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Improving the assessment of ICESat water altimetry accuracy accounting for autocorrelation

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Abstract

¹ Given that water resources are scarce and are strained by competing demands, it has become crucial to develop and improve techniques to observe the temporal and spatial variations in the inland water volume. Due to the lack of data and the heterogeneity of water level stations, remote sensing, and especially altimetry from space, appear as complementary techniques for water level monitoring. In addition to spatial resolution and sampling rates in space or time, one of the most relevant criteria for satellite altimetry on inland water is the accuracy of the elevation data. Here, the accuracy of ICESat LIDAR altimetry product is assessed over the Great Lakes in North America. The accuracy assessment method used in this paper emphasizes on autocorrelation in high temporal frequency ICESat measurements. It also considers uncertainties resulting from both in situ lake level reference data. A prob-

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¹ **ABBREVIATIONS:**

ICESat: Ice Cloud and land Elevation Satellite

GLAS: Geoscience Laser Altimeter System

RMSE: Root Mean Square Error

SDOM: Standard Deviation Of the Mean

abilistic upscaling process was developed. This process is based on several successive ICESat shots averaged in a spatial transect accounting for autocorrelation between successive shots. The method also applies pre-processing of the ICESat data with saturation correction of ICESat waveforms, spatial filtering to avoid measurement disturbance from the land-water transition effects on waveform saturation and data selection to avoid trends in water elevations across space. Initially this paper analyzes 237 collected ICESat transects, consistent with the available hydrometric ground stations for four of the Great Lakes. By adapting a geostatistical framework, a high frequency autocorrelation between successive shot elevation values was observed and then modeled for 45% of the 237 transects. The modeled autocorrelation was therefore used to estimate water elevations at the transect scale and the resulting uncertainty for the 117 transects without trend. This uncertainty was 8 times greater than the usual computed uncertainty, when no temporal correlation is taken into account. This temporal correlation, corresponding to approximately 11 consecutive ICESat shots, could be linked to low transmitted ICESat GLAS energy and to poor weather conditions. Assuming Gaussian uncertainties for both reference data and ICESat data upscaled at the transect scale, we derived GLAS deviations statistics by averaging the results at station and lake scales. An overall bias of -4.6 cm (underestimation) and an overall standard deviation of 11.6 cm were computed for all lakes. Results demonstrated the relevance of taking autocorrelation into account in satellite data uncertainty assesment.

Keywords: GLAS, LIDAR, accuracy, temporal correlation, block kriging, Great Lakes

1. Introduction

Although lakes and rivers correspond to only 0.27% of the global fresh water and 0.007% of the Earth's water budget, they constitute the most accessible inland water resources available for ecosystems and human consumption.

Given that these resources are scarce and are strained by competing demands, it has become crucial to develop and improve techniques to observe the temporal and spatial variations in the water volume of lakes, rivers and wetlands to meet human needs and assess the ongoing impacts of climate change.

For this reason, most countries operate a national network of inland water level stations to collect information for water resource development. The installation and maintenance of such networks are expensive tasks that only international cooperation programs can initiate and sustain in many countries. The availability and access to data from water level stations are therefore severely limited due to a decline in the number of stations, inadequate monitoring networks, gaps in records, differences in processing and quality control, differences in datum level and differences in data policies (Harvey and Grabs, 2003; Chen and Chang, 2009). As a consequence, water resource sampling is neither spatially nor temporally homogeneous.

Due to the lack of data and the heterogeneity of water level stations, remote sensing, and especially altimetry from space, appear as complementary techniques for water level monitoring (Calmant and Seyler, 2006).

Satellite radar altimetry first appeared in 1974 with Skylab. In 1975, the GEOS-3 radar altimeter was designed to monitor ocean surfaces, followed by the SEASAT (1978) and GEOSAT (1985-1989) missions. Radar altimetry

27 entered a pre-operational phase in 1992 with the satellites ERS and Topex-
28 Poseidon, followed by Envisat and Jason in 2001. All these missions were
29 originally designed for measuring the level of the ocean through a combi-
30 nation of a radar technique determining the distance from the satellite to
31 the reflecting surface and a satellite positioning technology identifying the
32 precise location (within centimeters) of the satellite. Since 1990, the radar
33 elevation measurements have demonstrated their relevance for inland water
34 observation (Bercher, 2008). The application of this technique in the liter-
35 ature has allowed monitoring of the inland seas (Aladin et al., 2005), lakes
36 (Birkett, 1995, 2000; Birkett et al., 2002; Crétaux and Birkett, 2006) and
37 large rivers (Birkett, 1998; Mercier, 2001; Maheu et al., 2003).

38 In addition to spatial resolution and sampling rates in space or time, the
39 most relevant criterion for satellite altimetry on inland water is the accuracy
40 of the elevation data; therefore, many studies aimed to quantify these accu-
41 racies. Morris and Gill (1994) found a Topex-Poseidon data RMSE (Root
42 Mean Square Error) of a few centimeters on the Great Lakes of North Amer-
43 ica. Studies over other world lakes indicated the following RMSE values: i)
44 greater than 10 cm for Lake Chad (Birkett, 2000); ii) approximately 5 cm
45 for Issyk Kul Lake, Kyrgyzstan; and iii) 10 cm for Chardarya Lake, Kaza-
46 khstan (Crétaux and Birkett, 2006). The accuracy of radar altimetry was
47 also studied for a selection of rivers and floodplains in the Amazon Basin.
48 Substantial errors were observed with RMSE values between 40 cm and 1.1
49 m (Birkett et al., 2002; Bercher, 2008).

50 In recent years, LIDAR onboard satellite also appears as a promising tool
51 for accurate, high resolution altimetry. The Geoscience Laser Altimeter Sys-
52 tem (GLAS) ranging instrument onboard the ICESat (Ice Cloud and land
53 Elevation Satellite) provides elevation data over all Earth surfaces. Its main

54 strength is its small footprint diameter averaged over 70 m (Zwally et al.,
55 2002) compared to the larger radar footprint size of 250 m to a few km.
56 This relative small footprint size is promising for inland water monitoring,
57 especially in rivers. ICESat was launched on the 13 January 2003 and the
58 mission stopped at 14 august 2010. It included three lasers that transmit-
59 ted short pulses (4-6 ns) of infrared light (1064 nm) and visible green light
60 (532 nm). GLAS used 1064-nm laser pulses to measure the heights of the
61 surface and dense cloud and 532 nm pulses to measure the vertical distribu-
62 tion of clouds and aerosols. The 1064-nm signal was also separately filtered
63 and digitized at 2 MHz for detection of dense clouds and aerosols at 76.8-m
64 vertical resolution. The three lasers have been operated one at a time, se-
65 quentially throughout the mission. To extend mission life, the operational
66 mode included 33-day to 56-day campaigns, several times per year. Each
67 period has been assigned a campaign or operations period identifier, such
68 as Laser 2a, to denote the operating laser (2) and the operations period (a)
69 (Schutz et al., 2005). Laser pulses or shots at 40 Hz illuminated sites spaced
70 at 170-meter intervals along track over Earth's surface. The primary mission
71 of GLAS was to measure changes in ice sheet elevation, and secondary ob-
72 jectives included the measurement of cloud and aerosol height profiles, land
73 elevation, vegetation cover and sea ice thickness (Zwally et al., 2002; Schutz
74 et al., 2005). Although less devoted to water monitoring compared to radar
75 altimetry, these LIDAR data could also be used to observe the inland water
76 altimetry (Urban et al., 2008).

77 To date, few studies assessed GLAS elevation data accuracy for inland
78 waters. The estimated standard deviation of GLAS elevation data com-
79 puted on Lake Nasser in southern Egypt range from 3 to 8 cm (Chipman
80 and Lillesand, 2007). On Otter Tail County lakes (USA), Bhang et al. (2007)

81 indicates differences between GLAS elevation and hydrologic station eleva-
82 tion ranging from 2 to 35 cm. [Urban et al. \(2008\)](#) reports GLAS elevation
83 RMSE of approximately 3 cm under clear conditions, 8-15 cm under cloudy
84 skies and 25 cm under very cloudy skies on the Tapajos Rivers (Brazil).

85 Several problems were revealed in previous satellite altimetry accuracy
86 studies. First, detailed descriptions of the assumptions and accuracy statis-
87 tics computation are lacking. Second, most of the studies compute errors
88 between satellite and ground data considering ground data as 'truth', or
89 exact and free from uncertainty. Consequently, in terms of error distribu-
90 tion estimation, most studies only compute RMSE as an accuracy statistic,
91 but despite its common use, RMSE is inadequate because it mixes the bias
92 (exactness) and dispersion (standard deviation) of satellite measurements,
93 which can have very different consequences on their final utility. Moreover,
94 no study compares a single shot elevation value to the ground reference data;
95 rather, studies compare reference data to an average of successive shots, con-
96 sistent with the bodies of water under consideration, such as a river section
97 or a continuous lake transect. Therefore, before accuracy statistics compu-
98 tation, an implicit aggregating or upscaling process, which is typically an
99 average based on the arithmetic mean, involves successive shot elevation val-
100 ues that occurs at the scale of the studied water body. As a result from
101 this aggregating process, the satellite 'measurement' is thus compared to the
102 corresponding ground data. The use of an arithmetic average assumes that
103 successive shots are considered as independent ([Morris and Gill, 1994](#)) and
104 identically distributed, allowing the usual statistics computation on measure-
105 ment uncertainties, such as the SDOM (Standard Deviation of the Mean).

106 The centimeter differences observed between satellite measurements and
107 ground measurements and the uncertainty of both measurements can make

108 the error word inappropriate to qualify the observed deviations between
109 satellite and ground measurements. If not, how to estimate the bias (mean)
110 and dispersion of these deviations ? To answer this question, we need to
111 first consider the satellite and ground measurements as random variables and
112 to verify their significant deviations by computing the uncertainty of each
113 measurement, ground measurements and satellite measurements, at water
114 body scale. The uncertainty of satellite measurements at water body scale
115 can be estimated using the SDOM only if the shot elevation values are, for
116 high frequencies, independent in time and space. If not, the correlation be-
117 tween successive shot altimetric values, denoted further as autocorrelation,
118 must be modeled and estimated. Uncertainty at the water body scale must
119 be computed accordingly. Although infrequent in satellite elevation data,
120 the support effect accounts for the dependence between sequential measure-
121 ments in upscaling and is a typical practice used on spatial data ([Chiles and](#)
122 [Delfiner, 1999](#)) ([Atkinson and Tate, 2000](#)). It has already been used for re-
123 mote sensing data accuracy assessments ([Crosson et al., 2010](#)) and even on
124 LIDAR data ([Bailly et al., 2010](#)).

125 This paper aims to i) explore the high frequencies autocorrelation in
126 GLAS-ICESat water elevation shot data, ii) assess the consequences of this
127 autocorrelation in the uncertainty statistics on water level estimates and iii)
128 assess the consequences of this autocorrelation in deviations to ground sta-
129 tion elevation data from the Great Lakes. To ensure a proper comparison,
130 ICESat data pre-processing was first performed. It consisted of i) the ex-
131 clusion of shots with waveform saturation corresponding to data near land
132 ([Baghdadi et al., 2011](#)), ii) the exclusion of shot outliers from atmospheric
133 disturbance, iii) the application of saturation corrections to initial elevations
134 ([Urban et al., 2008](#)) and iiiii) the exclusion of data when lake water surface

can not be considered as flat for accuracy and deviations estimates. The autocorrelation between successive shot elevation values was first tested and modeled for each of the considered sets of shots. A set of shots consist of a GLAS transect within a Great Lake, spatially coherent with a given ground water-level station (a water body) and temporally located in the same satellite track. We thus proposed an explicative model of the autocorrelation presence. In cases of significant autocorrelation and absence of trend in transect shot data, a block kriging process (Wackernagel, 1995) was used to estimate a mean water elevation at the transect scale and its uncertainty. Finally, the ground measurements and satellite measurements and their relative uncertainties at the transect scale were estimated. By considering these two water elevation estimates as random variables, according deviations statistics (bias and standard deviations) were proposed.

2. Study site and data set description

2.1. Study site

Due to the lack of data on one of the five Great Lakes in North America, the assessment of GLAS-ICESat elevation data accuracy was assessed for the following lakes: Superior, Michigan, Erie and Ontario. One of the youngest natural features on the North American continent, the Great Lakes make up the largest surface freshwater system on Earth. Covering more than 94,000 square miles and draining more than twice as much land, these freshwater seas hold an estimated 22.7 trilliards cubic meters of water, approximately one-fifth of the world's surface freshwater and nine-tenths of the U.S. supply. A network of 52 hydrometric stations monitor the Great Lakes (25 Canadian MEDS station and 27 US NOAA stations) for level measurement (Fig. 1).

160 The Great Lakes have from 1 to 4 cm tides but no prevalent ocean tides.

161 Thus, the Great Lakes are an excellent site for accuracy studies.

162 *Here is located Fig. 1*

163 2.2. Data set

164 2.2.1. ICESat data

165 The GLAS elevation data used in this study are the Level-2 altimetry
166 products GLA14 and GLA01 (Release 31) that provide surface elevation
167 measurements (land, water, etc.) and corresponding waveforms. GLA14
168 data also include the laser footprint geolocation with a precision smaller
169 than 4 m (Duong et al., 2006). GLA01 data include waveforms that have
170 been decomposed into multiple Gaussian distributions (Wagner et al., 2006;
171 Jutzi and Stilla, 2006; Chen, 2010) corresponding to 544 or 1000 samples of
172 received power in volts at 1 ns sampling rate (see Zwally et al. (2002) for a
173 detailed description of ICESat full waveform data). These data record the
174 period between 20 February 2003 and 11 October 2009. In this study, 237
175 ICESat transects, with lengths ranging from 5 to 20 km, containing 20,224
176 shots have been used (Table 1). These 237 selected transects are the set of
177 continuous tracks of shots that are i) in a radius of 20 km from an available
178 hydrometric station to avoid the influence of natural spatial lake level varia-
179 tions and ii) at least 2 km from the shore to avoid measurement disturbance
180 from land-water transition effects on waveform saturation (Baghdadi et al.,
181 2011).

182 Next we developed a two step GLA14 data cleaning procedure, close to
183 the one proposed by Zhang et al. (2011). In step 1, each of the 237 GLAS

ICESat transects was first visually inspected on time-elevation bivariate plots (Figs. 5-a and 5-b) in order to remove obvious outliers and to verify that the water level was almost constant. Some parts of the transects were accordingly excluded when the mean water level varied or when observations were 'constant' due to i) cloudy episodes with outlier elevations in transect (indicating a difference in elevation of approximately 1000 m) (Wesche et al., 2009), ii) the proximity of river outlets. Fig. 2 shows the only example of this phenomenon: the extended transect of 14 June 2005 for Station 21 (Holland station) on Lake Michigan is located near an important river outlet (Fig. 2-a). The transect profile shows the 85 km elevation profile track that increases in the middle near the outlet, producing an upper water level of approximately 70 cm. In Step 2, for each transect, the median elevation value of the remaining shots was calculated and the shots which were at least 4 meters far from this median value were removed.

Here is located Fig. 2

2.2.2. Water level reference data

The reference lake level data in this study were obtained from 27 of the 52 water level stations located throughout the Great Lakes basin. The selected stations are near (less than 20 km) the transect of the GLAS footprints. Eleven stations are operated by the Marine and Environmental Data Service (MEDS) of Canada's Department of Fisheries and Oceans, and 16 stations are operated by the U.S. National Oceanic and Atmospheric Administration (NOAA). Both NOAA and MEDS stations continuously monitor the surface levels of the four lakes at 6 minutes intervals (Braun et al., 2004) with a

208 standard deviation of 2 cm (Hovis et al., 2004).

209 North American Great Lakes are known to have low tides but are sensi-
210 tive to short-term water-level fluctuations, such as up to 2.44 m in approxi-
211 mately 2 hours, caused by wind or storm surges, which are known as seiches
212 (Touchart, 2002). Considering this phenomenon and because the ICESat
213 transect lasts very few seconds and a hydrometric station may have a timing
214 bias of a few minutes, this study analyzed the dispersion of recorded ground
215 measurement (hydrometric station data) in a 6-minute range around transect
216 ICESat times for all stations. This analysis exhibits a constant dispersion
217 for each station of 7 mm for one standard deviation.

218 In addition, the geoid model G99SSS used in this study to convert the ref-
219 erence data from ellipsoidal height (WGS84) to orthometric height (NAVD88)
220 has a mean error of approximately 2.5 cm (Smith and Roman, 2001).

221 Given that these different sources of uncertainty are independent, they
222 can be summed (in variance). As a result, the computed uncertainty on
223 reference ground data was estimated to 3.3 cm for one standard deviation
224 (σ_R).

225 2.2.3. Data consistency

226 GLA14 products provide original elevation data with ellipsoidal heights
227 based on the same ellipsoid used by the Topex satellite. The lake level data
228 collected from hydrometric stations are in the International Great Lakes
229 Datum of 1985 (IGLD85). Consequently, data transformations are required
230 in order to conduct a consistent comparison in the same reference frame.
231 GLAS heights and lake level heights were therefore converted to the same
232 vertical datum NAVD88. Two successive transformations are required for
233 GLAS heights: the first converts the Topex ellipsoidal heights to WGS84

234 ellipsoidal heights using the geoid model EGM96; the second transforms the
235 WGS84 ellipsoidal heights to NAVD88 orthometric heights using the geoidic
236 model G99SSS. For hydrometric station elevation data, the IGLD85 lake
237 level datum converts to orthometric height NAVD88.

238 3. Methods

239 3.1. GLAS water elevation saturation correction

240 Some ICESat waveforms exhibit distortions, or saturation events, when
241 the high energy emitted by the laser returns, passes the inadequate automatic
242 gain controls and overloads the detector (Sun et al., 2005). This occurs
243 when the amplitude of the energy returned by a number of 1-ns bins is
244 greater than the threshold function of gain (Urban et al., 2008; Abshire
245 et al., 2005), producing an incorrect elevation. The ICESat science team
246 has developed an analytical saturation correction, also available on the data
247 products. Adding this correction to the elevation is recommended for ice
248 and calm water data, but not over oceans (Urban et al., 2008). Corrections
249 vary between 0 and 1.5 m. For some waveforms, the saturation should be
250 corrected but the method used to calculate the correction coefficient cannot
251 provide a correct value and is marked by '-999.00' flags. Fig. 3 shows some
252 ICESat waveforms obtained across Lake Superior; the saturated waveform
253 is clipped and widened artificially by the returning high energy.

254 *Here is located Fig. 3*

255 Fig. 4 illustrates an example of elevation transects before and after ap-
256 plication of the saturation correction. The saturation correction allows a

reduction of error bias but does not reduce the error dispersion in the figure.

Here is located Fig. 4

3.2. GLAS water elevation estimation at transect scale

To compute the GLAS water elevation estimate $\hat{Z}_G$ and uncertainty σ_G at the transect scale and considering autocorrelation, we used a statistical framework based on the regional variable and random field theories (Cressie, 1993). In this framework, a GLAS transect is viewed as a temporal block, or a delimited part of a temporal random field ($z(t)$). For each GLAS transect, we developed the usual block kriging process (Wackernagel, 1995, p.77) based on an autocorrelation model, allowing both the estimation of the water elevation $\hat{Z}_G$ and its corresponding uncertainty σ_G , at the transect scale.

3.2.1. Autocorrelation test and modeling

A GLAS transect is composed from $(t_1 \dots t_n)$ and $(z_1 \dots z_n)$ series, respectively, where t refers to the laser shot (pulse) time, z to the elevation in the NAVD88 altimetric system and n is the number of shots in the transect. These series are denoted as $z(t)$ and are considered to be a realization of a stationary temporal random function. We want to infer the main property of $z(t)$, its temporal correlation (autocorrelation), especially the high frequency autocorrelation. When $z(t)$ is stationary, with constant expectation and homogeneous temporal covariance, this inference is possible using the variogram modeling of the field $z(t)$, equivalent to the covariance.

Elevation trend test at transect scale. To ensure a stationary process and reinforce the high frequency autocorrelation test power (Armstrong, 1984),

280 a linear trend test is first performed. A linear model $z(t) = m(t) + y(t)$, where
281 $m(t) = at + b$ is the linear regression of z by t , and $y(t)$ are the residuals of
282 this linear regression, is fitted. Using the usual T-test on the coefficient a it
283 is tested if a linear trend is significant.

284 Next, when the trend tests positively, the initial $z(t)$ field is decomposed
285 in two additive term $m(t) + y(t)$, with $m(t)$ a deterministic trend term and
286 $y(t)$ a term consisting of random residuals. When the trend is negative, the
287 $m(t)$ term disappears and we write $z(t) = y(t)$ for the sake of simplicity. To
288 enable a valid comparison between ground station and GLAS measurements
289 and to avoid natural spatial variations of lake water levels at high spatial fre-
290 quencies, only transects without linear trends were kept further to compute
291 the GLAS deviations and accuracy.

292 *Autocorrelation significance test.* Next, to estimate the autocorrelation of
293 $z(t)$ transect data, an experimental variogram $\gamma(\hat{h})$, with h equal to lag
294 time, is computed on the $y(t)$ data (see [Wackernagel \(1995, p.35\)](#) for the
295 usual experimental variogram formulation). This variogram was computed
296 on 16 regular lag times each 62.5 ms ranging from 0 to 1 s, chosen to ob-
297 tain numerous shot pairs for an accurate variogram estimation for each lag
298 time h . An autocorrelation is considered significant when the experimental
299 variogram graph shows a clear increasing shape from small time differences
300 to large time differences. When the corresponding experimental variogram
301 graph shows a flat variogram, no autocorrelation for this GLAS transect
302 exists. To test the significance of the autocorrelation calculated from the ex-
303 perimental variogram, we used the standard empirical Mantel test ([Legendre](#)
304 [and Fortin, 1989](#)), which simulates data corresponding to the null hypothe-
305 sis H_0 through data permutations, where H_0 corresponds to the absence of

306 autocorrelation (Fig. 5-c). At each permutation of the z data, a correspond-
307 ing experimental variogram is computed. For numerous replications of the
308 permutations, we obtained a quintile distribution of variograms representing
309 H_0 for each lag time h . The H_0 acceptance area is thus represented in the
310 variogram graph through a 95% confidence band of H_0 . In the case of sig-
311 nificant autocorrelation, the actual experimental variogram for small values
312 of h is below the 2.5% quintile of H_0 (the lower line of the band). Here, we
313 chose to reject H_0 only when the first variogram point was below the 2.5%
314 quintile of H_0 .

315 *Here is located Fig. 5*

316 *Autocorrelation modeling.* In the case of a significant experimental variogram
317 (Fig. 5-d), we chose to model it with a single spherical model function given
318 by:

$$\gamma(h) = \begin{cases} nu + (si - nu)\left(\frac{3h}{2r} - \frac{h^3}{2r^3}\right) & \text{if } h < r \\ (nu + si) & \text{if } h \geq r \end{cases} \quad (1)$$

319 Using a weighted least-square estimation (Pebesma and Wesseling, 1998),
320 the model parameters nugget (nu), range (r) and sill (si) were fitted. This
321 was done automatically for all GLAS transects from initial fitting parameters
322 corresponding to a nugget equal to the experimental variogram at a smaller
323 lag time, a sill equal to the maximum value of the experimental variogram
324 and a range equal to the time duration at which the variogram reaches its
325 maximum. After the fitting process, a variogram model $\gamma(h)$ was obtained as
326 shown in the example by the fitted line in Fig. 5-d.

3.2.2. Transect water elevation estimation with autocorrelation: block kriging

For a GLAS transect, when autocorrelation is significant and modeled, a mean value $\hat{Z}_G$ for the transect is estimated from transect data $z(t)$ from $\hat{Y}$. The $\hat{Y}$ estimate is computed through a block kriging process of $y(t)$ (Wackernagel, 1995, p.77) using the variogram model $\gamma(h)$. $\hat{Y}$ is therefore a linear combination of $y(t)$ data with kriging weights β_i :

$$\hat{Y} = \sum_{i=1}^n \beta_i y_i \quad (2)$$

Uncertainty on $\hat{Z}_G$ is represented in the block kriging estimation standard deviation σ_G given by (Wackernagel, 1995, p.77):

$$\sigma_G = \sqrt{\mu_{BK} + \bar{\gamma} + 2 \sum_{i=1}^n \beta_i \bar{\gamma}(t_i, T)} \quad (3)$$

In this equation, μ_{BK} is the Lagrange multiplier deduced from the block kriging system, $\bar{\gamma}(t_i, T)$ is the average variogram computed between the sample point t_i and all points of the transect T (block) and $\bar{\gamma}$ is the variance within the transect. In practice, both $\hat{Z}_G$ and σ_G are approximated through the average of gridded points within the considered GLAS transect. We chose a gridding step of 10ms here corresponding to 1/4 of the time lag between pulses. Note that σ_G only depends on the data temporal sampling scheme, not on the elevation values z . Consequently, given that the temporal sampling scheme of ICESat data is almost regular, except when outliers are excluded from the initial transect data, σ_G primarily depends on the transect total duration.

When no autocorrelation is observed for a given GLAS transect (H_0 is accepted), $\gamma(h)$ is a pure nugget effect variogram. In this particular case,

kriging weights β_i in equation 2 are all equal and equation 3 is simplified to the common SDOM formulation. Consequently $\hat{Z}_G$ equals the arithmetic mean $\bar{z}$ of the values z_i .

3.3. GLAS deviations to reference water elevation at transect scale

For each transect j where no linear trend has been observed, a GLAS estimated value $\hat{Z}_G$ having σ_G Gaussian uncertainty was compared to a reference value Z_R having σ_R Gaussian uncertainty. As GLAS and reference elevations can be considered independent Gaussian random variables, the distribution of the deviations between GLAS and reference water elevations can be assumed also to be of Gaussian distribution $N(\mu_j, \sigma_j)$, with $\mu_j = \hat{Z}_G - Z_R$ and standard deviation $\sigma_j = \sqrt{\sigma_G^2 + \sigma_R^2}$.

From these Gaussian deviation distributions obtained for a transect, GLAS deviation statistics (accuracy) were computed at station, lake or Great Lakes scales, by simply averaging the cumulative probability functions of the Gaussian laws $N(\mu_j, \sigma_j)$ and computing the resulting empirical deviation distribution (not necessarily Gaussian).

From this empirical distribution, the first (bias) and second (standard deviation) moments were estimated to propose GLAS accuracy statistics.

4. Results and discussion

4.1. Autocorrelation between GLAS shot measurements

A significant high frequency autocorrelation is observed for 107 transects, i.e. 45% of the initial 237 transects. No direct explanation is known to the authors for the occurrence of the autocorrelation as shown in Fig. 6, although correlated and non-correlated transects look randomly distributed in space (Fig. 6-a), or in time (Fig. 6-b). It does not depend on the overall water

level (low or high) in the lake (Fig. 6-b). For the transects that do experience significant correlation the 107 fitted variogram models show:

- a $\frac{nugget}{nugget+sill}$ ratio ranging from 0.24 to 0.52 with a mean value of 0.4. This value means that there is in average 40 % of randomness between two consecutive, i.e. very close, shots.
- a range ranging from 0.27 s to 0.34 s with a mean value of 0.3 s (time the variogram model becomes flat at sill value). This range corresponds to the duration of 11 pulses and a distance along the transect of approximately 1.9 km.

Here is located Fig. 6

4.2. Autocorrelation explanation

To explore the physical explanation of the significant autocorrelation observed for 45% of the GLAS transects, we attributed to each one of the 237 transects i) the environmental parameters from the ICESat data at the transect time (surface temperature, surface humidity and pressure) and ii) the GLA14 instrument parameters (transmitted energy, received energy, gain, incidence angle, laser campaign, transect direction and transect dates according to the beginning and end of each laser campaign (Schutz et al., 2005, table 1, p.2)). To explore relationships between the presence of autocorrelation and these available system or environmental parameters, they were all first considered as potential temporal autocorrelation predictors. We used the multivariate classification tree (CART) method of Breiman et al. (1984) that computes predictor importance that explains autocorrelation by

396 using indifferently quantitative or qualitative predictors. The obtained clas-
397 sification tree in Fig. 7 shows separation between the autocorrelated (1) and
398 non-autocorrelated (0) transects based respectively on the transmitted en-
399 ergy (TE), temperature (temp) and pressure (pressure). This tree explain
400 68% of the autocorrelation. These results show that the transmitted energy
401 plays a major role in autocorrelation among all parameters. We thus draw
402 from this analysis that significant autocorrelation occurs when the GLAS
403 instrument transmits low energy which notably occurs at the end of each of
404 three lasers life times, and when bad weather conditions are marked by either
405 lower temperature or lower pressure. These results are consistent with no
406 systematic autocorrelation observed in space or time that could have come
407 from satellite system behaviour.

408 *Here is located Fig. 7*

409 4.3. Autocorrelation effect on GLAS water elevation uncertainties at transect 410 scale

411 Z_G estimates and corresponding σ_G uncertainty parameters were com-
412 puted for the 117 transects where no significant trend has been observed.
413 When no autocorrelation is observed for the transect, we used the block
414 kriging process (Equation 2), and if not, we used the Standard Deviation
415 Of the Mean (SDOM). Fig. 8 depicts the distribution of the σ_G uncertainty
416 parameters for transects as a function of the pulse number composing the
417 transect and the presence or absence of autocorrelation. It appears clearly on
418 this figure that the presence of autocorrelation multiplies the σ_G uncertainty
419 by 8 on average. As expected, accounting for autocorrelation drastically

420 changes the σ_G estimation, even if the $\hat{Z}_G$ values differ only slightly (due to
421 the regular time sampling of GLAS measurements). This usual geostatistical
422 result comes from autocorrelation that acts as diminishing the number of
423 data.

424 *Here is located Fig. 8*

425 4.4. GLAS water elevation deviation distribution

426 The GLAS deviation, the difference between the GLAS and reference
427 elevation, is considered as a random variable. The distributions of these
428 deviations were computed for all Great Lakes together, for individual lakes
429 and at station scale. For all Great Lakes, the probability of a GLAS water
430 elevation deviation to be lower than 1 cm, 10 cm and 20 cm in absolute values
431 is 7.5%, 66.8% and 91.9%, respectively, which seems close to a $N(0, 10\text{cm})$
432 value. The 2.5% and 97.5% quantiles are 29 cm and 16 cm, respectively.
433 The expectation of this distribution is -4.6 cm.

434 Examples of distributions are depicted in Fig. 9, for all Great Lakes,
435 at lake scale (for lake Erie and lake Ontario), at station scale (for station
436 Erie, Fermi Power, Rochester and Toronto) and at transect scale (transect
437 number 5,8,26,24,88,85,92,90). The mix of deviation distributions at the
438 lake scale gives the overall Great Lakes deviation distribution. Normality
439 of deviation distributions is clearly low when downscaling. At station scale,
440 there are various shapes of deviation distribution, non-symmetric, with positive
441 or negative pseudo-biases. The mix of these deviation distributions at the
442 station scale, with weights equal to transect numbers for each station of a
443 lake, provides the lake deviation distribution.

444 However, these results show that when aggregating numerous data, i.e.
445 transects at the Great Lakes scale, and due to the general Law of Large Num-
446 bers, the obtained shapes of deviation distribution become nearly Gaussian.
447 This is not true at the station scale where shapes are asymmetrical and com-
448 plex. In this latter case, attention must be paid in using common accuracy
449 statistics, especially for dispersion parameters.

450 *Here is located Fig. 9*

451 4.5. GLAS accuracy parameters

452 The right part of Table 1 summarizes the results of the biases and stan-
453 dard deviations statistics at the Great Lakes, lake and station scales. At
454 the Great Lakes scale, the GLAS deviation bias is -4.6 cm. In other words,
455 GLAS is slightly underestimating the water elevation on average. The bias
456 values range from -11.4 cm to -2.1 cm at the lake scale and from -14.5 cm
457 to 3.8 cm at the station scale. The bias found on the stations of the Michi-
458 gan Lake is the higher in magnitude, reaching up to -14.5 cm for Station
459 Kewaunee. A standard deviation of 11.6 cm was computed at the Great
460 Lakes scale. It varies from 7.9 cm to 12.9 cm at the lake scale and from
461 3.3 cm to 13.7 cm at the station scale. The highest standard deviation was
462 found at Station Ludington on Lake Michigan. Bias and standard deviation
463 statistics clearly differ from one lake, or one station, to the next. All these
464 standard deviations must be compared in magnitude with the reference data
465 uncertainties (3.3 cm for one standard deviation) and GLAS water elevation
466 estimate uncertainty at the transect scale (Fig. 8). They are clearly of higher
467 magnitude than the reference data uncertainties but are of the same order

468 as the GLAS water elevation estimate uncertainty when autocorrelation is
469 significant.

470 *Here is located table 1*

471 5. Conclusions

472 This study explored the accuracy of GLAS-ICESat inland water eleva-
473 tion data at various spatial scales with a specific emphasis on uncertainties
474 originating from in situ measurements and impacts of autocorrelation be-
475 tween successive ICESat shots, i.e. at temporal high frequencies. This study
476 also benefited from the pre-processing of the GLAS data with the saturation
477 correction of the GLAS waveforms and spatial filtering to avoid measure-
478 ment disturbance from land-water transition effects on waveform saturation
479 as previously observed. A set of 237 GLAS transects near the available hy-
480 drometric ground stations for four of the Great Lakes of North America was
481 analyzed. A significant autocorrelation between successive shot elevation
482 values was observed for 45% of the transects. This autocorrelation of an
483 approximately 11 pulses duration seems to occur when a combination of a
484 low transmitted energy from the GLAS instrument and bad weather with
485 low temperature and low pressure occurs. The main consequence of this
486 autocorrelation is a drastic increased uncertainty (by 8 times) of the GLAS
487 water elevation at the transect scale.

488 After removing the 120 transects where a linear trend was observed and
489 assuming Gaussian uncertainties for both reference data and GLAS data
490 upscaled at the transect scale, we derived empirical distributions on GLAS
491 deviations at the Great Lakes, lake and station scales. At the Great Lakes

492 scale, a bias of -4.6 cm (underestimation) and a standard deviation of 11.6
493 cm were computed on the various shapes of GLAS deviation distributions.
494 However, these statistics were highly variable among the stations.

495 This study indicates that accuracy statistics computation is highly de-
496 pendent to the assumptions made on satellite data and reference data as
497 well. These assumptions can highly affect the computed accuracy statistics
498 and conclusion. Even if the impact of the temporal correlation in GLAS raw
499 data was partially smoothed by the reference data uncertainty, this can be
500 crucial when reasoning with few data, such as a small number of transects,
501 at the station scale.

502 The accuracy results of this study confirm that satellite ranging LIDAR
503 provides data with a decimeter accuracy to monitor water level in inland
504 water for the Great Lakes or a wide river section.

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Lake	Id	Station	Number of shots used	Number of transects used	Bias (m)	Standard Deviation (m)
Erie	1	Bar Point	975	8	0.008	0.035
Erie	2	Fermi Power	1634	16	-0.057	0.102
Erie	3	Marblehead	198	2	-0.012	0.034
Erie	4	Cleveland	607	8	0.006	0.055
Erie	5	Fair Port	240	6	0.038	0.054
Erie	6	Erie	711	10	-0.058	0.112
Erie	7	Sturgeon	2148	18	-0.051	0.089
Erie	8	Port Colborne	2034	16	-0.012	0.093
Erie	9	Port Dover	287	5	-0.044	0.051
Erie	10	Port Stanley	782	9	0.028	0.061
Erie	11	Erieau	651	18	-0.038	0.059
Erie				Mean	-0.021	0.109
Ontario	12	Port Weller	1220	14	-0.097	0.092
Ontario	13	Rochester	979	14	-0.031	0.084
Ontario	14	Oswego	253	5	-0.140	0.034
Ontario	15	Kingston	221	5	-0.033	0.038
Ontario	16	Cobourg	1631	17	-0.028	0.074
Ontario	17	Toronto	743	8	-0.022	0.084
Ontario				Mean	-0.048	0.087
Michigan	18	Green bay	213	3	-0.088	0.124
Michigan	19	Kewaunee	384	4	-0.145	0.056
Michigan	20	Calumet	571	7	-0.143	0.128
Michigan	21	Holland	264	4	-0.022	0.084
Michigan	22	Ludington	425	6	-0.120	0.137
Michigan				Mean	-0.114	0.129
Superior	23	Ontanagon	213	15	-0.048	0.093
Superior	24	Marquette	384	8	-0.091	0.042
Superior	25	Ross Port	571	12	-0.042	0.062
Superior	26	Thunder Bay	264	5	-0.004	0.087
Superior	27	Grand Marais	425	6	0.010	0.033
Superior				Mean	-0.042	0.079
ALL LAKES				Mean	-0.046	0.116

Table 1: Left : Number of GLAS shots and transects used across each hydrometric station of the four Great Lakes; Right: biases and standard deviation of deviations (GLAS-reference) resulting from comparison between ICESat elevations and reference elevations on the Great Lakes of North America at lake and hydrometric station scales.

Fig 1: GLAS-ICESat shots forming transects over the Great Lakes and the location of the 27 hydrometric stations.

Fig 2: (a) GLAS transect of 14 June 2005 at Holland station (Number 21) on Lake Michigan; (b) the corresponding ICESat elevation profile (with abscissae = shot number) in comparison to hydrometric station data (reference elevation).

Fig 3: Example of GLAS waveforms on Lake Superior: (a) Unsaturated waveform ; (b) Waveform with low saturation ; (c) and (d) waveforms with high saturation. Ordinate = energy in volts and abscissae = bins number (bins spacing = 1 ns).

Fig 4: Example of a GLAS-ICESat transect compared to reference elevation. Abscissae = shot number and ordinate = elevation (ICESat with and without saturation correction and hydrometric station).

Fig 5: (a) and (b): temporal series $z(t)$, and (c) and (d): corresponding experimental variograms obtained on the transect at Port Colborne station from 2 February 2005 (a, c) and Bar Point station from 10 May 2007 (b, d). The dashed lines in (c, d) represent the two H_0 envelopes, the straight lines in (a, b) represent the reference elevation, and the curve lines in (c, d) are the spherical model function fitted to the experimental variogram (points on c, d). (a, c): absence of autocorrelation. (b, d): significant autocorrelation. (d) Variogram range = 0.32 s.

Fig 6: (a) Correlated and non-correlated GLAS transects on the Great Lakes - exact locations of transects have been slightly translated to depict overlapping transects; (b) correlated and non-correlated GLAS transects along the ICESat mission dates - the ordinate is the deviation between the reference elevation of a given lake at each transect date and the mean elevation of the lake calculated using reference elevations for all dates.

Fig 7: Classification tree explaining the autocorrelation of the transects. A value of 0 on leaves denotes the absence of autocorrelation, and a value of 1 on leaves denotes autocorrelation. The 0/1 value on a leaf means that it mixes correlated and non-correlated transects in equal proportions.

Fig 8: Distribution of the standard deviation σ_G characterizing the uncertainty of estimated water elevations at the transect scale from GLAS data. This distribution is shown as a function of the shot number composing the transect and presence (right) or absence (left) of autocorrelation.

Fig 9: GLAS water elevation deviation distribution and upscaling: For transect scale (down), for station scale, for lake scale and all lake scale (up). Not all distributions for lake, station and transect scales are depicted but only examples. The black wide central line on density plots denote the biases values and the thin lines denotes the 2.5 % and 95.5 % quantiles respectively. The two examples of deviation distribution selected at transect scale for each lake are for a correlated transect (wide on the left) and a not-correlated transect (thin on the right).