



HAL
open science

The influence of seasonal signals on the estimation of the tectonic motion in short continuous GPS time-series

M.S. Bos, L. Bastos, R.M.S. Fernandes

► To cite this version:

M.S. Bos, L. Bastos, R.M.S. Fernandes. The influence of seasonal signals on the estimation of the tectonic motion in short continuous GPS time-series. *Journal of Geodynamics*, 2010, 49 (3-4), pp.205. 10.1016/j.jog.2009.10.005 . hal-00615313

HAL Id: hal-00615313

<https://hal.science/hal-00615313>

Submitted on 19 Aug 2011

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Accepted Manuscript

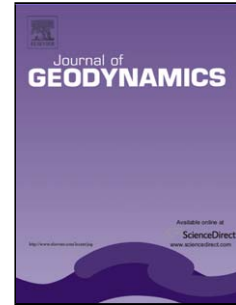
Title: The influence of seasonal signals on the estimation of the tectonic motion in short continuous GPS time-series

Authors: M.S. Bos, L. Bastos, R.M.S. Fernandes

PII: S0264-3707(09)00116-1
DOI: doi:10.1016/j.jog.2009.10.005
Reference: GEOD 943

To appear in: *Journal of Geodynamics*

Received date: 24-12-2008
Revised date: 24-7-2009
Accepted date: 6-10-2009



Please cite this article as: Bos, M.S., Bastos, L., Fernandes, R.M.S., The influence of seasonal signals on the estimation of the tectonic motion in short continuous GPS time-series, *Journal of Geodynamics* (2008), doi:10.1016/j.jog.2009.10.005

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

The influence of seasonal signals on the estimation of the tectonic motion in short continuous GPS time-series

M.S. Bos^{*,a}, L. Bastos^b, R.M.S. Fernandes^{c,d}

^a*CIIMAR, University of Porto, Rua dos Bragas, 289, 4050-123 Porto, Portugal*

^b*Astronomical Observatory, University of Porto, Monte da Virgem, 4430-146 V.N. Gaia, Portugal*

^c*University of Beira Interior, CGUL, IDL, Covilhã, Portugal*

^d*Delft Earth-Oriented Space Research (DEOS), DUT, Kluyverweg 1, 2629HS Delft, The Netherlands*

Abstract

Most GPS time-series exhibit a seasonal signal that can have an amplitude of a few millimetres. This seasonal signal can be removed by fitting an extra sinusoidal signal with a period of one year to the GPS data during the estimation of the linear trend.

However, Blewitt and Lavallée (2002) showed that including an annual signal in the estimation process still can give a larger linear trend error than the trend error estimated from data from which the annual signal has been removed by other means. They assumed that the GPS data only contained white noise and we extend their result to the case of power-law plus white noise which is known to exist in most GPS observations. For the GPS stations CASC, LAGO, PDEL and TETN the difference in trend error between having or not having an annual signal in the data is around ten times larger when a power-law plus white noise model is used instead of a pure white noise model.

*Fax: +351 223 390 608

Email address: mbos@ciimar.up.pt (M.S. Bos)

Next, our methodology can be used to estimate for any station how much the accuracy of the linear trend will improve when one tries to subtract the annual signal from the GPS time-series by using a physical model.

Finally, we demonstrate that for short time-series the trend error is more influenced by the fact that the noise properties also need to be estimated from the data. This causes on average an underestimation of the trend error.

Key words: GPS, time-series, noise

1. Introduction

The time-series analysis of daily GPS positions to estimate the secular motion of discrete points due to plate tectonics, has become a routine operation. Examples are the routinely processing of the European Permanent Network of EUREF (Bruyninx, 2004), and the daily processing carried out at the Scripps Orbit and Permanent Array Center (Prawirodirdjo and Bock, 2004). At both initiatives hundreds of permanent GPS stations are analysed in a semi-automatic manner.

Mostly a linear plate motion, also called a linear trend, is assumed. In addition, the fact that these daily GPS observations are correlated in time is nowadays usually taken into account. This results in a larger uncertainty of the estimated linear trend compared to the formal error of uncorrelated observations (Johnson and Agnew, 1995).

It has been observed that most GPS position time-series exhibit an annual signal with an amplitude of a few millimetres (e.g., Dong et al., 2002). For 27 GPS stations located over Iberia, taken from the WEGENER's GEODynamic Data and Analysis Center (GEODAC), we found on average 1 mm amplitude

in North and East component and 2 mm in the vertical component.

Although the causes are not yet completely understood, the most likely explanations are a combination of atmospheric loading (e.g., van Dam et al., 1997), hydrological loading (e.g., van Dam et al., 2001), and thermal expansion of the GPS stations (e.g., Romagnoli et al., 2003).

Blewitt and Lavallée (2002) demonstrated that an annual signal within the data deteriorates the accuracy of the estimated linear trend in time-series with an observation time span of a few years, even when this annual signal is taken into account during the estimation process.

They also showed that the presence of an annual signal has no influence on the accuracy of the linear trend when the observation period is around 1.5, 2.5, 3.5 and 4.5 years. At these specific observation periods there is no correlation between the annual signal and the linear trend. For longer observation spans the correlation between the annual signal and the linear trend can be neglected.

However, their results are based on the assumption of having white noise in the GPS observations while we already mentioned that it is nowadays accepted that GPS noise is correlated in time. In this research we investigate how temporal correlated noise alters the conclusions of Blewitt and Lavallée (2002). In addition, since we also have to estimate the parameters of the noise that is present within the data, we investigate how our imperfect knowledge of their properties influences the estimated trend error.

2. Theory

Let us assume that we have a data set of N daily GPS positions which we designate by the vector \mathbf{x} . These could be positions in East, North or Up direction. Since each direction is analysed separately, we only describe the procedure in one component. To these data we fit a linear trend that represents the tectonic motion and an arbitrary offset using Weighted Least-Squares. The design matrix is simply:

$$\mathbf{H} = \begin{pmatrix} 1 & t_0 \\ 1 & t_1 \\ \vdots & \vdots \\ 1 & t_{N-1} \end{pmatrix} \quad \text{with } t_0 = 0, t_1 = 1, \dots \quad (1)$$

To include an annual signal in the design matrix, we need to modify it as follows:

$$\mathbf{H} = \begin{pmatrix} 1 & t_0 & \cos(\omega_a t_0) & \sin(\omega_a t_0) \\ 1 & t_1 & \cos(\omega_a t_1) & \sin(\omega_a t_1) \\ \vdots & \vdots & \vdots & \vdots \\ 1 & t_N & \cos(\omega_a t_N) & \sin(\omega_a t_N) \end{pmatrix} \quad (2)$$

where ω_a is the angular velocity of the annual signal.

If we also assume that we know the covariance matrix of the noise that is present within the signal, designated by \mathbf{C} , then the covariance matrix of the estimated parameters $\hat{\theta}$ is (Kay, 1993):

$$\text{Cov}(\hat{\theta}) = (\mathbf{H}^T \mathbf{C}^{-1} \mathbf{H})^{-1} \quad (3)$$

Eq. (3) does not account for modelling errors. If for example the data would contain a quadratic signal (the tectonic plate is accelerating) while we

don't account for it in our design matrix, then the fit between the model and observations would be worse than it could be. This normally results in larger values in the covariance matrix \mathbf{C} , which is estimated from the misfit between model and observations. As a result, the uncertainty of the estimated parameters is larger than it could be. The better we model the signal, the better is the accuracy of the estimated parameters.

On the other hand, if we try to fit a too complex model to the data with many parameters there is the risk that the accuracy of the estimated parameters decreases. This happens when there is a large correlation between the different parameters which complicates their separation.

The separation of different signals within the data is also less accurate when the noise is correlated in time. If the noise is not correlated in time then it is called white noise, otherwise it is called coloured noise. When the spectrum of the noise is of the form $1/f^\alpha$, where f is the frequency, one speaks about power-law noise. The parameter α is called the spectral index. Caporali (2003) and Williams et al. (2004), among others, have shown that the noise in GPS data can be well described as the sum of white and power-law noise.

As a result, the covariance matrix of the noise can be written as (Williams, 2003b):

$$\mathbf{C} = \sigma_w^2 \mathbf{I} + \sigma_{pl}^2 \mathbf{E}(\alpha) \quad (4)$$

where σ_w^2 and σ_{pl}^2 are the variances of the white and power-law noise. \mathbf{I} is the unit matrix and \mathbf{E} represents the covariances due to the power-law noise and depends on the spectral index α .

3. Observations

To illustrate the effects related to analysing short time-series we used GPS data from four stations of which two are in Portuguese Mainland: CASC and LAGO. The other stations are PDEL, Ponta Delgada in the Azores, and TETN which is situated in the north of Morocco. The first three time-series have an observation span of longer than nine years while TETN only has 2.4 years of continuous GPS observations. Only the last station can be considered to be a short time-series but we will use the longer time-series to validate our results.

Data have been processed using JPL's GIPSY software package (Webb and Zumberge, 1995), following the precise point positioning strategy which resulted in time-series of daily coordinate solutions. These time-series were afterwards converted to the ITRF2005 reference frame (Altamimi et al., 2007) and filtered to remove outliers. Offsets were estimated at epochs when the GPS receiver or antenna were replaced.

For CASC, the time-series of the North component is presented in Fig. 1. The power spectral density of the differences between observations and the fitted model, is given in Fig. 2. In this last figure also the estimated power-law plus white noise model has been plotted which fits well to the observed power spectral density. The plots of the position time-series and power spectral density for the other stations and components look similar.

INSERT FIGURE 1 HERE.

INSERT FIGURE 2 HERE.

The values of the estimated trend and its associated error for these time-series were estimated using the Maximum Likelihood Estimation method

(Mao et al., 1999; Williams, 2003b; Langbein, 2004) and are presented in Table 1. One can see that the East component is always less accurate than the North component. This table also contains the estimated values of the white plus power-law noise model discussed in section 2. We also listed the value of the standard deviation σ_w when only white noise is assumed to exist in the GPS observations.

INSERT TABLE 1 HERE.

The uncertainty of the linear trend was computed using Eq. (3) as function of the observation span. For the covariance matrix \mathbf{C} we used two models: the power-law plus white noise model and a pure white noise model. The values for both noise models were taken from Table 1. In addition, we performed the computations with and without estimating the annual signal in the design matrices, see Eqs. (1) and (2). The results for the North component of CASC are plotted in Fig. 3. It shows that the trend error for data with power-law plus white noise is larger than when only white noise is, wrongly, assumed to be present in the data. This was already observed by Mao et al. (1999) who stated that the difference can vary by a factor of 5–11.

INSERT FIGURE 3 HERE.

The trend error for the white noise model in Fig. 3 corresponds to Fig. 4 of Blewitt and Lavallée (2002) although our values are almost three times smaller because we used a value for σ_w of 2.36 mm (last column Table 1) instead of 4 mm that was used by Blewitt and Lavellée.

Fig. 3 shows that the predicted trend error is larger when an annual signal is included in the design matrix. To see this effect more clearly, we

computed the difference between the errors associated with the two different design matrices. The results are plotted in Fig. 4 and show that for power-law plus white noise the difference is around ten times larger compared to pure white noise. The same result was obtained at the other stations for both the East and North component.

INSERT FIGURE 4 HERE.

This figure demonstrates that having an annual signal in your data produces larger uncertainties in your trend value compared to the situation of having no annual signal in your data. Estimating an additional annual signal in your estimation process does therefore not completely eliminate its effect on the linear trend.

For the pure white noise model we can see minimum influence of the annual signal on the trend error at observation spans of integer plus a half year intervals (Blewitt and Lavallée, 2002). However, for power-law plus white noise, which is found in most GPS time-series, we find minimal influence closer to integer plus a quarter year intervals.

4. Influence of estimating the noise

To predict the trend error in short time-series, we have until now assumed that we know the values of the power-law plus white noise model within the GPS time-series. However, this is normally not the case and we must estimate these parameter values from the data.

To investigate the influence of estimating the noise properties from the data we have cut up the CASC time-series in non-overlapping segments of equal lengths. By analysing each segment separately, we obtained informa-

tion about the spread in the predicted trend error for short time-series. The results for the North component have been plotted as black dots in Fig. 5 where the segment lengths was varied between two and six years. The large trend error of 2.4 mm/year for an observation span of two years in one of the segments of the CASC time-series has been caused by the fact that it contains a gap of 150 days.

The predicted trend error using the power-law plus white noise properties of Table 1 is represented by the solid black line (see also Fig. 3).

To get a better idea of the spread in the predicted trend error one can expect when analysing short GPS time-series, we performed a Monte Carlo simulation. For each observation span we computed and analysed 100 synthetic time-series that contained the same power-law plus white noise properties as is listed in Table 1 for CASC, North component. Afterwards, we computed for each observation span the mean and standard deviation of the predicted trend error. The area between ± 1 standard deviation around the mean has been plotted as a grey area in Fig. 5.

INSERT FIGURE 5 HERE.

The Monte Carlo results in Fig. 5 show that the predicted trend error is on average underestimated for short time-series (Williams et al., 2004). That is, the estimated trend values in the Monte Carlo simulation vary more than one would expect from these predicted trend errors. This underestimation caused by the fact that some of the power-law noise is considered to be part of the linear trend by the MLE method which results in smaller residuals.

This influence of estimating the noise properties from the data has a larger effect on the trend error than having an annual signal in the GPS

observations. It is therefore more effective to try to improve our knowledge of the noise within GPS observations than to improve our knowledge about what is causing the annual signal when one is interested in the linear trend.

To reduce the spread in the predicted trend error we note from Table 1 that the value of the spectral index lies between 1.1 and 1.5. Furthermore, the value of σ_w is roughly three times that of σ_{pl} . If we assume that we can keep the value of α and the ratio σ_w/σ_{pl} fixed, the covariance matrix can be written as (Williams, 2008):

$$\mathbf{C} = \sigma^2 \mathbf{J} \quad (5)$$

Another argument for using this simplified model for the covariance was given by Bos et al. (2008) who showed that power-law noise has a larger influence than white noise on the linear trend.

Having fixed the structure of our noise model, we only need to estimate the scale factor σ^2 to determine the covariance matrix \mathbf{C} . Before doing so, it is convenient to define the following parameter vector $\beta = (\theta, \sigma^2)$.

The logarithm of the probability density function is (Williams, 2003b):

$$\ln p(\mathbf{x} | \beta) = -\frac{1}{2} [N \ln 2\pi + \ln \det(\mathbf{C}) + (\mathbf{x} - \mathbf{H}\theta)^T \mathbf{C}^{-1} (\mathbf{x} - \mathbf{H}\theta)] \quad (6)$$

For any unbiased estimator, the variance of the estimated parameters is given by the Cramer-Rao lower bound (Kay, 1993):

$$\text{Var}(\beta_i) \geq [\mathbf{I}(\beta)^{-1}]_{ii} \quad (7)$$

where $\mathbf{I}(\beta)$ is the Fisher information matrix. The latter is defined by:

$$\mathbf{I}(\beta) = -E \left[\frac{\partial \ln^2 p(\mathbf{x} | \beta)}{\partial \beta^2} \right] \quad (8)$$

The E operator represents the expected value. After computing the various derivatives of Eq. (6), we obtain the following expression for the variance in the estimated values of σ^2 :

$$\text{Var}(\sigma^2) = \frac{2\sigma^4}{N} \quad (9)$$

Here we replaced the inequality sign of Eq. (7) with an equal sign because we used the Maximum Likelihood Estimation (MLE) method to estimate its value. MLE is asymptotically efficient and approaches the Cramer-Rao lower bound when the sample size becomes large (Kay, 1993). Using Eq. (5), we can write the variance of the variance of θ as:

$$\text{Cov}(\hat{\theta}) = \frac{2\sigma^4}{N} (\mathbf{H}^T \mathbf{J}^{-1} \mathbf{H})^{-1} \quad (10)$$

Instead of having one uncertainty for the trend error, say σ_t , we now have a range of trend errors because the value of σ is not exactly known. This causes a varying predicted trend error:

$$\sigma_t \sqrt{1 \pm \sqrt{\frac{2}{N}}} \approx \sigma_t \pm \frac{\sigma_t}{2} \sqrt{\frac{2}{N}} \quad (11)$$

The last term represents the standard deviation in the predicted trend error itself.

We repeated the analysis of the CASC time-series but now we set the values $\alpha = 1.3$ and $\sigma_{pl}/\sigma_w = 3.3$. Only σ_{pl} was estimated which corresponds to the noise model of Eq. 5. The results are plotted in Fig. 6.

INSERT FIGURE 6 HERE.

The Monte Carlo results, the grey area, show that the spread in the predicted trend error is much smaller compared to those plotted in Fig. 5. This

spread agrees well with the one predicted by Eq. (11). In addition, they are unbiased. The spread in the predicted trend error for the CASC segments has also decreased although the variations are still significantly larger than one would expect from the Monte Carlo simulations. The assumption that the noise properties are constant over time seems therefore questionable. The reason why the noise properties vary over time is unknown and deserves further investigation. One possible explanation could be the existence of small offsets which have not been detected but are altering the noise properties (Williams, 2003a).

5. Conclusions

Under equal noise conditions, the accuracy of the estimated linear trend is worse in GPS time-series that have a seasonal signal compared to those which have not, even when an annual signal is included in the estimation process. We have shown in Fig 4 that for realistic GPS time-series with power-law plus white noise this difference in trend error is larger than for the situation when only white noise is assumed to exist in the data as was done by Blewitt and Lavallée (2002).

Our results can be used to estimate how much the accuracy of the linear trend will improve when one tries to reduce the annual signal in short GPS time-series by, for example, subtracting atmospheric and hydrological loading values.

We have also demonstrated that for short time-series the trend error is significantly influenced by the fact that the noise properties also need to be estimated from the data. This causes a variation in the predicted trend

error that is larger than the effect of having an additional annual signal in the estimation process. It is therefore more effective to try to improve our knowledge of the noise within GPS observations than to improve our knowledge about what is causing the annual signal when one is interested in the linear trend.

Our Monte Carlo simulation confirmed the result of Williams et al. (2004) that the trend error is on average underestimated for short time-series.

Finally we have shown that when the noise model can be simplified to a simple scaling of a priori known covariance matrix, Eq. 5, the underestimation of the trend error and the spread in the predicted trend error is significantly reduced. For this simple noise model we derived Eq. (11) that provides the uncertainty in the predicted trend error.

References

- Altamimi, Z., Collilieux, X., Legrand, J., Garayt, B., Boucher, C., 2007. ITRF2005: A new release of the International Terrestrial Reference Frame based on time series of station positions and Earth Orientation Parameters. *J. Geophys. Res.* 112 (B09401).
- Blewitt, G., Lavallée, D., 2002. Effect of annual signals on geodetic velocity. *J. Geophys. Res.* 107, 2145–+.
- Bos, M. S., Fernandes, R. M. S., Williams, S. D. P., Bastos, L., 2008. Fast error analysis of continuous GPS observations. *J. Geod.* 82, 157–166.
- Bruyninx, C., 2004. The EUREF Permanent Network; a multidisciplinary

- network serving surveyors as well as scientists. *GeoInformatics* 7 (5), 32–35.
- Caporali, A., 2003. Average strain rate in the Italian crust inferred from a permanent GPS network - I. Statistical analysis of the time-series of permanent GPS stations. *Geophysical Journal International* 155, 241–253.
- Dong, D., Fang, P., Cheng, M. K., Miyazaki, S., 2002. Anatomy of apparent seasonal variations from GPS-derived site position time series. *J. Geophys. Res.* 107 (B4), 10.1029/2001JB000573.
- Johnson, H. O., Agnew, D. C., 1995. Monument motion and measurements of crustal velocities. *Geophys. Res. Letters* 22 (21), 2905–2908.
- Kay, S. M., 1993. *Fundamentals of Statistical Signal Processing: Estimation Theory*. Prentice Hall, Englewood Cliffs, NJ.
- Langbein, J., 2004. Noise in two-color electronic distance meter measurements revisited. *J. Geophys. Res.* 109 (B04406), 10.1029/2003JB002819.
- Mao, A., Harrison, C. G. A., Dixon, T. H., 1999. Noise in GPS coordinate time series. *J. Geophys. Res.* 104 (B2), 2797–2816.
- Prawirodirdjo, L., Bock, Y., 2004. Instantaneous global plate motion model from 12 years of continuous GPS observations. *J. Geophys. Res.* 109 (B18), 8405–+.
- Romagnoli, C., Zerbini, S., Lago, L., Richter, B., Simon, D., Domenichini, F., Elmi, C., Ghirotti, M., 2003. Influence of soil consolidation and thermal

- expansion effects on height and gravity variations. *J. Geodyn.* 35 (4-5), 521–539.
- van Dam, T., Wahr, J., Milly, P. C. D., Shmakin, A. B., Blewitt, G., Lavallée, D., Larson, K. M., 2001. Crustal displacements due to continental water loading. *Geophys. Res. Letters* 28, 651–654.
- van Dam, T. M., Wahr, J., Chao, Y., Leuliette, E., 1997. Predictions of crustal deformation and of geoid and sea-level variability caused by oceanic and atmospheric loading. *Geophys. J. Int* 129, 507–517.
- Webb, F., Zumberge, J., 1995. An introduction to GIPSY/OASIS-II. Tech. Rep. JPL D-11088, California Institute of Technology, Pasadena, California.
- Williams, S. D. P., 2003a. Offsets in Global Positioning System time series. *J. Geophys. Res.* 108 (B6), 10.1029/2001JB002156.
- Williams, S. D. P., 2003b. The effect of coloured noise on the uncertainties of rates estimated from geodetic time series. *J. Geod.* 76, 483–494.
- Williams, S. D. P., 2008. CATS: GPS coordinate time series analysis software. *GPS Solutions* 12 (2), 147–153.
- Williams, S. D. P., Bock, Y., Fang, P., Jamason, P., Nikolaidis, R. M., Prawirodirdjo, L., Miller, M., Johnson, D. J., 2004. Error analysis of continuous GPS position time series. *J. Geophys. Res.* 109 (B03412), doi:10.1029/2003JB002741.

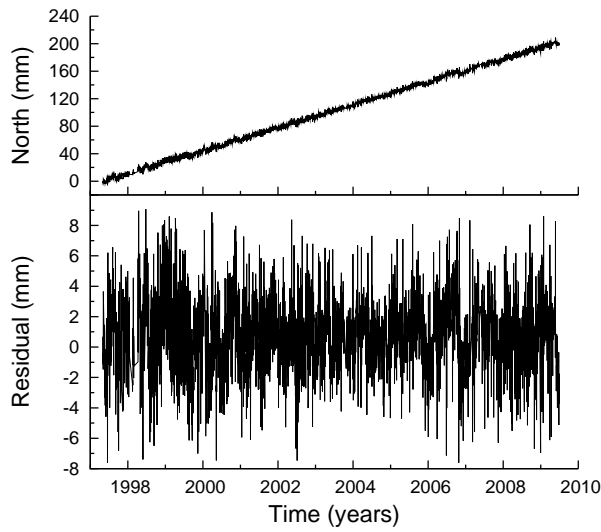


Figure 1: The upper panel shows the North component of the GPS position time-series at CASC. The lower panel shows the same data set after subtraction of a linear trend and a yearly signal.

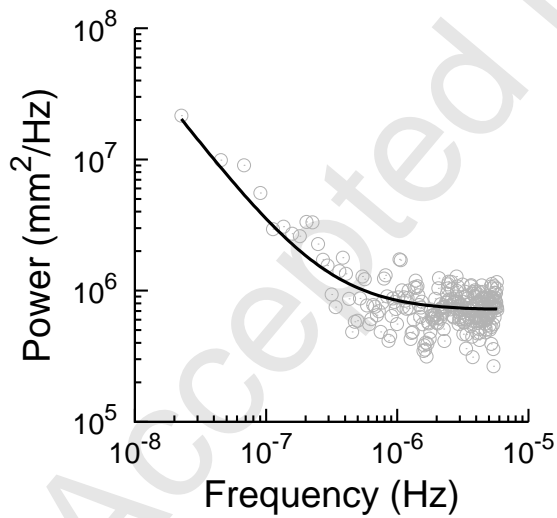


Figure 2: Power spectral density of the GPS residuals at CASC, North component. The circles denote the spectral density computed from the observations and the solid line is the fitted power-law plus white noise model.

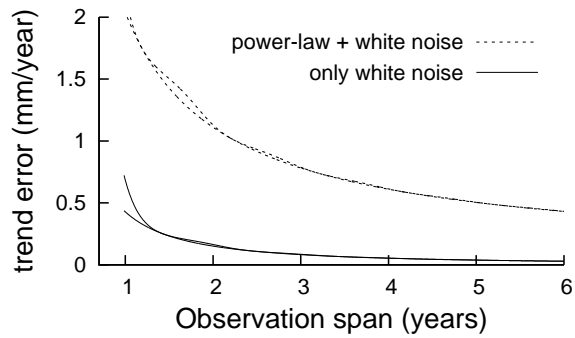


Figure 3: The predicted trend error as function of the observation span for CASC, North component, for different noise models. These errors have been computed with and without having an annual signal in the design matrix. Having an annual signal in the estimation process produces slightly larger errors.

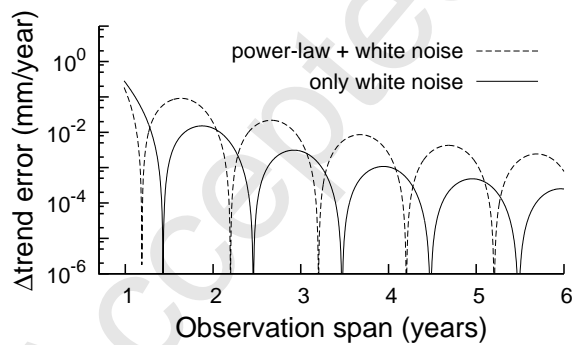


Figure 4: The difference of the predicted trend errors shown in Fig. 3 computed with and without an annual signal in the design matrix for different noise models.

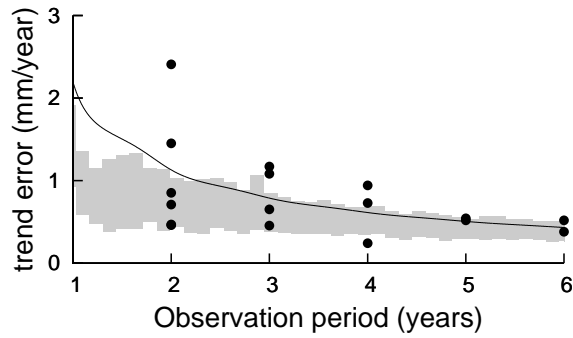


Figure 5: The predicted trend error as function of the observation span for CASC, North component. The black dots represent the predicted trend error for different segments of the GPS time-series. The black line corresponds to the predicted trend error using the power-law plus white noise model values listed in Table 1. The grey area has been produced by Monte Carlo simulation.

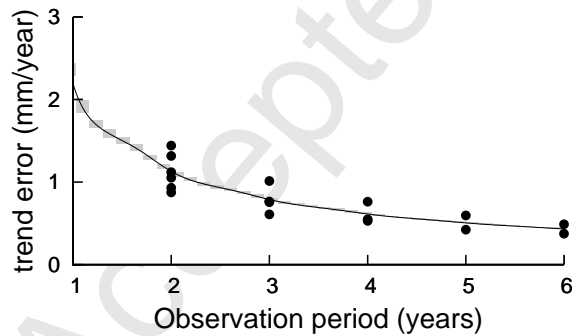


Figure 6: The same as Fig. 5 but with $\alpha = 1.3$ and $\sigma_{pl}/\sigma_w = 3.3$. Only σ_{pl} was estimated from the data.

Table 1: The values of the estimated trend with its associated error for the North and East component. For each station the time span of the observation is given in years. Also listed are the estimated standard deviations of the power-law and white noise present in the data, σ_{pl} and σ_w , and the spectral index α of the power-law noise. The last column contains the value of σ_w when only white noise is assumed to exist within the data. An annual signal was included in the estimation process.

Station	ΔT (years)	Comp.	trend \pm std (mm/year)	α	σ_{pl} (mm)	σ_w (mm)	only σ_w (mm)
CASC	12.3	E	17.5 \pm 0.6	1.4	1.06	2.85	3.81
		N	16.7 \pm 0.3	1.3	0.61	2.01	2.36
LAGO	9.6	E	17.1 \pm 0.8	1.5	0.84	2.83	3.70
		N	17.0 \pm 0.3	1.4	0.53	1.60	2.06
PDEL	9.4	E	12.2 \pm 0.7	1.4	1.03	2.92	3.92
		N	16.8 \pm 0.3	1.1	1.16	2.45	3.38
TETN	2.4	E	13.7 \pm 2.0	1.1	2.06	3.05	4.51
		N	16.3 \pm 0.8	1.1	0.92	2.05	3.02