1   # Argo salinity: bias and uncertainty evaluation

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11   **Abstract.** Argo salinity is a key set of in-situ ocean measurements for many scientific applications.

12   However, use of the raw, unadjusted salinity data should be done with caution as they may contain

13   bias from various instrument problems, most significant being from sensor calibration drift in the

14   conductivity cells. For example, inclusion of raw, unadjusted Argo salinity has been shown to lead

15   to spurious results in the global sea level estimates. Argo delayed-mode salinity data are data that

16   have been evaluated and, if needed, adjusted for sensor drift. These delayed-mode data represent

17   an improvement over the raw data because of the reduced bias, the detailed quality control flags,

18   and the provision of uncertainty estimates. Such improvement may help researchers in scientific

19   applications that are sensitive to salinity errors. Both the raw data and the delayed-mode data can

20   be accessed via https://doi.org/10.17882/42182 (Argo, 2022). In this paper, we first describe the

21   Argo delayed-mode process. The bias in the raw salinity data is then analyzed by using the

22   adjustments that have been applied in delayed-mode. There was an increase in salty bias in the raw

23   Argo data beginning around 2015 and peaked in 2017-2018. This salty bias is expected to decrease

24   in the coming years as the underlying manufacturer problem has likely been resolved. The best

25   ways to use Argo data in order to ensure that the instrument bias is filtered out are then described.

26   Finally, a validation of the Argo delayed-mode salinity dataset is carried out to quantify residual

27   errors and regional variations in uncertainty. These results reinforce the need for continual re-

28   evaluation of this global dataset.

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1. Introduction

In-situ ocean salinity can be measured accurately by well-calibrated conductivity-temperature-depth (CTD) sensors. By using CTDs mounted on autonomous floats, the global Argo Program has collected over two million vertical profiles of temperature-salinity (T/S) versus pressure (P) in the past 20 years. Many of these floats receive pre-deployment CTD accuracy checks to ensure that the sensor calibrations are within the manufacturer's specifications. However, over time these sensors can become affected by contamination, or undergo physical changes that alter their accuracy. Since recalibration of these CTDs involves retrieval of the floats, which is impractical for such a large-scale program, Argo uses a set of delayed-mode procedures to determine if post-deployment adjustment of its data is necessary. These delayed-mode data are typically available about 12 to 18 months after the vertical profiles are collected.

Argo data are used in many oceanographic applications, forecasting services, climate research, ocean modeling, and data products. However, using the data without post-deployment adjustment can lead to spurious scientific results. This effect has been shown to be especially impactful when using Argo salinity data collected after 2015, when a higher-than-average number of CTDs on Argo floats developed sensor calibration drift towards higher salinity values (Wong et al., 2020). Ponte et al. (2021) compared estimates of in-situ global mean salinity $\bar{S}$ from 5 different data products that included Argo data. They found a spurious increase in $\bar{S}$ after 2015 in all the products, except the Roemmich & Gilson (2009) climatology (hereafter referred to as RG2009). The spurious increase in $\bar{S}$ after 2015 was postulated to be the result of using unadjusted Argo salinity, while the absence of this artificial increase in $\bar{S}$ in RG2009 was attributed to stricter quality control of the affected data. Similar discrepancies were seen in comparisons between global ocean mass change (Chen et al., 2020) and global mean sea level budget (Barnoud et al., 2021) derived from GRACE/GRACE-FO and Altimeter-Argo. In both studies, the discrepancies become substantially larger after 2015 and are likely related to using unadjusted Argo salinity.

The Joint Committee for Guides in Metrology (2008) defines *measurement error* as the difference between the measured and the true value of a variable. It has two components: a random component and a systematic component. The random component is influenced by unpredictable effects and cannot be corrected. The systematic component, or bias, arises from recognized effects and thus can be corrected. When all the components of error have been evaluated and corrected, *uncertainty* refers to the doubt about the validity of the evaluation and the correction. Quantifying

62 the uncertainties of an ocean dataset increases its usefulness to scientists and other stakeholders

63 (Elipot et al., 2022).

64   The instruments used in Argo and the impacts that their respective technical limitations

65 have on the data have been described in Wong et al. (2020). The uncertainties of Argo data have

66 been assessed by comparison with high-quality shipboard measurements, and are concluded to be

67 near the manufacturer instrument accuracy specifications of 0.002°C for temperature and 2.4 dbar

68 for pressure. For salinity, even though the manufacturer specified instrument accuracy is 0.0035

69 psu, the uncertainties of Argo salinity are assessed to be around 0.01 psu.

70   This paper aims to improve understanding of the treatment and uncertainty of Argo salinity

71 data. Section 2 describes the evolution behind Argo's salinity adjustment method and its

72 implementation. Section 3 describes the temporal and spatial distribution of bias in the raw Argo

73 salinity. The best ways to use Argo data are described in Sect. 4. Lastly, an evaluation of the

74 uncertainty in Argo's delayed-mode salinity data against a shipboard CTD reference database is

75 discussed in Sect. 5.

76

77 2. Argo salinity adjustment method and implementation

78

79 2.1. Argo's salinity adjustment method

80 Measurement stability refers to an instrument's ability to repeat the same measurement over time.

81 The change in the instrument's bias over time is referred to as sensor drift. A system for correcting

82 sensor drift in Argo salinity data was originally developed by Wong et al. (2003). The system uses

83 an objective mapping technique to estimate the background salinity field on a set of fixed potential

84 temperature surfaces from nearby reference data. Float salinity data are fitted to the objectively

85 mapped field in potential conductivity space by weighted least squares. The time-varying

86 component is smoothed out by another least squares fit over multiple profiles to filter out the

87 transient oceanic noise in the float data and the reference data. The result is an additive correction

88 in salinity for each vertical profile. Böhme and Send (2005) improved on the original method by

89 using float-observed θ surfaces and introduced potential vorticity as a factor for selecting reference

90 data in areas affected by topographic constraints. Owens and Wong (2009) combined the original

91 method with the improvements of Böhme and Send (2005) and introduced a piecewise linear fit

92 with the Akaike Information Criteria in the treatment of the time series. More recently, Cabanes

93 et al. (2016) suggested modifications to better account for interannual variability and provide more

94 realistic error estimates.

95 As these methods evolve, their authors have maintained a set of computational code that

96 can be used by all Argo float providers. Transparency and reproducibility of the salinity

97 adjustments are achieved via this provision of code that operates on the raw measurement inputs

98 to produce the delayed-mode adjusted data. Currently, the code used for salinity adjustment in

99 Argo is a combined set from Owens and Wong (2009) and Cabanes et al. (2016). See

100 github.com/ArgoDMQC/matlab_owc.

101 These salinity adjustment methods rely on accurate reference data. To that end, two

102 reference databases are provided internally in Argo for salinity adjustment: 1. a reference database

103 which consists of shipboard CTD data (internally named CTD_for_DMQC, maintained by

104 Coriolis Data Center), and 2. a reference database which consists of Argo data that have been

105 verified as having good quality without needing adjustments (internally named Argo_for_DMQC,

106 maintained by Scripps Institution of Oceanography). These two reference databases are updated

107 yearly to account for the constantly changing oceans.

108

2.2. How is salinity adjustment implemented in Argo?

110 Delayed-mode salinity evaluation in Argo is carried out by each data-providing group, and not by

111 a central institution. Each data-providing group in Argo has a team of delayed-mode operators who

112 manually inspect the data. As both pressure and temperature are required to measure salinity, all 3

113 parameters (*P, T, S*) are evaluated together in delayed-mode. Random point-wise errors, such as

114 spikes, are flagged as bad data. Sensor drifts are identified and either adjusted or flagged as

115 unadjustable data. Evaluation of sensor drifts, not to be confused with real ocean signals, requires

116 significant oceanographic knowledge, scientific judgment, and insights based on experience. To

117 ensure all data-providing groups are consistent in following best practices, two technical

118 documents are maintained internally in Argo to describe the data processing procedures and to

119 provide examples. These are: 1. Argo Quality Control Manual for CTD and Trajectory data (Wong

120 et al., 2022), and 2. DMQC Cookbook for core Argo parameters (Cabanes et al., 2021). These are

121 living documents, modified and updated as the data processing procedures develop and evolve.

122 Due to the need to accumulate a time series for reliable evaluation of sensor drifts, delayed-

123 mode data may not be available until a sufficiently long time series has been accumulated. The

124   timeframe for availability of delayed-mode data is therefore dependent on the nature of the sensor

125   drift, as well as the availability of the delayed-mode operators. In general, most Argo delayed-

126   mode salinity data are available about 12–18 months after the raw measurements are collected.

127   These data are re-evaluated periodically to reduce inconsistencies between the various data-

128   providing groups. Therefore, Argo delayed-mode data are "dynamic" data that continually change

129   and improve over time.

130   Some Argo data centers can extract the most recent delayed-mode salinity adjustment and

131   apply it to later, newly collected profiles. This near-real-time procedure can result in some

132   improvement over the original reported data, but some bias can remain. Nonetheless, it provides

133   intermediate-quality salinity data to users in near-real-time.

134

135   3. Bias in Argo raw salinity data

136   Bias in raw Argo salinity can contain effects from three different sources:

137   1. error from the pressure measurements (Barker et al., 2011);

138   2. error from conductivity cell thermal inertia, due to the lag between the temperature and

139   conductivity measurements (Johnson et al., 2007; Martini et al., 2019; Dever et al., 2022);

140   3. error from conductivity cell sensor drift (Wong et al., 2020).

141   The effect of pressure error on salinity is not negligible. For example, assuming standard

142   seawater properties of $S = 35$ and $T = 15°C$, a pressure error of 10 dbar will result in a salinity error

143   of about 0.004 psu. However, less than 1% of Argo vertical profiles have identifiable pressure

144   error of greater than 10 dbar. The effect of the conductivity cell thermal inertia error on salinity is

145   pronounced in regions of strong temperature gradients, such as the base of the mixed layer, but is

146   negligible (<0.002 psu) elsewhere.

147   The bias caused by conductivity cell sensor drift is the most significant error in Argo

148   salinity. Some of this bias cannot be corrected, as severe sensor drift (and other CTD malfunctions)

149   can cause data corruption that is beyond salvage. The remaining adjustable bias, ∂S, can be

150   estimated by using the salinity adjustments that have been applied in delayed-mode:

151

152    $$\partial S = \overline{S_{raw} - S_{adjusted}}$$

153

154   where *Sraw* are the raw Argo measurements and *Sadjusted* are the corresponding delayed-mode

155   adjusted values. Here, we compute ∂S for each Argo vertical profile that has delayed-mode

156   adjusted data, but only use measurements deeper than 600 dbar to exclude the effects of the cell

157   thermal inertia error. Profiles with identifiable pressure error greater than 10 dbar are excluded to

158   factor out the effects of pressure error on salinity. Profiles with $|\partial S| < 0.002$ are considered as good

159   data because we consider them to not have been affected significantly by sensor drift. Thus, the

160   remaining ∂S represents the typical bias magnitude identified mostly from conductivity cell sensor

161   drift. Here, a positive ∂S means the raw values are higher than true, or drifted towards saltier values

162   (salty drift). Similarly, a negative ∂S means the raw values are lower than true, or drifted towards

163   fresher values (fresh drift).

164   Salty drift is the dominant mode of sensor drift in Argo salinity, with about 10% of all Argo

165   vertical profiles having a positive adjustable bias (Fig. 1a, blue bars). Most of the physical causes

166   of salty drift are unknown. One known cause was determined to be due to the early deterioration

167   of the encapsulant material in CTDs manufactured by Sea-Bird Scientific starting in 2015.

168   Changes at the manufacturing level were introduced in 2018 to reduce such occurrences. The

169   number of Argo profiles with adjustable salty drift increased steadily from 2000 and peaked in

170   2017-2018 at about 17% of the annual profiles count. This 2017-2018 peak (Fig. 1a), as well as

171   the annual average of adjustable bias (Fig. 1b), may shift slightly as more delayed-mode evaluated

172   profiles become available in the future, but the present result is consistent with the timeline of the

173   CTD encapsulant issue.

174   On the other hand, fresh drift occurred more frequently in the early years of Argo (Fig. 1a,

175   red bars), reaching a peak of about 28% of annual profile count in 2001-2002. The subsequent

176   decline is broadly coincident with the introduction of Iridium in 2005 for data communication.

177   Fresh drifts are mostly caused by contamination of the CTD while the floats remain at the sea

178   surface for communication with satellites. Earlier floats that used the ARGOS System, which was

179   the predominant telecommunication system before Iridium, typically spent between 6 to 18 hours

180   at the sea surface for data telemetry. With Iridium, the time spent at the sea surface is reduced to

181   about 20 minutes, thus reducing the risk of CTD contamination. The number of Argo profiles with

182   adjustable fresh drift accounts for 4% of all Argo profiles.

183

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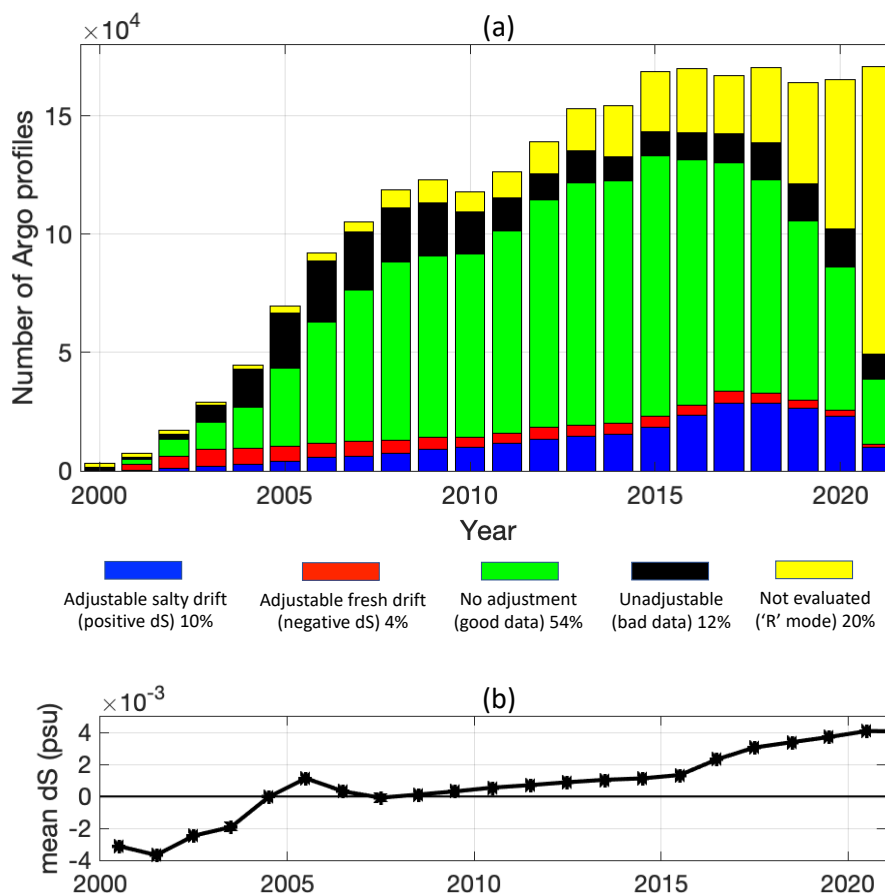
Figure 1: (a) Temporal distribution of Argo salinity delayed-mode evaluation. Values are from
April 2022. (b) Annual average of all delayed-mode salinity adjustment, which is an estimate of
the adjustable bias in the raw Argo salinity data.

188

The magnitude of adjustable bias can be an indicator of sensor limitation. Amongst all the
salinity profiles with adjustable sensor drift, salty or fresh, about 90% have magnitude < 0.03
(Fig.2, Fig.3). Only 2-3% of adjustable sensor drift have magnitude > 0.05. Beyond that limit, the
salinity data usually show signs of unrecoverable damage. For those unrecoverable profiles, no
adjustment is applied, and the data are flagged as bad in the Argo data files. These unadjustable
salinity data, plus those corrupted by other CTD or float malfunctions, account for about 12% of

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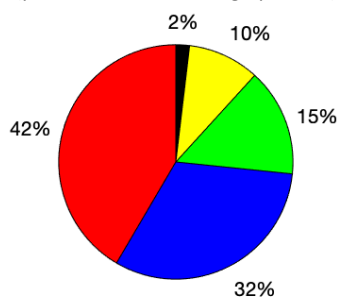
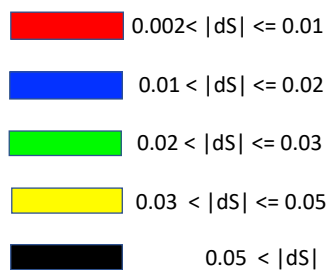
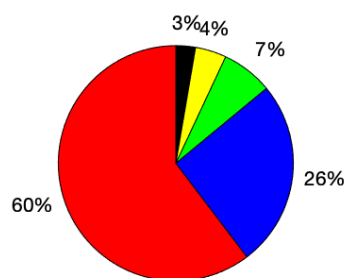
195   all Argo vertical profiles. As of time of analysis, about 54% of Argo profiles were considered to

196   be of good quality and contain no identifiable bias, and about 20% of Argo profiles remained in

197   waiting for delayed-mode evaluation.

198

199

200   Figure 2: Magnitude of Argo delayed-mode salinity adjustments, as of April 2022. (a) Adjustable

201   salty drift. (b) Adjustable fresh drift.

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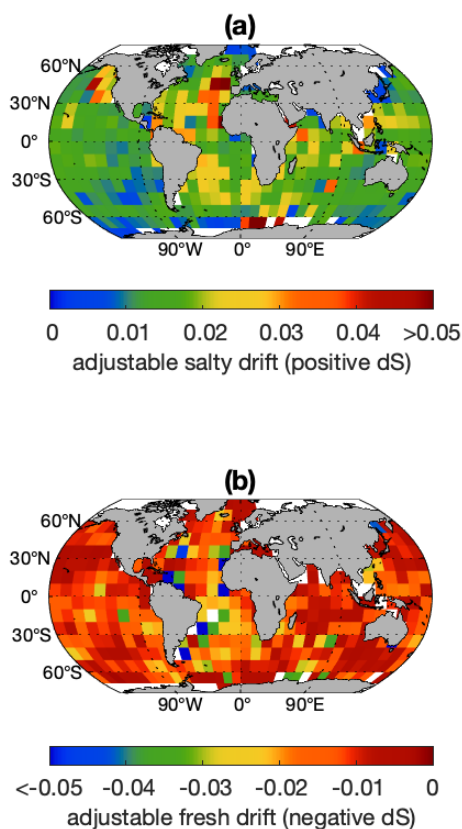

203

204   Figure 3: Spatial distribution of Argo delayed-mode salinity adjustments, as of April 2022. (a)

205   Adjustable salty drift. (b) Adjustable fresh drift. White color denotes areas with no adjustment >

206   ±0.002 at the time of this analysis.

207

208   4. How to use Argo data: raw data, adjusted data, data products

209   In all the Argo data files, parameter values are stored in two variables: PARAM and

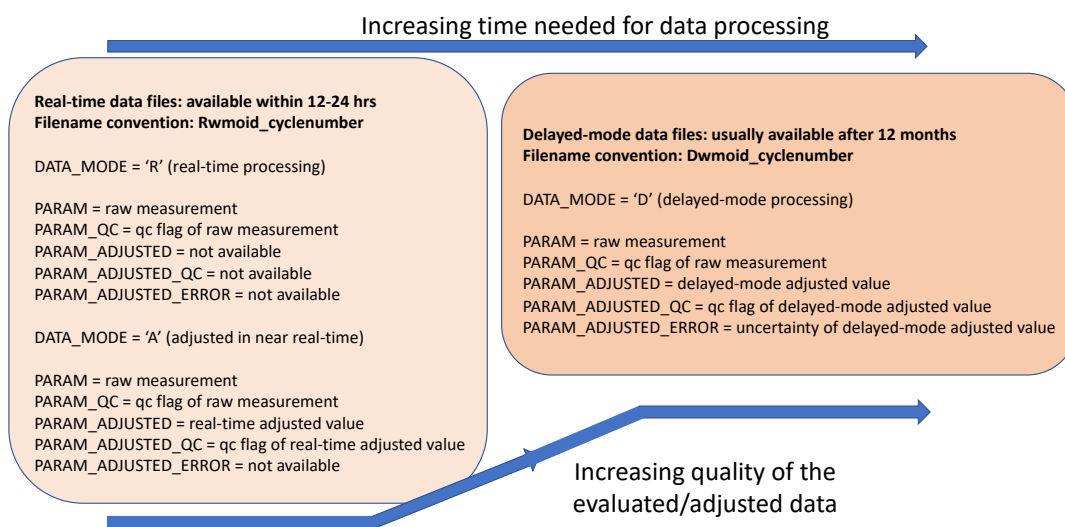
210   PARAM_ADJUSTED. Data from the CTDs are stored in PARAM = PRES, TEMP, PSAL. The

211   PARAM variables store the original raw measurements, while the PARAM_ADJUSTED variables

212   store the corresponding evaluated/adjusted values. Both the raw data and the corresponding

213   evaluated/adjusted data are available in the same Argo data files as a practice of good data

214   stewardship. Since the evaluated/adjusted data are based on the original raw measurements,

215 archival of the original raw measurements are important to allow checking of the data processing
216 procedures. Therefore, the raw data are preserved as originally received, to serve as a record if
217 questions arise later.
218   The evaluated/adjusted data are generated in delayed-mode (DATA_MODE = 'D'), and
219 sometimes in real-time (DATA_MODE = 'A' if available; DATA_MODE = 'R' if not available),
220 as described in Sect. 2.2 and illustrated in Fig. 4. Each data point, raw and evaluated/adjusted, has
221 an associated quality control (QC) flag that provides qualitative assessment of the value (Table 1).
222 In addition, each delayed-mode evaluated/adjusted data point has an associated variable,
223 PARAM_ADJUSTED_ERROR, that records the quantitative uncertainty of the
224 evaluated/adjusted value. Scientific users should use the evaluated/adjusted values
225 (PARAM_ADJUSTED), together with their QC flags (PARAM_ADJUSTED_QC) and
226 uncertainty values (PARAM_ADJUSTED_ERROR), whenever possible. The highest quality data
227 are obtained by selecting PARAM_ADJUSTED with PARAM_ADJUSTED_QC = '1' and
228 DATA_MODE = 'D'.

229
230 Figure 4: The variables in an Argo data file and their different timeframe of availability. Data from
231 CTDs are stored with PARAM = PRES, TEMP, PSAL. For biogeochemical data, please refer to
232 Bittig et al. (2019). The highest quality Argo data are those stored in PARAM_ADJUSTED, with
233 PARAM_ADJUSTED_QC = '1' and DATA_MODE = 'D' (delayed-mode).

QC Flag	Meaning	Real-time comment (applicable to <PARAM>_QC in 'R' mode and <PARAM>_ADJUSTED_QC in 'A' mode)	Delayed-mode comment (applicable to <PARAM>_ADJUSTED_QC in 'D' mode)
'0'	No QC is performed	No QC is performed.	No QC is performed.
'1'	Good data	Good data. All Argo real-time QC tests passed. These measurements are good within the limits of the Argo real-time QC tests.	Good data. No adjustment is needed, or the adjusted value is statistically consistent with good quality reference data. An error estimate is supplied.
'2'	Probably good data	Probably good data. These measurements are to be used with caution.	Probably good data. Delayed-mode evaluation is based on insufficient information. An error estimate is supplied.
'3'	Probably bad data that are potentially adjustable	Probably bad data. These measurements are not to be used without scientific adjustment, e.g. data affected by sensor drift but may be adjusted in delayed-mode.	Probably bad data. An adjustment may (or may not) have been applied, but the value may still be bad. An error estimate is supplied.
'4'	Bad data	Bad data. These measurements are not to be used. A flag '4' indicates that a relevant real-time qc test has failed. A flag '4' may also be assigned for bad measurements that are known to be not adjustable, e.g. due to sensor failure.	Bad data. Not adjustable. Adjusted data are replaced by FillValue.
'5'	Value changed	Value changed	Value changed
'6'	Not used	Not used	Not used
'7'	Not used	Not used	Not used
'8'	Estimated value	Estimated value (interpolated, extrapolated, or other estimation)	Estimated value (interpolated, extrapolated, or other estimation)
'9'	Missing value	Missing value. Data parameter will record FillValue.	Missing value. Data parameter will record FillValue.
' '	FillValue	Empty space in netcdf file.	Empty space in netcdf file.

234

235   Table 1. Argo quality control (QC) flags.

236

237   The two Argo Global Data Assembly Centers (Argo GDACs, at Coriolis France and at

238 FNMOC USA) hold a "grey list", which contains a list of active Argo floats that are suspected of

239 malfunctioning. This grey list is a means for the Argo real-time data centers to automatically flag

240 incoming data from suspicious floats with lower-quality QC flags. When these suspicious floats

241 reach their end of life and become inactive, they are removed from the grey list. As such, the grey

242 list is not a comprehensive list of problematic floats. Therefore, users should not rely on the Argo

243 grey list alone to filter out bad data, but should use the QC flags. The most complete information

244 regarding the quality of the Argo data is contained in the Argo QC flags.

245   Since Argo delayed-mode data can become available at different times and are subject to

246 revisions, users should refresh their data holdings periodically from the Argo GDACs to obtain

247 the most recent evaluation and adjustments. There are currently many scientific data products that

248 include Argo data. However, these data products are not part of the Argo data system and are not

249 held accountable by Argo. When using scientific data products derived from Argo data, users are

250 urged to check to what extent raw data are used, what data quality control is done beyond those

251 provided by Argo, and how often reanalysis is done that includes the most recent Argo delayed-

252 mode data.

253

5. Uncertainty in Argo delayed-mode salinity data

255 As described in Sect. 3, Argo's delayed-mode salinity data consist of three different evaluation

256 outcomes:

257 1. data are considered to be of good quality and contain no identifiable bias, hence no adjustment

258 is applied;

259 2. data are considered to be affected by sensor drift that are adjustable, hence adjustments are

260 applied;

261 3. data are considered to be bad and unadjustable.

262 The uncertainty in Argo's delayed-mode salinity data is therefore a combination of uncertainties

263 in the evaluation and in the applied corrections, both of which are due to incomplete knowledge

264 of the true value of the measurements. Such is the nature of oceanographic data collected by

265 autonomous instruments operating without contemporaneous and co-located reference data.

266   As described in Sect. 4, the highest quality Argo data are those stored in the variables

267 PARAM_ADJUSTED with PARAM_ADJUSTED_QC = '1' and DATA_MODE = 'D', where

268 PARAM = PRES, TEMP, PSAL. Here, we evaluate the uncertainty in these highest quality Argo

269 delayed-mode salinity data from 2000 to 2021 by comparing them to the shipboard CTD reference

270 database, CTD_for_DMQC. The CTD_for_DMQC reference database contains data from the

271 World Ocean Database and GO-SHIP, which are considered the best estimates of the true ocean

272 salinity field. This same database is also used as part of the Argo delayed-mode salinity evaluation

273 and adjustments. Hence this analysis may not satisfy the standard of a rigorous regression

274 validation, where a completely independent dataset is needed. Nonetheless it provides a means to

275 examine the global dataset for any egregious residuals.

276 This analysis is focused on Argo profiles that extend to 2000 dbar. Additional visual

277 inspection was done on the delayed-mode salinity profiles to remove gross outliers that remained.

278 These are generally contaminated profiles that have not been adjusted or flagged properly, and

279 amount to <1% of the delayed-mode dataset as of the time of this analysis. The remaining Argo

280 delayed-mode profiles and reference CTD profiles were grouped into grid squares of 10° latitude

281 by 10° longitude. In each square, an isotherm with relatively uniform salinity (small salinity

282 variance) was selected. In the upper 2000 dbar of the world's oceans, this isotherm is usually at

283 >1000 dbar. But in regions where there is a confluence of multiple water masses at >1000 dbar,

284 this isotherm can be from shallower pressures. For example, in the subtropical South Atlantic,

285 Upper Circumpolar Water overrides the warmer but saltier Upper North Atlantic Deep Water, thus

286 creating a slight temperature inversion at around 1600 dbar (Mémery et al. 2000). Hence the

287 isotherm with lesser salinity variance in the subtropical South Atlantic is in the mode water or

288 central water pressure range of 400-1000 dbar. Comparison of salinity is better done on isotherms

289 than on isobars, because differences on isobars can contain effects of the vertical movement of

290 isotherms over time.

291 In each square, each Argo delayed-mode profile was compared against the nearest

292 reference CTD profile within a 3° radius circle and 15 years of age. Argo/refCTD salinity

293 differences, $\Delta S_{\text{Argo-refCTD}}$, were then computed on the selected isotherms. This comparison method

294 is limited by the spatial and temporal availability of the shipboard CTD data. For example, with

295 the search criteria of 3° radius circle and 15 years of age, only about 20% of Argo delayed-mode

296 profiles had nearby reference CTD profiles with which to compare at the time of this analysis.

297 The statistical distribution of $\Delta S_{\text{Argo-refCTD}}$ provides a measure of the overall uncertainty

298 (Fig. 5). The mean and the median of the distribution of $\Delta S_{\text{Argo-refCTD}}$ are at approximately 0 (mean

299   = −0.0003, median = −0.0007), with the standard deviation σ = 0.017. This means the Argo

300   delayed-mode profiles selected in this comparison agree with nearby shipboard CTD data on

301   average. About 64% of $\Delta S_{\text{Argo-refCTD}}$ are within ±0.01.

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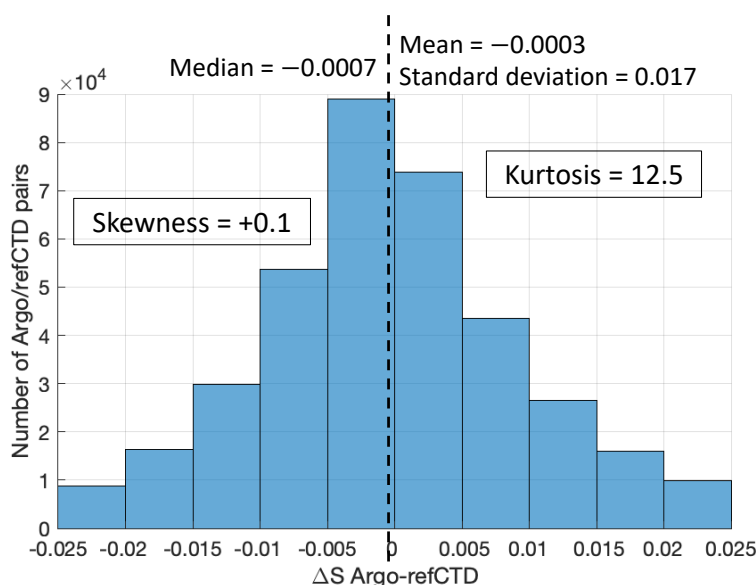
303

304   Figure 5: Statistical distribution of $\Delta S_{\text{Argo-refCTD}}$, as of April 2022. Note that this analysis only

305   accounts for about 20% of the Argo delayed-mode data. As a reference, a normal distribution has

306   skewness = 0 and kurtosis = 3.

307

308   The kurtosis of the statistical distribution of $\Delta S_{\text{Argo-refCTD}}$ is 12.5. (For reference, a normal

309   distribution has a kurtosis of 3). About 18% of $\Delta S_{\text{Argo-refCTD}}$ are outside the range of ±0.017 (±1σ).

310   These are regions with higher uncertainties in delayed-mode evaluation (Fig. 6), due to either

311   inadequate reference CTD data, or higher regional salinity variability, or both. The main high-

312   uncertainty regions are the western Indian Ocean, the subtropical North and South Atlantic Ocean,

313   and other near-coast areas that are influenced by coastal processes.

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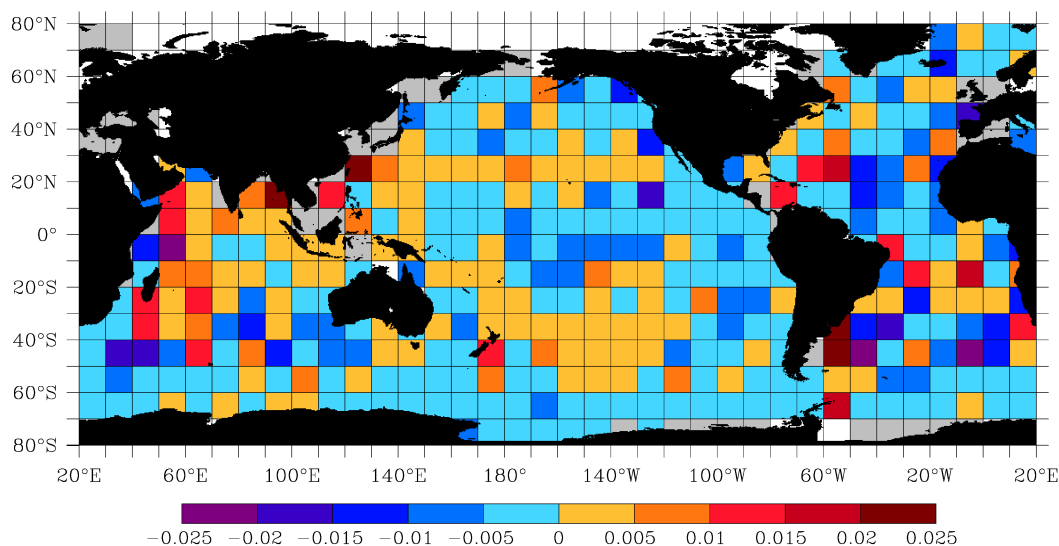
315

316 Figure 6: Spatial distribution of $\Delta S_{\text{Argo-refCTD}}$, averaged in 10°x10° grid squares, as of April 2022.

317

318   The statistical distribution of $\Delta S_{\text{Argo-refCTD}}$ is slightly skewed to the fresh side (skewness =

319 +0.1). Figure 6 shows that the Argo delayed-mode profiles that are slightly fresher than shipboard

320 CTD data are mostly located in the equatorial band 10°S to 10°N in the Pacific and Atlantic oceans,

321 and in the circumpolar Southern Ocean south of 60°S. The selected isotherms for estimating $\Delta S_{\text{Argo-}}$

322 $_{\text{refCTD}}$ typically have potential density anomalies $\sigma_0 > 27.6$ kg m^{-3} in the equatorial Pacific, > 27.7

323 in the equatorial Atlantic, and > 27.8 south of 60°S. Hence these are deep water masses that do not

324 show much decadal change. We speculate that this minor fresh skewness is instrument noise that

325 has remained in the Argo delayed-mode dataset. During delayed-mode evaluation, it is often easier

326 to identify strong sensor drifts than mild instrument calibration offsets, as the latter requires

327 verification from contemporaneous, high quality reference data, which are often lacking. It is

328 therefore possible that many mild fresh instrument offsets have not been adjusted. The residual

329 fresh bias is more apparent in regions such as the equatorial Pacific and Atlantic, where the deep

330 T/S relations allow for easier delayed-mode adjustment of sensor drifts, and which then emphasize

331 the unadjusted fresh offsets. In other regions where delayed-mode evaluation is more difficult, this

332 residual fresh bias could be masked by the surrounding variability, and so is not as apparent.

333

6. Discussions and Summary

This paper uses the salinity adjustments that have been applied in delayed-mode to estimate the bias in the raw, unadjusted Argo salinity data from 2000 to 2021. There is an increase in the annual average of adjustable bias since 2015, due to the disproportionately high number of salty-drifting CTDs since 2015. The amount of salinity data that have been declared as bad and unadjustable has also increased during that period. While Argo salinity data that are adjustable typically have bias of magnitude < 0.05, those that are unadjustable can have bias with magnitude > 0.05. Inclusion of these raw data in scientific applications, such as gridded ocean salinity products, has been demonstrated to create spurious results (e.g. Liu at al., 2022).

This salty bias in the raw Argo salinity data is expected to decrease in the coming years as the underlying manufacturer problem has likely been resolved. We note that even though the period 2015–2020 saw a large percentage of data loss due to the CTD problem that caused the increased salty drifts, historically there was a larger percentage of data loss from the period 2004–2011 (Fig. 1a, black bars). Those earlier CTD failures were partly the results of the Druck "snowflakes" and the Druck "oil microleak" problems (Wong et al, 2020). These instrument issues emphasize the importance of improving sensor stability, especially in light of the increase in float lifetime. As the average lifetime of an Argo float increases, the sensors will be required to spend more time in the ocean, which will increase the likelihood of sensor drift or malfunction. Hence sensor reliability needs to be improved to ensure a healthy return of good quality data.

When accessing data from Argo data files, the highest quality Argo data are obtained by selecting values in PARAM_ADJUSTED with PARAM_ADJUSTED_QC = '1' and DATA_MODE = 'D' (delayed-mode). We analyzed these highest quality Argo salinity data (PARAM = PSAL) to 2000 dbar against a shipboard CTD reference database to assess their uncertainty. The statistical distribution of $\Delta S_{\text{Argo-refCTD}}$, computed on isotherms, shows mean and median values close to zero, suggesting good agreement on average between the selected Argo delayed-mode data and nearby shipboard CTD data. The distribution has a kurtosis of 12.5 and a skewness of +0.1. Hence it is not exactly a normal distribution, which has a kurtosis of 3 and a skewness of 0. We note that such statistics are dependent on sample sizes, and this analysis only accounts for about 20% of all Argo delayed-mode salinity data (as of April 2022), being limited by the availability of nearby shipboard CTD data.

364   Our analysis of $\Delta S_{\text{Argo-refCTD}}$ shows that there are significant regional variations in the
365   uncertainty of the Argo delayed-mode salinity dataset. In addition, there may be some residual
366   fresh bias that remains, possibly due to the difficulty in verifying small instrument calibration
367   offsets in the absence of contemporaneous shipboard CTD data. These findings highlight several
368   important points:

369   1. Even after delayed-mode adjustment, some residual uncertainty can still remain in Argo salinity
370   data. Historically, Argo's expected accuracy for salinity is 0.01. This is not a metrologically-
371   derived value, but is based on our experience regarding the limitations of a delayed-mode system
372   where data quality is assessed against sparse reference data and a changing ocean. Users should
373   therefore take into account these residual uncertainties when using Argo delayed-mode salinity
374   data.

375   2. There is a need for continual re-evaluation of the delayed-mode outcome against other
376   independent references. These re-evaluation efforts need to be coordinated with the Argo delayed-
377   mode community, and accompanied by collaborative efforts to update the data files and the
378   relevant manuals to ensure common best practices.

379   3. Synergy between Argo and other ocean observing systems is vital in ensuring good data quality.
380   Argo floats can provide good spatial and temporal coverage of the world's oceans, but high-quality
381   reference data from independent platforms are needed to adjust and validate the data from floats.

382   4. Argo delayed-mode data can become available at different times and are subject to revisions as
383   more reference data become available. Users should therefore refresh their data holding
384   periodically to obtain the most recent evaluation and adjustments.

385

386   **Data availability.** The Argo data used in this study are those available from the Argo Global
387   Data Assembly Center in April 2022, https://doi.org/10.17882/42182#93132.

388

389   **Author contributions.** AW developed the concept for the manuscript, analyzed the data, wrote
390   the manuscript, and produced the figures. JG compiled the data for analysis, produced one of the
391   figures, and contributed to the writing and discussions of the results. CC contributed to the
392   writing and discussions of the results.

393

394   **Competing interests.** The authors have no competing interests to declare.

395

396 **Acknowledgements.** The authors wish to thank all the Argo delayed-mode operators for their
397 work in improving this global dataset. Argo data are collected and made freely available by the
398 International Argo Program and the national programs that contribute to it. Argo is part of the
399 Global Ocean Observing System.

400

401 **Financial support.** AW was supported by the NOAA Global Monitoring and Observing
402 Program via CICOES at the University of Washington through the project titled "The Argo
403 Program - Global Observations for Understanding and Prediction of Ocean and Climate
404 Variability". JG was supported by US Argo through NOAA Grant NA20OAR4320278
405 (CIMEAS/SIO Argo). CC was supported by the French National Centre for Scientific Research
406 (CNRS).

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490

491   Short Summary (500 character non-technical text)

492   This article describes the instrument bias in the raw Argo salinity data from 2000 to 2021. The

493   main cause of this bias is sensor drift. Using Argo data without filtering out this instrument bias

494   has been shown to lead to spurious results in various scientific applications. We describe the Argo

495   delayed-mode process that evaluates and adjusts such instrument bias, and estimate the uncertainty

496   of the Argo delayed-mode salinity dataset. The best ways to use Argo data are illustrated.

497