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1 A realistic and easy-to-implement weighting model for
2 GPS phase observations

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8 **Abstract**

9 Observation weighting is an essential component of the GPS stochastic model
10 and plays a key role in reliable outlier detection and parameter estimation.
11 Nowadays, satellite elevation angle and signal-to-noise ratio (SNR) are used
12 as quality indicators for GPS phase measurements in high-accuracy geode-
13 tic applications. In comparison to elevation-dependent models, SNR-based
14 weighting schemes represent the reality better, but usually require greater
15 implementation efforts. Relying upon a representative analysis of empirical
16 SNR-based weights, this paper proposes an elevation-dependent exponential
17 weight function EXPZ, which benefits from realistic SNR-based weights and
18 enables easy software implementation. To process GPS data from a regional
19 network, this advanced weighting scheme is implemented in the Bernese GPS
20 Software 5.0 and compared with the conventional elevation-dependent COSZ
21 model in terms of phase ambiguity resolution, troposphere parameter esti-

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22 mation, and site coordinate determination. The results show that the pro-
23 posed EXPZ model significantly attenuates the downweighting effects on low-
24 elevation observations and improves the success rates of ambiguity resolution
25 by about 10%, the standard deviations of site-specific troposphere parame-
26 ters by about 40%, and the repeatabilities of daily coordinate estimates by
up to 2.3 mm (50%).

27 *Keywords:* GPS; Stochastic model; Observation weighting; Satellite
28 elevation angle; Signal-to-noise ratio (SNR)

29 1. Introduction

30 Weighting GPS measurements, which allows the user to specify observa-
31 tional contributions to an overall solution, is necessary for reliable GPS data
32 analysis. This simply arises from the fact that GPS observations from differ-
33 ent satellites at different epochs have different degrees of precision, e.g., due
34 to different atmospheric effects. Accordingly, a precise measurement should
35 contribute more to parameter estimation and have a larger weight than an
36 imprecise one.

37 The importance of appropriate weighting methods has been realised long
38 ago, e.g., by Teunissen et al. (1998). They stated that the least-squares
39 method, which is widely applied in GPS data processing, will lose its prop-
40 erty of minimum variance if a misspecified weighting scheme is used. Fur-
41 thermore, the power of the statistical tests employed for model validation and
42 quality control (e.g., outlier and cycle slip detection) is significantly reduced
43 if the noise characteristics are not properly considered (Kim and Langley,
44 2001; Wieser and Brunner, 2002). In addition, any misspecification in ob-

45 servation weighting will inevitably produce biased parameter estimates and
46 overly optimistic accuracy measures (Howind, 2005, Sect. 5.3.3; Schön and
47 Brunner, 2008). For example, applying an identical weight of $w = 1$ to all
48 observations is inadequate for high-precision GPS applications, particularly
49 when including low-elevation data (Bischoff et al., 2005; Luo et al., 2007;
50 Satirapod and Luansang, 2008; Amiri-Simkooei et al., 2009). In spite of its
51 importance, a realistic observation weighting model, which sufficiently copes
52 with receiver and antenna characteristics, signal strength, multipath and at-
53 mospheric effects, etc., still remains a difficult task (Wieser, 2007).

54 Instead of an equal weight, the satellite elevation angle is often used as a
55 quality indicator for GPS observations. The basic idea is that measurements
56 at lower elevation angles suffer more strongly from atmospheric and multi-
57 path effects, hence are noisier. Also, receiver antenna gain is typically less
58 at lower elevation angles, leading to lower signal quality. Under weak multi-
59 path and calm atmospheric conditions, the relationship between observation
60 precision and elevation angle can be adequately described by cosecant (King
61 and Bock, 2002, Chap. 5, pp. 9, 12; Dach et al., 2007, p. 144) or exponen-
62 tial (Euler and Goad, 1991; Han, 1997) functions. The main advantage of
63 elevation-dependent weighting schemes is easy implementation. Therefore,
64 they are widely used in GPS data processing software. However, for observa-
65 tions that are strongly affected by multipath effects, signal diffraction, and
66 receiver characteristics, the elevation-dependent weighting concept becomes
67 inappropriate. Moreover, it ignores the frequency-related differences in obser-
68 vation quality and downweights low-elevation data so that their contributions
69 to parameter estimation are extremely limited (Wieser, 2007).

70 In addition to the satellite elevation angle, signal-to-noise ratio (SNR)
71 was introduced as a more realistic quality indicator for GPS observations.
72 Langley (1997) published a relationship between phase variances and SNR
73 measurements, which was used to develop the SIGMA- ϵ and SIGMA- Δ mod-
74 els, coping with low-elevation data, signal diffraction, and multipath effects
75 (Hartinger and Brunner, 1999; Brunner et al., 1999; Wieser and Brunner,
76 2000). However, the formula provided by Langley (1997) ignores any con-
77 tribution to the noise characteristics from local oscillators and is only valid
78 for relatively strong signals (Collins and Langley, 1999, p. 4). To overcome
79 these deficiencies, Mayer (2006, p. 62) and Luo et al. (2008a,c) proposed em-
80 pirical site-specific SNR-based weighting models, which properly deal with
81 low-quality measurements of weak signals and sufficiently reflect variations
82 in observation quality due to receiver properties, multipath effects, and at-
83 mospheric conditions. Being superior to the elevation-dependent weighting
84 schemes, the SNR-based models realistically consider site-specific influences,
85 appropriately handle low-elevation data, and directly produce frequency-
86 related weights. Nevertheless, they suffer from the non-standardisation of
87 SNR and the generally more complex software implementation (Collins and
88 Langley, 1999, p. 4; Mayer, 2006, p. 59; Luo et al., 2008c; Joseph, 2010).

89 To combine the advantages of the elevation-dependent and SNR-based
90 weighting concepts, this paper proposes a realistic and easy-to-implement
91 weighting model for GPS phase observations. It makes use of the exponential
92 function suggested by Euler and Goad (1991) and is denoted as EXPZ. The
93 proposed approach is realistic, since it relies upon a representative analysis of
94 empirical SNR-based weights and appropriately attenuates the downweight-

95 ing effects on low-elevation measurements. The EXPZ model can be easily
96 implemented, as it depends only on the satellite elevation angle, which is
97 used as an indicator for observation quality in many GPS software products.

98 The rest of this paper is organised as follows. In Sect. 2, the proposed
99 EXPZ model is presented, along with a brief introduction of the underlying
100 empirical SNR-based weighting scheme. Sect. 3 describes the case study and
101 the GPS data analysis. In Sect. 4, the results of the case study are discussed
102 with respect to (i) phase ambiguity resolution, (ii) troposphere parameter
103 estimation, and (iii) site coordinate determination. Finally, Sect. 5 provides
104 concluding remarks and an outlook on future research work.

105 **2. Methodology**

106 *2.1. Empirical SNR-based weighting model (ESNR)*

107 The underlying weighting model ESNR is completely independent from
108 the variance function provided by Langley (1997) and is realised as fol-
109 lows. First, environment-specific signal quality measurements are extracted
110 from RINEX observation files and, if necessary, converted into signal-to-noise
111 power density ratio ($SNR0$ in dBHz) by means of model- and manufacturer-
112 specific formulas (Collins and Stewart, 1999). The post-correlation quantity
113 $SNR0$ refers to the ratio of the signal power and the noise power per unit
114 bandwidth (Butsch, 2002), and can be considered as a synonym for carrier-
115 to-noise density C/N_0 (Butsch and Kipka, 2004). Then, for each antenna-
116 receiver combination (ARC) within the network, the minimum and maximum
117 $SNR0$, denoted as $SNR0_{ARC,i}^{\min}$ and $SNR0_{ARC,i}^{\max}$, respectively, are searched over
118 the entire period of investigation, where the subscript i denotes the carrier

119 frequency. Finally, the SNR-based weights are obtained using the minimum-
 120 related ratio between the actual $SNR0$ and the corresponding maximum.
 121 For the phase observation $\Phi_{R,i}^s(t)$ related to receiver R , satellite s , frequency
 122 i , and epoch t , the empirical SNR-based weight $w [\Phi_{R,i}^s(t)]$ is computed as

$$123 \quad w [\Phi_{R,i}^s(t)] = \left[a + (1 - a) \cdot \left(\frac{SNR0_{R,i}^s(t) - SNR0_{ARC,i}^{\min}}{SNR0_{ARC,i}^{\max} - SNR0_{ARC,i}^{\min}} \right) \right]^2. \quad (1)$$

124 The parameter $a = 0.1$ prevents the singularity of the cofactor $q = w^{-1}$
 125 if $SNR0_{R,i}^s(t) = SNR0_{ARC,i}^{\min}$, and is empirically determined as described in
 126 Luo (2013, Sect. 5.3.1). For representative antenna-receiver combinations,
 127 Fig. 1 compares the ESNR weighting scheme with the elevation-dependent
 128 COSZ model implemented in the Bernese GPS Software 5.0 (Dach et al.,
 129 2007, p. 144), i.e.,

$$130 \quad w = \cos^2 z = \sin^2 e, \quad (2)$$

131 where z and e denote the zenith distance and the satellite elevation angle,
 132 respectively. As Fig. 1a, c, and d show, in comparison to COSZ, the ESNR
 133 model reflects the differences in antenna-receiver combination and produces
 134 considerably larger weights for low- and medium-elevation measurements.
 135 Moreover, comparing Fig. 1a and b with each other, the frequency-related dif-
 136 ferences in observation quality can be taken into account when using ESNR,
 137 whereas they are completely ignored if COSZ is applied. For a more detailed
 138 discussion of ESNR, the reader is referred to Luo et al. (2008a,c) and Luo
 139 (2013, Chaps. 5 and 6).

140 **FIGURE 1**

141 *2.2. Exponential elevation-dependent weighting model (EXPZ)*

142 The proposed weighting model EXPZ relies upon the empirical SNR-
 143 based weights calculated by Eq. (1) and makes use of the exponential function

$$144 \quad \sigma^2 = \left[b_0 + b_1 \cdot \exp\left(\frac{-e}{e_0}\right) \right]^2, \quad (3)$$

145 where σ^2 denotes the variance of the phase measurement at elevation angle
 146 e (Euler and Goad, 1991). Depending on the receiver type, the unknown
 147 parameters b_0 , b_1 , and e_0 can be determined by applying the least-squares
 148 method to elevation-dependent observation uncertainties (Euler and Goad,
 149 1991; Han, 1997). Considering the variance in the zenithal direction as a
 150 reference, i.e., $\sigma_0^2 = \sigma^2(e = 90^\circ)$, the weight for an individual phase measure-
 151 ment is derived using

$$152 \quad w = \frac{\sigma_0^2}{\sigma^2}. \quad (4)$$

153 In this paper, the model parameters of EXPZ are determined in an ad-hoc
 154 manner by approximating the mean behaviour of the empirical SNR-based
 155 weights (see Eq. (1)) from different case studies. Thereby, various aspects
 156 were taken into account, such as antenna-receiver combination, observation
 157 period, atmospheric conditions, and site-specific multipath effects (Luo et al.,
 158 2008a,c; Luo, 2013, Chaps. 5 and 6). The parameter values for one-way
 159 carrier-phase are $b_0 = 1.7$ mm, $b_1 = 3.3$ mm, and $e_0 = 40^\circ$ (see Eq. (3)). In
 160 Fig. 2, the standard deviations (σ) and observation weights (w) produced by
 161 the COSZ and EXPZ models are compared.

162 **FIGURE 2**

163 In terms of the σ values (see Fig. 2a), the proposed EXPZ model decreases
164 much more slowly than COSZ for $e < 15^\circ$, which attenuates the differences
165 in observation quality at low elevation angles. As e increases from 5° to 80° ,
166 the EXPZ-related σ decreases from about 5 to 2 mm, coinciding with the
167 phase accuracy estimates presented by Li et al. (2008) for different types of
168 receivers. Regarding the observation weights shown in Fig. 2b, one can clearly
169 discern that, in comparison to COSZ, the EXPZ curve exhibits significantly
170 larger weights for low- and medium-elevation measurements, and lies below
171 COSZ at high elevation angles. This sufficiently reflects the main elevation-
172 dependent characteristics of the empirical SNR-based weights depicted in
173 Fig. 1. Within the framework of this study, the EXPZ model is implemented
174 in the Bernese GPS Software 5.0 (subroutine `WGTELV.f`; Dach et al., 2007,
175 p. 144), and its effects on static relative positioning are examined using GPS
176 data from a regional network.

177 3. Study area and GPS data analysis

178 The case study was carried out using 7 days of 30 s GPS data from a
179 regional network that comprises three stations of the International GNSS
180 Service (IGS) and one station of the Integrated German Geodetic Reference
181 Network (GREF) (see Fig. 3). The IGS sites include Zimmerwald (ZIMM),
182 Wettzell (WTZR), and Hugelheim (HUEG), while the GREF site BFO1 is
183 located at the Black Forest Observatory (BFO) in southwest Germany (Luo
184 and Mayer, 2008). The period of investigation is DOY2010:301–307, where
185 DOY2010 denotes day of year 2010. The shortest and longest baselines shown
186 in Fig. 3 are HUBF (HUEG \rightarrow BFO1) and ZIWT (ZIMM \rightarrow WTZR),

187 reaching about 77 and 476 km, respectively (see Table 1). The absolute
 188 difference in ellipsoidal height between two endpoints of a baseline, denoted
 189 as $|\Delta h|$ in Table 1, varies from 24.30 m (WTBF) to 678.03 m (ZIHU).

190 **FIGURE 3**

191 Table 1: Characteristics of the formed baselines (see Fig. 3).

Baseline	From ¹	To	Length [km]	$ \Delta h $ [m]
HUBF	HUEG	BFO1	77.4	412.01
ZIHU	ZIMM	HUEG	106.9	678.03
ZIBF	ZIMM	BFO1	174.1	266.03
WTBF	WTZR	BFO1	346.9	24.30
WTHU	WTZR	HUEG	416.6	387.71
ZIWT	ZIMM	WTZR	475.9	290.32

¹ Reference site for baseline solution

192 Using the Bernese GPS Software 5.0, static relative positioning was per-
 193 formed by applying the observation weighting schemes COSZ and EXPZ.
 194 According to the previous finding that higher performance of the ESNR
 195 model can be reached by decreasing the elevation cut-off angle, e.g., from
 196 10° to 3° (Luo et al., 2008a,c), a minimum elevation angle of 3° was cho-
 197 sen. Despite potentially stronger multipath effects, the use of low-elevation
 198 observations improves satellite geometry (Hartinger and Brunner, 1999) and
 199 decorrelates station height and troposphere parameter estimates (Dach et al.,
 200 2007, p. 247). In terms of external data and correction models, precise and
 201 up-to-date products were incorporated (see Table 2). The final daily and
 202 weekly solutions were obtained from stacking the normal equations in order
 203 to achieve a more sophisticated definition of the geodetic datum (e.g., min-
 204 imum constraint solution; Dach et al., 2007, p. 216). In Table 2, important
 205 specifications of the GPS data analysis are listed.

Table 2: Important specifications of the GPS data analysis using the Bernese Software.

Geodetic datum	IGS05, epoch 2000.0
GPS observations	30 s phase double differences
Processing time interval	DOY2010:301–307 (daily/weekly solutions)
Observation weighting model	COSZ (see Eq. (2); Dach et al., 2007, p. 144) EXPZ (see Eqs. (3)–(4))
Elevation cut-off angle	3°
Satellite orbits/EOP ¹	Final IGS products (15 min/24 h)
Ionosphere model	Final CODE ² products
Troposphere a priori model	Saastamoinen model (Saastamoinen, 1973)
Tropospheric mapping function	Niell mapping functions (Niell, 1996)
Time span of troposphere parameter	1 h
Time span of tropospheric gradient	24 h (Dach et al., 2007, p. 249)
Phase ambiguity resolution	SIGMA-dependent strategy (L5, L3)
Antenna correction model	IGS05 absolute model (Schmid et al., 2007)

¹ Earth orientation parameters

² Center for Orbit Determination in Europe

207 4. Results and discussion

208 In comparison to the conventional COSZ weighting scheme, the effects of
 209 the proposed EXPZ model on GPS parameter estimation were studied with
 210 regard to phase ambiguity resolution, troposphere parameter estimation, and
 211 site coordinate determination. While ambiguities are resolved in baseline
 212 solutions, site-specific troposphere parameters and coordinates are obtained
 213 from network solutions.

214 4.1. Effects on phase ambiguity resolution

215 Using the SIGMA-dependent algorithm provided by the Bernese GPS
 216 Software 5.0 (Dach et al., 2007, Sect. 8.3.3), a two-step ambiguity (AMB)
 217 resolution strategy is employed in this study (Dach et al., 2007, p. 182).
 218 For each baseline presented in Table 1, the wide-lane (WL/L5) ambiguities
 219 are first resolved by fixing all site coordinates, where the ionosphere model

220 from CODE is considered. Next, the resolved WL ambiguities are intro-
221 duced to perform a narrow-lane (NL) ambiguity resolution on the basis of
222 the ionosphere-free linear combination (L3). Taking the baselines HUBF
223 (77.4 km) and WTHU (416.6 km) as examples, Fig. 4 shows the percent-
224 ages of the resolved ambiguities with respect to observation weighting and
225 baseline length.

226 **FIGURE 4**

227 From both graphs it can be seen that more WL ambiguities are resolved
228 than NL ambiguities, which is attributed to the significantly larger WL wave-
229 length of about 86 cm in comparison to the NL wavelength of about 11 cm
230 (Dach et al., 2007, pp. 40, 41). For the short baseline HUBF, the WL am-
231 biguity resolution is only insignificantly affected by the use of EXPZ, while
232 it experiences an average improvement of nearly 10% for the long baseline
233 WTHU. In terms of NL ambiguity resolution, the results are enhanced by up
234 to about 10% for both baselines if the conventional COSZ model is replaced
235 by the advanced EXPZ scheme. For the longer baseline WTHU, the per-
236 centages of the resolved ambiguities are smaller, and the benefits of applying
237 EXPZ instead of COSZ are more obvious.

238 Considering all baselines analysed in this study, Table 3 presents the
239 overall results of ambiguity resolution using different observation weighting
240 schemes. Applying the COSZ and EXPZ models to the same data set, the
241 number of total ambiguities ($\#AMB$) can be slightly different (see HUBF and
242 WTBF), which originates from the residual-based outlier detection and ob-
243 servation deletion (Dach et al., 2007, pp. 133, 145). In comparison to COSZ,
244 the employment of EXPZ improves the average success rates of WL and NL
245 ambiguity resolution by up to 9.4 and 7.9%, respectively. The corresponding
246

Table 3: Results of ambiguity resolution using different observation weighting models (#/%: number/percentage of resolved ambiguities).

Analysed baseline	Length [km]	COSZ [#/%]			EXPZ [#/%]			Increase WL [%]		Increase NL [%]	
		#AMB	WL	NL	#AMB	WL	NL	Mean	Max	Mean	Max
HUBF	77.4	385	380/98.7	337/87.5	387	382/98.7	360/93.0	0.0	1.9	5.5	9.0
ZIHU	106.9	373	354/94.9	329/88.2	373	365/97.9	345/92.5	3.0	4.9	4.3	8.2
ZIBF	174.1	309	285/92.2	262/84.8	309	295/95.5	272/88.0	3.3	5.6	3.2	7.6
WTBF	346.9	381	316/82.9	294/77.2	383	348/90.9	312/81.5	8.0	11.4	4.3	7.5
WTHU	416.6	469	375/80.0	341/72.7	469	415/88.5	378/80.6	8.5	13.5	7.9	9.3
ZIWT	475.9	382	301/78.8	286/74.9	382	337/88.2	303/79.3	9.4	12.3	4.4	12.3

247 maximum daily enhancements are 13.5 and 12.3%. In addition, as the base-
248 line length increases, the performance of ambiguity resolution degrades, and
249 the EXPZ model becomes more beneficial (see the grey-marked column of
250 Table 3). An average improvement of 10% in ambiguity resolution was also
251 achieved by means of the ESNR approach (Luo et al., 2008a,c; Luo, 2013,
252 Chap. 6), verifying the sufficiency of the EXPZ method in characterising the
253 empirical SNR-based weights (see Eq. (1) and Fig. 1).

254 *4.2. Effects on troposphere parameter estimation*

255 GPS signals are delayed while propagating through the Earth's tropo-
256 sphere. In the zenithal direction, the tropospheric delay amounts to about
257 2.3 m at sea level (Hofmann-Wellenhof et al., 2008, p. 135). Analysing GPS
258 observations with the Bernese GPS Software 5.0, this delay term can be eval-
259 uated by estimating site-specific troposphere parameters (TRP; Dach et al.,
260 2007, Chap. 11). The quality of the parameter estimates is affected by various
261 factors, e.g., observation weighting (Luo et al., 2008b). The TRP estimates
262 have a temporal resolution of 1 h (i.e., 24 parameters per day per station)
263 and are obtained from network solutions by stacking the normal equations.
264 Since data from elevations below 10° are included, horizontal tropospheric
265 gradients are determined on a daily basis to account for the azimuthal asym-
266 metry of the local troposphere at the observation site (Meindl et al., 2004;
267 Dach et al., 2007, Sect. 11.4.3). For the IGS station WTZR, Fig. 5 shows
268 the TRP estimates and the associated standard deviations (STD) from the
269 daily and weekly network solutions using different weighting models.

270

FIGURE 5

271 Regarding the results of the daily network solutions (see Fig. 5a and b),
272 the use of EXPZ instead of COSZ leads to considerable changes in the TRP
273 estimates of up to 6 cm and a mean decrease in the corresponding STD
274 (Δ STD) of 1.7 mm (45%). The differences in TRP are mostly negative,
275 which was also found in Jin and Park (2005). Considering the increased
276 σ_0 from COSZ to EXPZ, the decreases in STD are caused by the larger
277 observation weights, particularly at low elevation angles (see Fig. 2). Similar
278 behaviour was observed in Luo et al. (2008b) when comparing the equal
279 weight and COSZ models. The daily solutions exhibit jumps in both the
280 TRP (e.g., days 302 and 307 in Fig. 5a) and the STD estimates (e.g., days
281 304 and 305 in Fig. 5b), which, however, disappear in the weekly solutions
282 (see Fig. 5c and d). In this case, the application of EXPZ changes the TRP
283 by as much as 4 cm and reduces the STD by 1.0 mm (40%) on average.

284 Table 4 presents the overall results of the TRP estimation using different
285 observation weighting models. For both the daily and weekly solutions, cm-
286 level root mean squares (RMS) of the differences between TRP(COSZ) and
287 TRP(EXPZ) are obtained. Moreover, applying the EXPZ scheme, the TRP
288 values of IGS sites WTZR and ZIMM are closer to the CODE products.
289 Being superior to COSZ, the EXPZ model improves the TRP precision by up
290 to 1.7 mm absolutely and 45% relatively, where the daily solutions experience
291 stronger benefits. Similar magnitudes of enhancements, achieved by means
292 of advanced stochastic models, were reported by Jin and Park (2005) and
293 Jin et al. (2010). With the context of GPS meteorology, cm-level changes
294 in TRP and mm-level improvements in STD are already significant (Bender
295 et al., 2008; Fuhrmann et al., 2010, Sect. 8.3).

Table 4: Results of troposphere parameter estimation using different weighting models.

Station	Height [m]	Daily solution		Weekly solution	
		RMS [cm]	Δ STD [mm/%]	RMS [cm]	Δ STD [mm/%]
HUEG	278.3	1.6	1.7/44	1.2	1.0/39
WTZR	666.0	1.6	1.7/45	1.4	1.0/39
BFO1	690.3	1.8	1.7/43	1.5	0.9/37
ZIMM	956.3	1.7	1.6/44	1.4	0.9/39

297 4.3. Effects on site coordinate determination

298 The effects of EXPZ on site coordinate (CRD) determination are assessed
 299 by examining the differences and increments of the coordinate estimates from
 300 daily network solutions. For the IGS sites WTZR and ZIMM, Fig. 6 il-
 301 lustrates the absolute differences between the coordinates from COSZ and
 302 EXPZ, as well as the height increments in a local topocentric system. As
 303 could be expected, Fig. 6a and b depict insignificant coordinate differences of
 304 less than 1 mm in the horizontal components northing (N) and easting (E),
 305 while considerably larger deviations of up to 8 mm are detected in the height
 306 (H) component (see WTZR). From both graphs it can be seen that more sig-
 307 nificant height differences are present on day 304, which can be explained by
 308 the fact that only about 2 hours of ZIMM data, i.e., from 00:00:00 to 01:56:30,
 309 were available on this particular day. Regarding the associated height incre-
 310 ments shown in Fig. 6c and d, the use of EXPZ instead of COSZ improves
 311 the height repeatability, especially on day 304 (cf. Fig. 6a and b). For WTZR
 312 and ZIMM, the RMS values of the height increments are decreased by 1.4
 313 and 2.3 mm, respectively, indicating a more reliable determination of the
 314 vertical component.

316 Table 5 presents the median and maximum absolute coordinate differences
 317 caused by applying different observation weighting models. The median val-
 318 ues are predominantly less than 1 mm in the horizontal components, but
 319 can reach up to about 7 mm in the vertical component (see BFO1). The
 320 maximum changes in the northing and easting coordinates amount to a few
 321 mm, while a maximum height difference of 1.5 cm is detected on day 304 for
 322 BFO1. This large deviation arises not only from the limited ZIMM data on
 323 this particular day, but also from the interference of GPS signals due to the
 324 heavy vegetation (Luo and Mayer, 2008).

325 To investigate the influence of EXPZ on coordinate repeatability, the
 326 RMS values of the daily coordinate increments are presented in Table 6. Ex-
 327 amining the magnitudes of the RMS first, the maximum is less than 2 mm for
 328 the horizontal components and 5 mm for the vertical. The small RMS values
 329 verify the high performance of the GPS data analysis using the Bernese GPS
 330 Software 5.0 (see Table 2). Furthermore, the easting coordinates appear to
 331 be more precise than the northing, which is due to the so-called “north hole”.
 332 Although the proposed EXPZ model degrades the horizontal coordinate re-
 333 peatability by up to 0.6 mm, it improves the height precision by as much as
 334 2.3 mm (50%).

335 Table 5: Median (Med) and maximum (Max) absolute topocentric coordinate differences
 in mm caused by applying the observation weighting models COSZ and EXPZ.

Station	Height [m]	Northing $ \Delta N $		Easting $ \Delta E $		Height $ \Delta H $	
		Med	Max	Med	Max	Med	Max
HUEG	278.3	0.4	0.8	0.2	0.6	2.0	4.4
WTZR	666.0	0.4	1.1	0.7	1.0	2.1	7.8
BFO1	690.3	0.5	1.3	2.0	3.4	6.6	15.0
ZIMM	956.3	0.3	0.9	0.5	1.0	1.8	5.9

Table 6: Root mean square (RMS) values of the daily coordinate increments in mm.

Station	Height [m]	COSZ			EXPZ			Decrease		
		N	E	H	N	E	H	N	E	H
HUEG	278.3	0.6	0.4	1.4	0.8	0.6	2.0	-0.2	-0.2	-0.6
WTZR	666.0	0.5	0.4	3.9	1.1	0.9	2.5	-0.6	-0.5	1.4
BFO1	690.3	0.8	0.8	3.5	1.4	1.2	3.4	-0.6	-0.4	0.1
ZIMM	956.3	1.2	0.7	4.5	1.6	1.1	2.2	-0.4	-0.4	2.3

337 5. Conclusions and outlook

338 On the basis of the empirical SNR-based weighting model proposed by
339 Luo et al. (2008a,c), this paper presented a realistic and easy-to-implement
340 weighting scheme for GPS phase observations. It uses the exponential func-
341 tion provided by Euler and Goad (1991) and is denoted as EXPZ. The
342 model parameters are derived in an ad-hoc manner by approximating the
343 mean elevation-dependent characteristics of representative empirical SNR-
344 based weights. Analysing GPS data from a regional network, the EXPZ
345 scheme is compared with the COSZ model implemented by default in the
346 scientific Bernese GPS Software 5.0 (Dach et al., 2007, p. 144). The main
347 findings of this study are summarised as follows:

- 348 1. The EXPZ model sufficiently captures the elevation-dependent prop-
349 erties of the empirical SNR-based weights. Differing from COSZ, it
350 produces larger weights for low- and medium-elevation observations,
351 increasing their contributions to GPS parameter estimation.
- 352 2. Using EXPZ instead of COSZ to resolve double-difference ambiguities,
353 an average improvement of 10% in wide-lane and narrow-lane ambiguity
354 resolution can be achieved, particularly for long baselines of several
355 hundred kilometres.

- 356 3. A switch from COSZ to EXPZ may lead to cm-level changes in the es-
357 timated site-specific troposphere parameters and mm-level (i.e., about
358 40%) decreases in the associated standard deviations.
- 359 4. Under weak multipath and calm atmospheric conditions, the use of
360 EXPZ instead of COSZ results in coordinate changes of less than 5 mm.
361 When analysing short-term and low-quality data, the EXPZ model may
362 significantly improve coordinate estimates at the centimetre level.
- 363 5. Within the framework of the presented case study, using EXPZ to spec-
364 ify larger weights for low- and medium-elevation observations degrades
365 the horizontal coordinate repeatability by as much as 0.6 mm, but en-
366 hances the height precision by up to 2.3 mm.

367 Future research work will focus on the verification and refinement of the
368 EXPZ model. For example, apart from static relative positioning, precise
369 point positioning and kinematic data processing can be performed. By ap-
370 plying EXPZ to GLONASS, Galileo, or BeiDou measurements, the model
371 efficiency can be assessed in a more generic GNSS sense. Instead of an
372 ad-hoc approach, a rigorous determination of the model parameters is rec-
373 ommended, which may be carried out considering the receiver and antenna
374 types. Moreover, a comparison of the refined EXPZ model with other obser-
375 vation weighting schemes is also planned.

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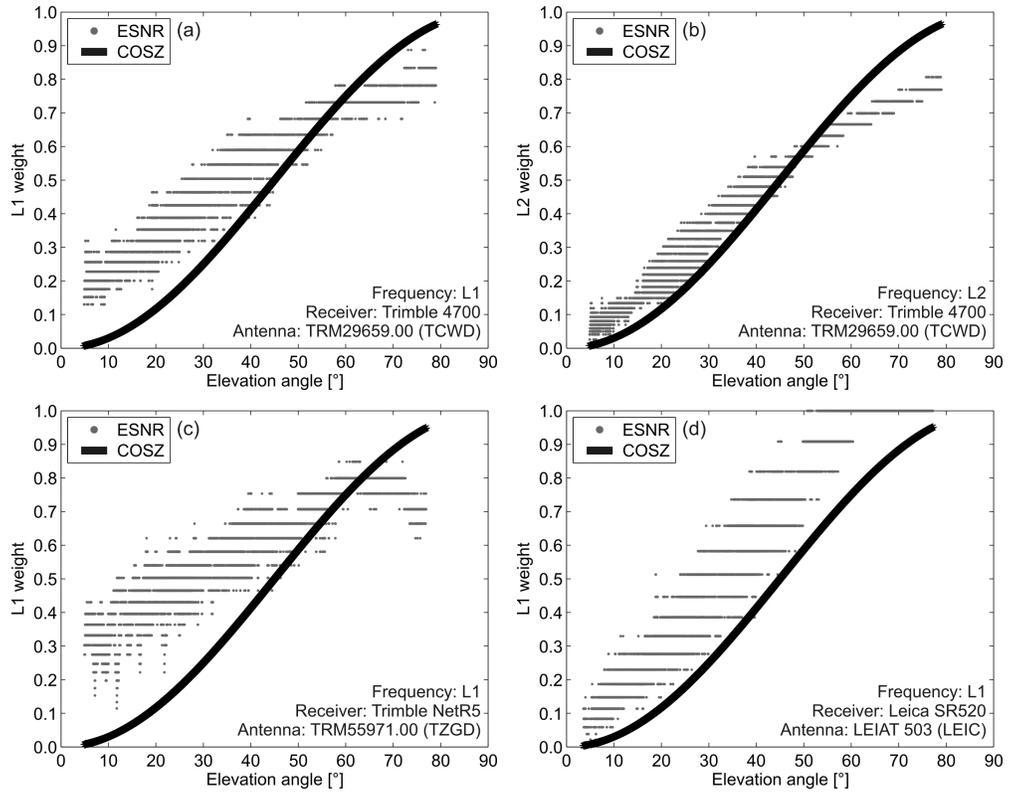


Figure 1: Comparison of the phase observation weights produced by different weighting schemes (ESNR: empirical SNR-based, $a = 0.1$, see Eq. (1); COSZ: elevation-dependent, see Eq. (2); TCWD, TZGD, LEIC: antenna radomes).

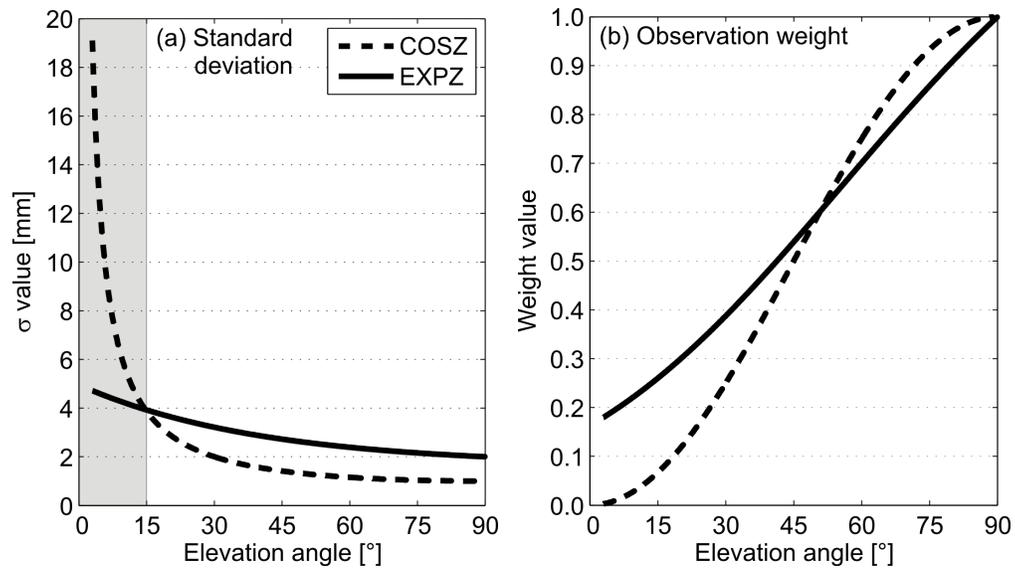


Figure 2: Comparison of the standard deviations (a) and observation weights (b) produced by the COSZ ($\sigma_0 = 1$ mm, see Eq. (2); Dach et al., 2007, p. 144) and EXPZ ($\sigma_0 = 2$ mm, see Eqs. (3)–(4); Hofmann-Wellenhof et al., 2008, p. 108) models.

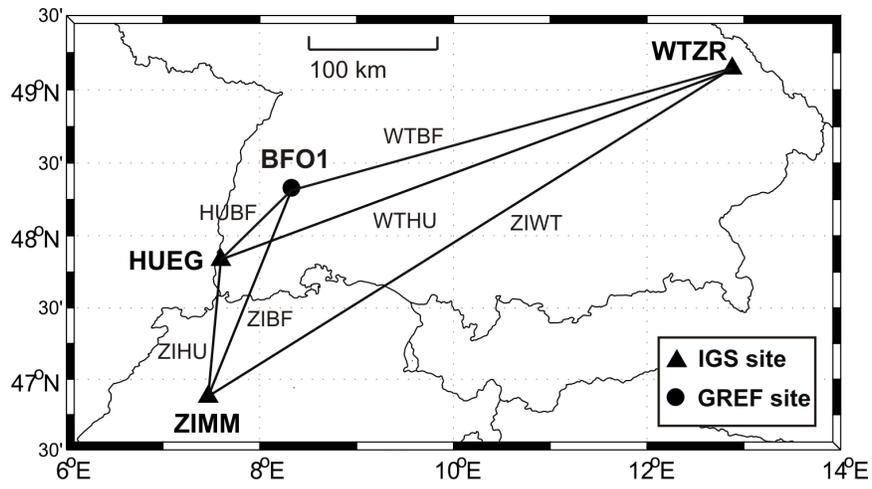


Figure 3: Regional network design and baseline creation (see Table 1).

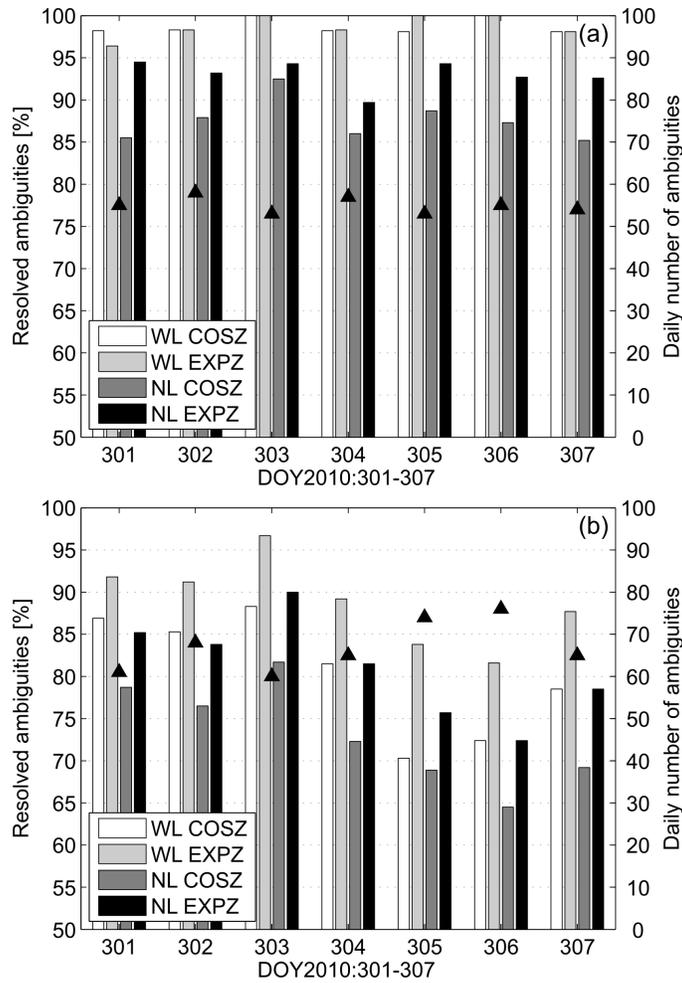


Figure 4: Examples of the results of phase ambiguity resolution with respect to observation weighting and baseline length (filled black triangle: daily number of ambiguities, see Table 1) (a) Short baseline HUBF: 77.4 km, (b) Long baseline WTHU: 416.6 km.

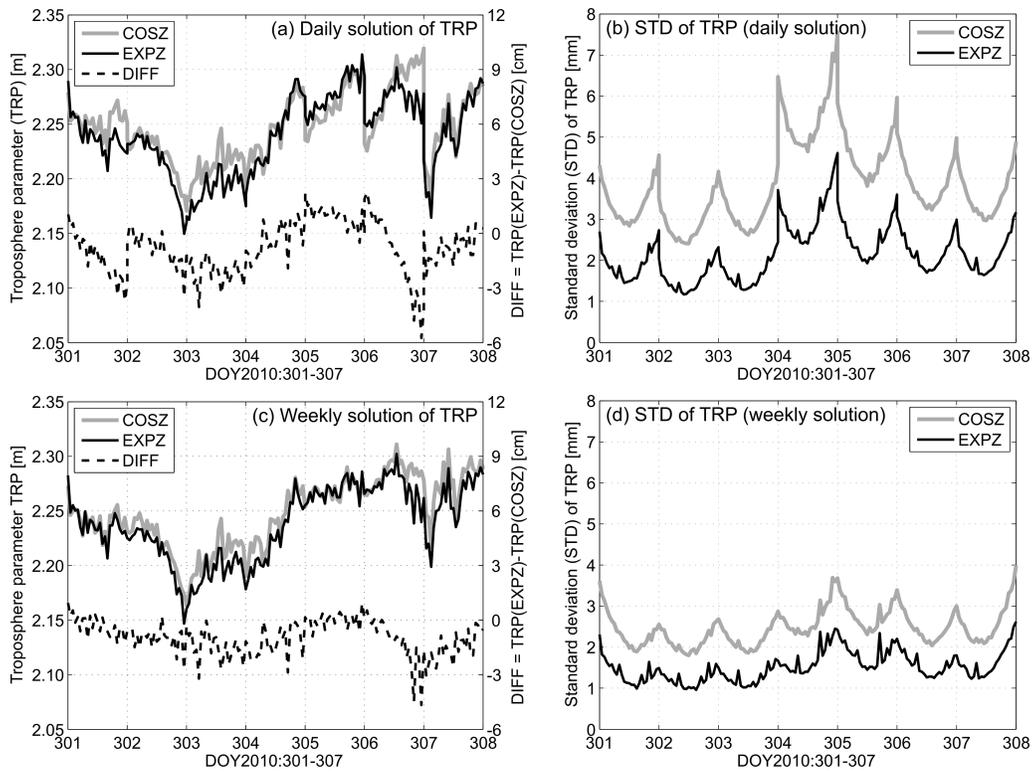


Figure 5: Examples of the results of troposphere parameter (TRP) estimation with respect to observation weighting (IGS site: WTZR, TRP time span: 1 h, STD: standard deviation).

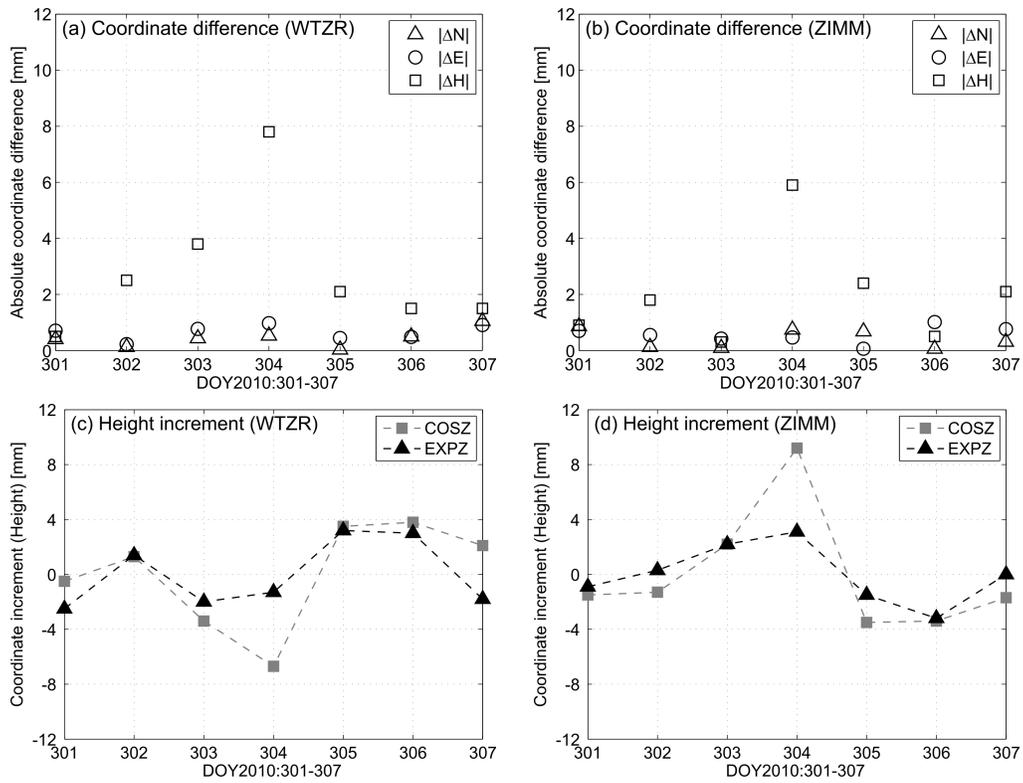


Figure 6: Examples of the results of site coordinate determination with respect to observation weighting (IGS sites: WTZR and ZIMM, daily network solutions).