bg} = 40$).

Figure 5 presents time-evolution of the ZTD bias correction for particular GNSS stations in one-month period. Note that both schemes are able to initialize the bias correction in about 10-days. The higher variation of bias correction detected for e.g. SKVK or SKZV stations is probably caused by higher contribution of NWP model errors (valley/mountain stations). It is still questionable what is optimum setting of N_{bg} parameter for GNSS ZTD in Arome/HU. Benacek and Mile (2017) suggested a new

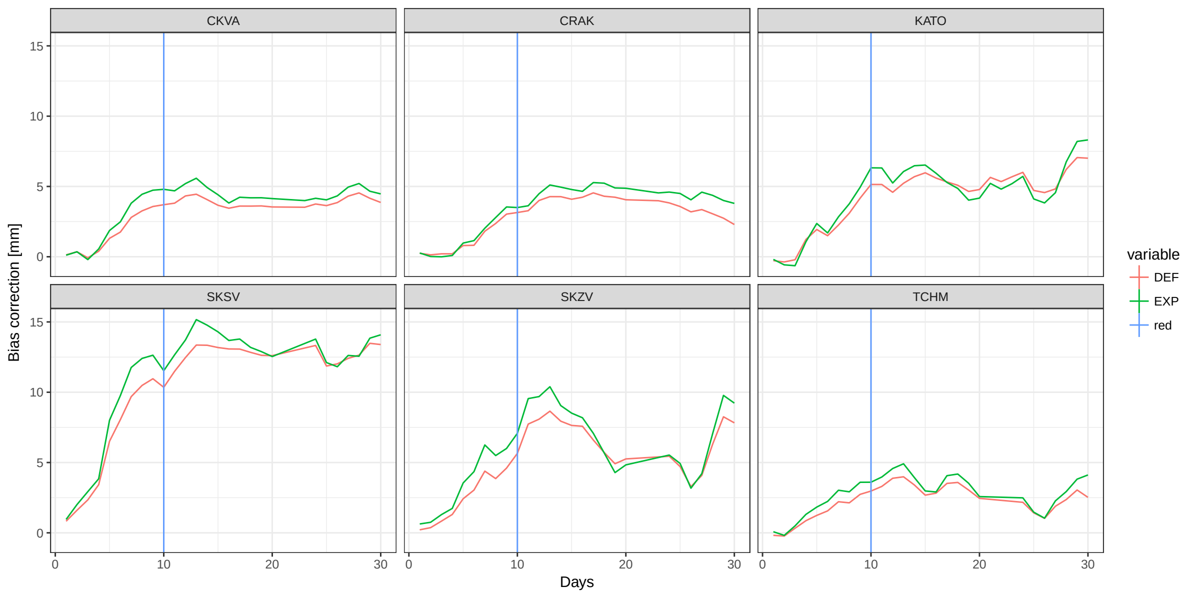

Figure 5: Time evolution of bias correction using DEF and EXP setting for particular GNSS stations from the GOP1 network.

estimation of N_{bg} for satellite observations that could be promising for GNSS ZTD. This new adaptivity setting should be tested by performing full DA experiments and forecast impact studies which is beyond the scope of this study.

4 Conclusion

1. p_0, p_2, p_3, p_4, p_9 are significant predictors for ZTD bias correction,
2. using these predictors in an offline ZTD bias model:

- provides similar quality of bias correction as the bias-offset model (only constant bias correction),
- provides lower standard error of OMG with respect to the bias-offset model (about 0.3 mm),
- requires significant code modifications in terms of gathering all GNSS stations into one-group,

3. 3-hour cycling of bias parameters seems to be more representative across the analysis cycle. This is pre-liminary result and should be confirmed via full DA experiments,
4. modset was prepared for VarBC adaptivity setting *~/home/guest/pack/cy38t1_gnssztd_DYG_varbc_passive.06.INTEL.x.pack/src/local/arpifs/module/varbc_sfcobs.F90*
5. default $N_{bg} = 60$ corresponds to 15-days spin-up period and seems appropriate (as first estimate) for AROME/HU,
6. finding optimum N_{bg} for VarBC ZTD bias correction would be desirable in future AROME/HU studies.

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