Source composition and historical wind reconstructions: two provenance-associated shifts in the CLIWOC aggregate, 1750–1855

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Abstract

Recovering Climates History with Artificial Intelligence used the CLIWOC ship-logbook database to argue that sailors wind observations reveal a previously undetected shift in global atmospheric circulation between the late eighteenth and early nineteenth centuries. We reproduce the article's principal annual aggregate from CLIWOC release 2.1 and find that this unstandardized, record-weighted series does not on its own identify a global atmospheric change. The observations contributing to it change materially in nationality, archival coverage, and—within Dutch material—the apparent form and provenance of wind-force values. BIC-based segmentation of the annual aggregate selects working boundaries at 1783, 1816, and 1833. For adjacent selected regimes, descriptive Oaxaca–Blinder decompositions show that the 1816 onset contrast is highly sensitive to nationality weights: under the stated reference convention, the nationality-weight component comprises a large share of the observed contrast, although a within-nationality component remains. The 1833 recovery contrast is likewise highly sensitive to whether Dutch records were classified historically or modern. These results demonstrate non-comparability risks in a pooled CLIWOC aggregate; they do not identify the causal effects of nationality, war, archival practice, or conversion pathway. The earlier 1783 decline is not accounted for by the nationality or geographic specifications examined here, and its cause remains unresolved. The appropriate conclusion is therefore methodological: a raw historical logbook aggregate requires an explicit target population, support and comparability diagnostics, and independent validation before it can support a global-atmospheric interpretation.

1 Introduction

CLIWOC (Climatological Database for the Worlds Oceans) is a landmark data-rescue (DARE) database containing more than 280,000 daily marine-weather observations from British, Dutch, French, and Spanish ship logbooks, mainly for 1750–1855. It was built by locating archival logbooks, transcribing observations made several times per day, and translating multilingual qualitative descriptions—among them wind direction and force—into standardized quantitative data while preserving source and voyage metadata [1–3]. Its main value is that it provides rare, high-frequency observations for the pre-instrumental oceans, although coverage is biased toward surviving archives and heavily travelled European shipping routes [4] (cf. Figure 1). Subsequent research has used CLIWOC and related logbook datasets to reconstruct historical wind fields, study circulation patterns such as the North Atlantic Oscillation (NAO) and the El Niño–Southern Oscillation (ENSO), improve reanalyses, and assess past climate variability and change [4, 5].

Published in the established journal *Environmental History*, environmental historian Dagomar Degroot undertook an exploration “whether, and to what extent, LLMs can also be useful for some forms of historical scholarship” [6, p. 573]. He comes to the following first conclusion which is also the starting point for this responding report:

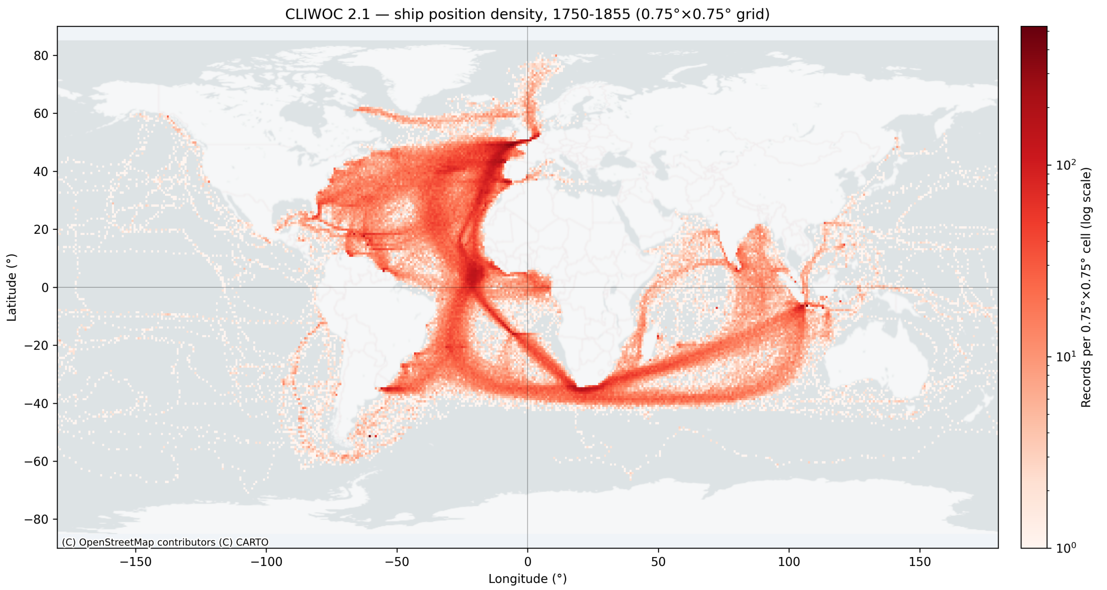

Figure 1: Positions of W-bearing wind records (N=225,326) from the CLIWOC database. Only data coded as reliable are used (`LatInd, LonInd` = 1,2, or 5). Basemap: © OpenStreetMap contributors.

> Overall, global wind speeds seemed to gradually decline beginning in about 1780, and then undergo a profound slump between 1816 and 1831, with the deepest low occurring in 1825. Wind speeds only recovered in the 1830s and 1840s. . . . Global wind speeds as recorded by sailors, which stood at nearly 34 kilometers per hour in 1758, had fallen to just over 16 kilometers per hour in 1830. If the hundreds of thousands of wind measurements compiled by sailors accurately recorded changes in global atmospheric circulation, then Earth's climate underwent a profound and hitherto undetected shift between the late eighteenth and early nineteenth centuries [6, pp. 576–7].

This is a strong and global claim for climatology, built on a genuinely large and valuable dataset. Although we confirm Degroot's key figures from the raw data (Section 2.1), his central claim is not justified. It is, we will argue, a claim built on an incomplete chain of source criticism—one that moves directly from an aggregated statistic to a planetary-scale conclusion without first interrogating what kind of object each underlying observation actually is, and without testing whether the aggregate is representative of anything beyond its own composition.

The original article is reported to have been produced with substantial assistance from a generative AI system, which computed the aggregate and framed its interpretation [6, pp. 573–4]. That detail is not incidental to this report's purpose: the errors identified below—treating a compositional characteristic as a physical signal, and skipping directly from arithmetic dataset to planetary climatology claim—are precisely the kind of errors that a fluent but uncritical AI-system is prone to make without further configuration. They are also one kind of misinterpretation that historical source criticism seeks to avoid and why it needs to be brought into the human-AI-pipeline. This report treats the claim on its merits regardless of how it was produced, however, and returns to the AI-assistance question only in the end.

Historical source criticism conventionally begins at the level of the individual source, not at the level of the finished aggregate. Three basic observations about the CLIWOC and comparable sources qualify that premise, cf. [1, 7, 8]:

1. **Local and nationally specific observation:** A wind-force entry was a local, time-specific observation, generally recorded on a daily or sub-daily basis, and expressed in the vocabulary of a particular national and historical reporting tradition;

2. **Non-random spatial coverage:** Spatially, each observation was tied to a ships position on a particular date and to historically specific shipping routes. The surviving record is concentrated along frequented routes and is disproportionately drawn from imperial and naval fleets, rather than from a random spatial sample of the oceans;

3. **Navigational rather than climatological purpose:** The immediate purpose of wind and weather recording was operational: navigation, estimating leeway, managing sail, maximizing speed, and avoiding damage. The entries were not collected as standardized climatological measurements.

None of this makes the CLIWOC data, with their included chain of references, untrustworthy—quite the opposite: ships logbooks are recognized in the literature as valuable sources of historical marine climate observations spanning the pre-instrumental and early instrumental periods [9–11]. They have also supported research on historical mobility, maritime trade, economic history, invasion biology, and genomic biogeography [12–16]. It does mean, however, that an aggregate built from hundreds of thousands of such observations is a statement about a sample, and the first question any such statement must answer is whether that sample's composition (who observed, where, why, and when) stays stable over the period being compared. A trend in the aggregate could reflect a genuine atmospheric signal, or it could just as easily reflect a change in whose logbooks, and from which waters, happen to dominate the record in a given year.

The remainder of this report is devoted to telling the two apart. One further qualification is worth stating before that task begins: even a composition-stable sample licenses, in the first instance, only a statement about the sample itself—not about the reality it is taken to represent. Moving from the one to the other requires justification of its own, considerably more than can be undertaken within the scope of this report.

2 Material and Methods

2.1 Data

We work with version 2.1 of the CLIWOC dataset, obtained as a tab-separated conversion of the original fixed-width release from PANGEA [3]. It contains 287,114 daily logbook records across 180 fields, spanning a nominal range of 1662–1855, though overwhelmingly concentrated in the core 1750–1855 period; an earlier project release had contained 274,269 records [17].

The 180 fields fall into two large sections ([18]; see [19] for a summarized documentation of the IMMA-format). The first, roughly 53 fields, follows the standardized IMMA (International Maritime Meteorological Archive) core format [20]: position, date, wind, temperature, pressure, cloud and sea-state codes, mostly expressed in modern SI units. Several of these core fields are marked "not in use" in this release and are consequently empty throughout; fill rates within this section are otherwise generally high but not universal. The second section, roughly 127 fields, is CLIWOC's own *attachment*: archival provenance, navigation detail (including how each position was derived), voyage and ship metadata, observer identities, free-text memoranda, and detailed weather and instrument descriptions. Fill rates here are considerably more uneven—some fields (nationality, ship identifier, position-derivation indicators) are complete or near-complete, while others (specific memoranda, instrument brand and type) are populated only sparsely. This attachment layer is nonetheless essential to the present analysis: it is here, rather than in the standardized core, that CLIWOC's compilers preserved the historical context—who observed, aboard which vessel, for which nation, drawing on which archive—that source criticism requires, and it is filled in exemplary detail relative to comparable historical datasets.

The original article reports 244,553 "weather and journey data" entries and 244,039 "wind force measurements" [6, p. 574]. Both figures match CLIWOC 2.1 exactly: the former is the full set of records with a numerical value in field `W`; the latter is the same set restricted to 1750–1855 in field `YR`. We therefore use that date-restricted W subset ($N = 244{,}039$) throughout.

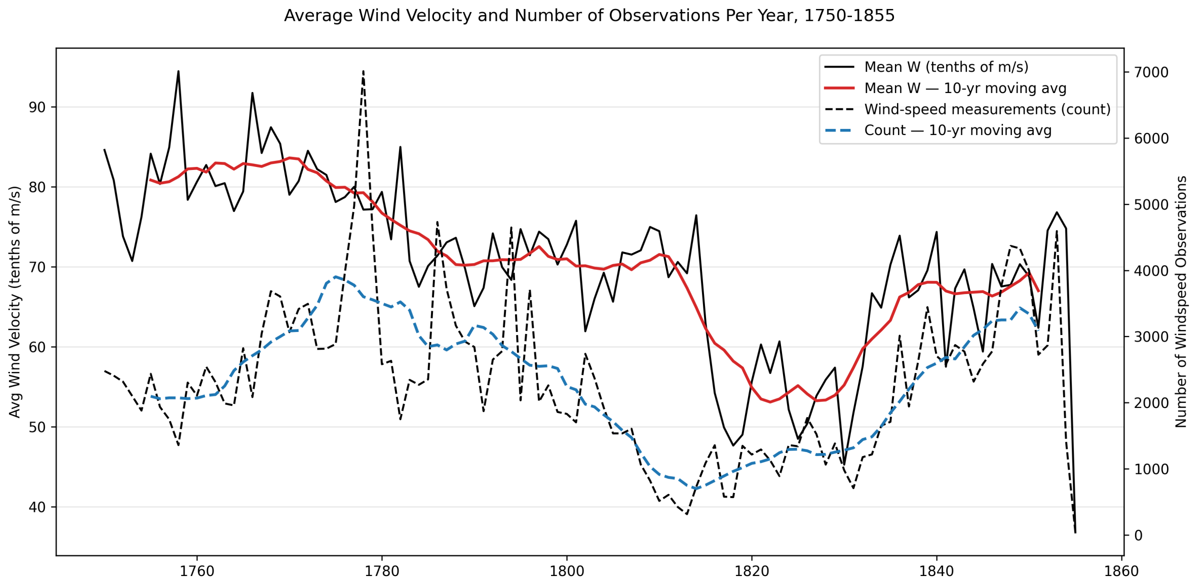

Figure 2: Reconstruction of Degroot's Figure 1: yearly mean W values and yearly record count, with moving averages; CLIWOC 2.1, 1750–1855.

Using this subset, we largely reconstruct the original Figure 1 (Figure 2). Its annual mean wind-speed series is correct, including the maximum of 34.00 km/h in 1758 and the minimum of 16.29 km/h in 1830 [6, p. 577]. Its caption is not: the plotted count is the total number of CLIWOC records per year, not the number carrying a wind-speed measurement. The replication therefore confirms that this report analyses the same release and effective W-bearing sample as the original article. GPT-translated values cannot be independently audited; the following analysis concerns the shared CLIWOC release and its reproduced aggregate pattern.

CLIWOC does not contain a homogeneous set of instrumental wind-speed observations. Most source logbooks record wind qualitatively, using national and historically changing vocabularies that were translated into standardized wind-force categories and numerical values. The CLIWOC multilingual dictionary provided a common coding framework, but country-specific studies show that the relationship between recorded terms and Beaufort force had to be reconstructed separately for English, Dutch, Spanish, and French sources [7, 8, 21–23]. These studies demonstrate that homogenization is possible, but not that the resulting values are automatically equivalent: terms can change meaning over time, qualifiers can be ambiguous, and fleets can differ in ship performance and reporting practice.

The English case illustrates why observational consistency and measurement comparability must be separated. Wheeler and Wilkinson show that English logbooks used a broadly coherent but historically evolving vocabulary for wind force, and that qualitative terms can be empirically mapped to Beaufort values. However, differences among British fleets, changes in term usage over time, and ambiguous expressions such as moderate gale mean that English observations should not automatically be treated as a temporally stable or fleet-independent measurement series [22]. Paired-voyage comparisons further show substantial agreement among ships observing the same conditions. This evidence primarily supports observational consistency within shared voyages, rather than cross-national measurement equivalence, and therefore does not eliminate the possibility of source-specific composition or calibration bias in pooled CLIWOC aggregates [21].

2.2 Analytical design and estimands

The original paper interpreted the annual CLIWOC aggregate as showing a long decline, then a trough beginning around 1816, and a subsequent recovery [6, pp. 576–77]. We first reproduce that descriptive aggregate. We do *not*, however, treat it as an estimator of global atmospheric circulation: it is a record-weighted mean of the observations that enter CLIWOC in a given year. Its substantive interpretation therefore depends on the population it represents and on whether the composition of the contributing observations is sufficiently comparable over time.

Our primary outcome is the numerical CLIWOC wind-force field W, as stored in tenths of metres per second. We analyse W as a documented database variable rather than attempting to reconstruct every original verbal observation or to assume that all national and archival source streams reached W through an identical conversion pathway. Possible heterogeneity in reporting, transcription, and conversion is therefore part of the source-comparability problem examined below. The replication sample comprises records dated 1750–1855 with a non-missing numerical W value ($N = 244{,}039$; Section 2.1). In particular, "ship" refers throughout to the CLIWOC ship/logbook identifier field `ID`, which behaves empirically as a voyage- or logbook-volume-level unit rather than a persistent per-ship-career identifier (median time span per `ID` is one year, and 387 of 974 distinct ship names are associated with more than one `ID`).

The analysis has two distinct aims. (1) we describe structural features of the annual record-weighted W series and identify Bayesian information criterion (BIC)-selected working regimes. These boundaries are analytical windows rather than exact historical dates or demonstrated causal discontinuities. (2) for each adjacent pair of working regimes, we assess whether the observed difference in mean W is sensitive to changes in the composition of the observed sample under specified descriptive standardizations. Neither aim estimates the causal effect of nationality, archival institution, historical event, extraction pathway, or atmospheric forcing.

The temporal concentration of the principal decline around 1815 makes several hypotheses historically and physically conceivable, including changes in maritime coverage after the Napoleonic Wars and changes in atmospheric circulation following the Tambora eruption. This study does not test either causal account. CLIWOC alone cannot establish the historical process producing a change in coverage, nor can an internal decomposition distinguish a source-composition mechanism from an atmospheric one. We therefore begin with the more limited question of whether selected changes in the dataset's observed composition are sufficient to alter the aggregate contrasts on which the broader interpretation rests.

For each regime pair, the descriptive estimand is the observed difference in mean W and its accounting under a stated reference distribution of the included categories. In the Oaxaca–Blinder analyses, the weight-change component is the portion of that selected contrast produced by replacing category shares while holding category-specific means fixed at the reference-regime values. It is not a causal effect. The within-category and interaction components may contain residual source composition below the chosen category grain, route and seasonal coverage, observing practice, conversion differences, and atmospheric variation. We report the reference convention, interaction treatment, direct-standardized means, record counts, ship and voyage counts where identifiable, and the share of observations removed by support restrictions for every regime comparison.

The analyses proceed as follows:

1. **Replication and outcome definition.** We reproduce the annual CLIWOC W aggregate used in the original article and document the analysed release, date restriction, outcome definition, and sample flow (Section 2.1).

2. **Temporal segmentation.** We estimate BIC-selected changes in the annual aggregate without fixing their number or dates in advance (Section 2.3). We assess their sensitivity to alternative annual aggregations, temporal specifications, and resampling procedures;

subsequent comparisons use the resulting regimes as working windows rather than as exact historical boundaries.

3. **Candidate discovery.** We use metadata screening to prioritize potentially relevant source-composition variables for descriptive investigation (Section 2.4). This screen generates hypotheses; it does not define an exhaustive adjustment set or establish that lower-ranked variables are irrelevant.

4. **Source-composition description.** We describe W levels, observation shares, and coverage by nationality and related provenance variables across the selected regimes (Section 2.5).

5. **Nationality standardization.** We decompose adjacent regime contrasts by nationality using descriptive Oaxaca–Blinder decomposition (Section 2.6). The analysis is restricted to observed common support and reports record-level bootstrap intervals under the stated resampling designs.

6. **Spatiotemporal sensitivity.** We examine whether the earlier contrast is sensitive to the sampled geographic distribution, using latitude, longitude, and joint spatial specifications, supplemented by location–season support diagnostics where data permit (Section 2.7). A residual under these specifications is interpreted only as evidence that the tested geographic standardization is insufficient.

7. **Dutch provenance refinement.** We examine whether the recovery contrast is sensitive to disaggregating Dutch records by the operational numeric-versus-verbal `AllWindForces` classification (Section 2.8). This classification is treated as a provenance proxy to be documented and validated against source metadata; it is not itself a causal measure of a conversion pathway.

8. **Residual-trend sensitivity.** We test whether nationality-specific trough means are consistent with specified pre-trough trend models (Section 2.9). These tests assess the adequacy of the stated extrapolation model, not whether an observed deviation identifies a particular historical or physical mechanism.

Across all analyses, inference is limited to the observed CLIWOC sample and to the support shared by the periods and source categories being compared. A global-atmospheric interpretation would require additional validation against genuinely independent observations after overlapping CLIWOC material has been removed.

2.3 BIC-selected working regimes

We use changepoint detection to define working comparison windows in the annual record-weighted W series. Estimated dates are not interpreted as exact historical boundaries, evidence of causal discontinuities, or proof that the underlying process was constant within a selected regime. For each candidate number of level changes, $m = 0, \ldots, 8$, exact dynamic programming identifies, subject to a minimum segment length of 5 years, the segmentation that minimizes within-segment residual sum of squares. We select m using the changepoint BIC proposed by Yao [24],

$$\mathrm{BIC}(m) = n \log\left(\frac{\mathrm{RSS}(m)}{n}\right) + 2(m+1)\log(n). \tag{1}$$

For the level-change model, this penalty corresponds to $m+1$ segment means, m selected breakpoint locations, and one pooled variance parameter [24, 25].

This criterion is derived for independent observations subject to changes in mean. Annual means in a logbook-record series pool unequal numbers of contributing records, and adjacent years may be serially dependent through persistent fleet composition or reporting practice. We therefore treat the segmentation as descriptive rather than definitive. Sensitivity analyses repeat the procedure using annual medians, trimmed means, ship-year means, and an effective-cluster-weighted annual series; they also delete one year at a time. Table S9 reports the selected number and location of changes for every specification.

Breakpoint-location uncertainty is assessed using 500 *year-stratified ship-cluster bootstrap* replicates [26]. Within each year, ships are resampled with replacement, and the BIC segmentation is reselected in every replicate. This procedure reflects clustering among observations from the same ship within a year, but it does not itself preserve serial dependence across years. The percentile intervals reported below are conditional on bootstrap replicates selecting $m = 3$ and are calculated separately for the first, second, and third breakpoint. Table S9 also reports the distribution of selected breakpoint counts across all bootstrap replicates.

Finally, we compare the selected level-change model with a discontinuous piecewise-linear specification. In this comparison, each of the $m + 1$ segments has its own intercept and slope; the model also selects m breakpoint locations and estimates one pooled variance. Its BIC is therefore

$$\mathrm{BIC}_{\mathrm{slope}}(m) = n \log\left(\frac{\mathrm{RSS}(m)}{n}\right) + 3(m + 1)\log(n). \quad (2)$$

The penalty contains $2(m + 1)$ segment coefficients, m breakpoint locations, and one variance parameter. This comparison asks whether allowing separate within-segment linear trends improves fit sufficiently to justify the additional complexity; it does not identify a causal form of temporal change.

Across the primary 1750–1855 series and the sensitivity analyses reported in Table S9, the preferred level-change specification selects three working boundaries at 1783 (conditional 95% bootstrap interval: 1780–1785), 1816 (1815–1817), and 1833 (1832–1835). Table 1 reports the resulting descriptive regimes. We use these windows in subsequent standardizations because they summarize features of the reproduced annual aggregate without fixing comparison periods from visual inspection alone. They do not establish that the same dates identify historical, archival, or climatic events.

Table 1: BIC-selected working regimes in the annual record-weighted W series. Breakpoint uncertainty, alternative annual aggregations, leave-one-year-out sensitivity, and the level-versus-slope comparison are reported in Table S9.

Regime (years)	Years	Mean W
1750–1782	33	81.02
1783–1815	33	70.58
1816–1832	17	53.34
1833–1855	23	67.02

2.4 Candidate-variable screening

We use random-forest screening to prioritize source-composition and provenance variables for subsequent descriptive analysis; the screen is not intended to identify an exhaustive adjustment set or to establish a causal explanation for any regime contrast. The model predicts W from 48 metadata columns on a random subsample of 50,000 records. We exclude the wind-force derivation chain (`W`, `WI`, `AllWindForces`, and `WindScale`), the time index, free-text and near-identifier fields, and raw coordinates; the latter are examined directly in Section 2.7. Permutation importance is the loss of predictive accuracy after shuffling a variable while retaining the remaining predictors [27–29]. The held-out R^2 is 0.22, which is sufficient for relative candidate ranking but not evidence that the model captures all determinants of W.

Categorical fields are alphabetically encoded, missingness indicators are added for every column, and missing values are median-imputed. The row subsample, train/test split, forest fit, and permutation procedure use seed 42. Full preprocessing, hyperparameters, and complete importance results are reported in Appendix D. The screen is used only to rank candidates for further scrutiny; marginal permutation importance may be divided or masked among correlated predictors [29, 30].

Several fields are near-total proxies for nationality: archival institution, operating company, logbook language, and `StartDay`, together with `C1` itself. Scoring these columns separately would fragment the predictive importance of the same underlying source-family distinction. We therefore shuffle these fields jointly, using a common row permutation that preserves their observed within-record combination, and refer to the resulting group as NationalityFamily. Cross-tabulations documenting this proxy structure are reported in Appendix D. The joint permutation block for NationalityFamily includes both the eight encoded fields and their eight missingness-indicator companion columns; all sixteen are relocated together under the same common row permutation (Appendix D), so that a field's missingness pattern—which can itself carry nationality information, since different archives and nationalities have systematically different reporting completeness—is broken along with its value, rather than left intact to leak signal past the permutation.

Because random row-level splits can understate prediction error when observations share hierarchical dependence, we assessed whether the result depended on leakage from ship-constant fields or on alphabetical category coding [31]. An `ID`-level train/test split, with no `ID` represented in both samples, produced a similar importance for NationalityFamily (0.061 versus 0.066 under the row-level split) and preserved the leading ranking. A second `ID`-level run using mean-target ordering fitted in the training sample increased the group's importance to 0.087 and did not change its rank. Because this latter encoding is not cross-fitted, it is used only as directional sensitivity evidence, not as a clean validation of its absolute importance.

We then classify highly ranked fields using two questions. (1) can the field plausibly describe source composition or provenance rather than a physical co-measurement of weather? (2) does its distribution change around the BIC-selected working regimes? Variables such as distance travelled, rainfall, wind direction, gusts, pressure, air temperature, and anchorage may predict W but do not, by themselves, diagnose sample composition. Geographic proxies are considered in the dedicated spatial analysis; position-quality indicators, calendar month, and other remaining candidates are described in Table 2 and Appendix D.

NationalityFamily is the leading interpretable source-composition candidate under this procedure. Its components move together across the working regimes: British and Dutch shares, archival institutions, operating fleets, and logbook languages change materially around the 1816 window. The `StartDay` signal is not independent, because its principal categories include language-specific placeholders (`UNKNOWN` and `ONBEKEND`). We therefore carry forward `C1` as the representation of this proxy family in the nationality standardization.

Other candidates are not thereby ruled out. `Release` is independent of the nationality family but is not pursued because the present analysis does not specify a testable provenance mechanism for it. `LatInd` and `LonInd` change monotonically over the century and may matter for longer-run comparability, even though that pattern does not reproduce a decline-and-recovery shape. The screening result should consequently be read as prioritizing nationality for targeted description, not as demonstrating that other compositional variables are absent or irrelevant.

The primary screening results reported in Table 2 use the alphabetical ID-level split; the row-level split is treated as a sensitivity analysis.

2.5 Nationality: levels and shares over time

Figure 3 describes raw yearly mean W by nationality. Dutch observations have lower mean W values than British observations and the pooled Other category throughout most of 1750–1855.

Table 2: Leading metadata candidates from the permutation-importance screen. Importance prioritizes descriptive follow-up; it is not a causal effect or an exhaustive test of source-composition variables. NationalityFamily jointly permutes eight nationality-proxy fields and their missingness indicators.

Field / group	Importance	Interpretation
`Distance`	0.230	Physical correlate; not a source-composition test
NationalityFamily	**0.061**	**Priority source-composition candidate**
`Decl`	0.053	Geographic proxy; examined separately
`D`	0.023	Physical correlate
`Rain`	0.021	Physical correlate
`Release`	0.015	Independent processing field; not pursued here
`Gusts`	0.009	Physical correlate
`HR`	0.005	Physical/procedural correlate
`LatInd`	0.003	Monotonic position-quality change
`Anchored`	0.003	Situational correlate
`AT`	0.002	Physical correlate
`TairReading`	0.002	Physical correlate
`SLP`	0.002	Physical correlate
`Month`	0.001	No material regime shift
`LonInd`	0.001	Monotonic position-quality change
`LongitudeUnits`	0.001	Partly collinear; not pursued here
`BaroReading`	0.001	Physical correlate
`DayOfTheWeek`	−0.000	No specified source-composition mechanism
`LMdistance1`	−0.000	Geographic proxy

This difference predates the 1816 working boundary; it is therefore not itself evidence of a new change at the trough. Nor do the nationality-specific series display the same pattern as the pooled annual aggregate. The British series declines mainly before 1800, whereas the Dutch series is comparatively flat before the trough and rises thereafter. The BIC-selected working boundaries in the pooled series should consequently not be read as identical changes in every nationality-specific series.

A persistent between-nationality difference affects the pooled aggregate only if nationality shares also change. Figure 4 therefore reports the annual composition of the W-bearing sample. British representation declines and Dutch representation rises around the 1816 working boundary, with the two shares crossing within the following years. Given the lower mean W among Dutch observations, this shift makes a lower pooled mean mechanically possible even if nationality-specific means were held fixed. The descriptive plots do not quantify that contribution or exclude other changes in coverage, route, season, or reporting. Section 2.6 therefore estimates the selected regime contrast under fixed nationality weights, while Section 2.9 examines the remaining within-nationality component.

2.6 Descriptive standardization of regime contrasts

For each adjacent pair of BIC-selected working regimes—an earlier regime A and a later regime B—we describe the observed difference in mean W,

$$\Delta = \bar{W}_B - \bar{W}_A = \sum_g s_B(g)\mu_B(g) - \sum_g s_A(g)\mu_A(g), \tag{3}$$

where g denotes nationality or, in the later provenance analysis, a finer nationality–provenance category. Shares s and category means μ are calculated after applying the stated minimum cell-count restriction. Regime A is the reference distribution throughout.

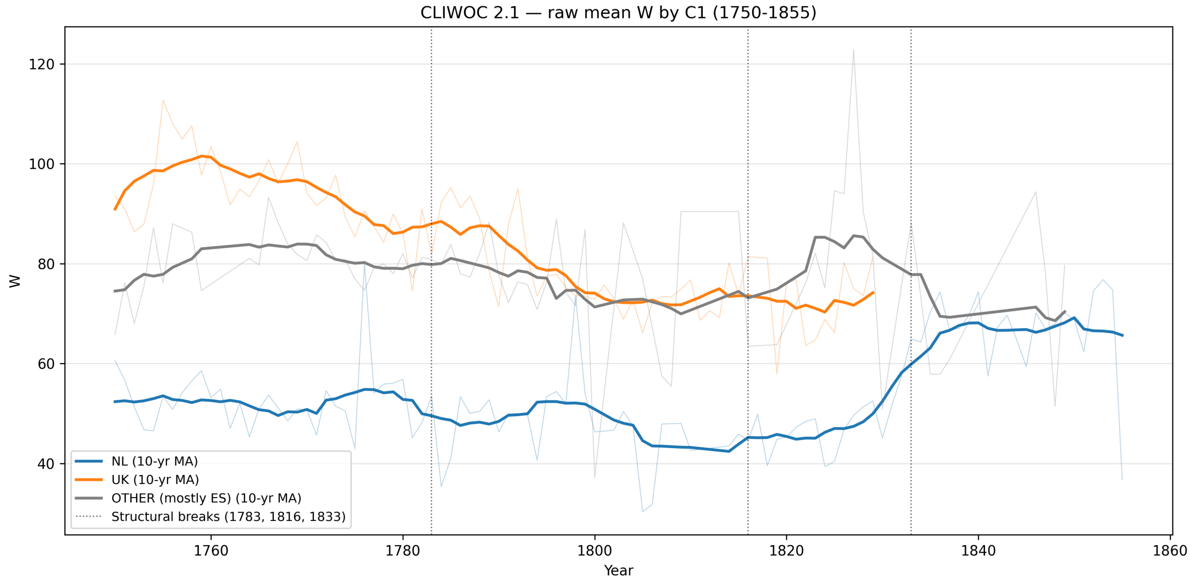

Figure 3: Raw yearly mean W by nationality (`C1`), 1750–1855. Thin lines show yearly means; heavy lines show 10-year moving averages. The pooled OTHER category is dominated by Spanish records. Dotted lines mark BIC-selected working boundaries (1783, 1816, and 1833).

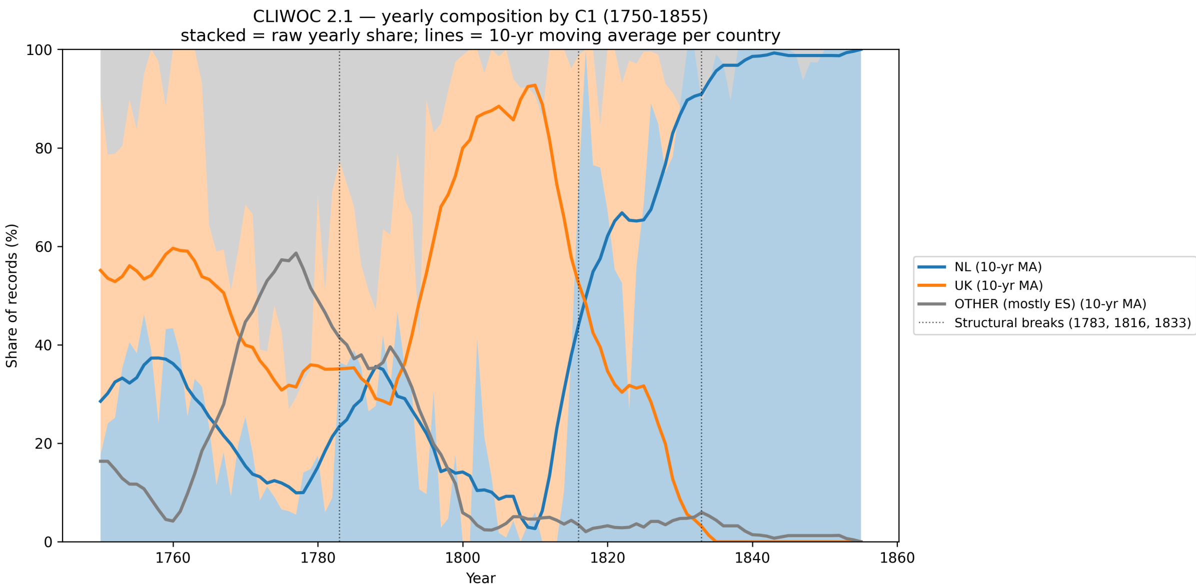

Figure 4: Composition of the W-bearing CLIWOC sample by nationality (`C1`), 1750–1855. Stacked areas show raw yearly shares; lines show 10-year moving averages. Dotted lines mark BIC-selected working boundaries (1783, 1816, and 1833).

We use the Oaxaca–Blinder decomposition identity to partition Δ into a reference-weight component,

$$E = \sum_g [s_B(g) - s_A(g)]\, \mu_A(g), \tag{4}$$

a within-category component,

$$C = \sum_g s_A(g)\, [\mu_B(g) - \mu_A(g)]\,, \tag{5}$$

and their interaction,

$$I = \sum_g [s_B(g) - s_A(g)]\, [\mu_B(g) - \mu_A(g)]\,, \tag{6}$$

such that $\Delta = E + C + I$ exactly [32–35]. E is the part of the selected contrast obtained by substituting regime-B category shares for regime-A shares while holding category means at their regime-A values. It is a descriptive standardization, not the causal effect of nationality, archive, war, or processing pathway. C and I may contain residual source composition below the selected category grain, route and season mix, reporting practice, measurement conversion, and atmospheric variation.

We apply a minimum of 30 records per category in each regime in order to avoid the estimation of regime-specific means from very sparse cells. This is a pragmatic cell-count rule, not evidence of complete spatiotemporal common support. Table 3 reports 95% intervals from 2,000 nonparametric record-level bootstrap resamples within regimes. These intervals quantify sampling variation under the record-resampling design; they do not fully represent dependence among entries from the same ship, voyage, or logbook.

The nationality standardization gives different results for the three selected contrasts. For 1750–1782 to 1783–1815, the reference-weight component is small and positive (+0.4), whereas the within-category component is negative (−9.0). For 1783–1815 to 1816–1832, the reference-weight component is −14.3 of a total contrast of −16.7, while a smaller negative within-category component remains (−4.0). For 1816–1832 to 1833–1855, the nationality-weight component is close to zero (−0.5) and the within-category component is positive (+20.5). The last result applies only to nationality as classified here; Section 2.8 shows that it is sensitive to a finer Dutch provenance classification.

Table 3: Descriptive Oaxaca–Blinder accounting of mean-W contrasts between BIC-selected working regimes. E is the reference-weight component, C the within-category component, and I their interaction; total gap equals $E+C+I$, subject to rounding. Bracketed values are 95% intervals from 2,000 record-level bootstrap resamples within regime.

Transition	Total gap	E: weights	C: within category	I: interaction
1750–1782 → 1783–1815	−10.3 [−10.7, −9.7]	+0.4 [0.2, 0.6]	−9.0 [−9.5, −8.6]	−1.6 [−1.8, −1.5]
1783–1815 → 1816–1832	−16.7 [−17.4, −15.9]	−14.3 [−14.7, −13.9]	−4.0 [−5.3, −2.9]	+1.7 [0.8, 2.7]
1816–1832 → 1833–1855	+20.4 [19.6, 21.2]	−0.5 [−0.6, −0.4]	+20.5 [19.8, 21.3]	+0.4 [0.3, 0.5]

As a sensitivity check for the recovery contrast, we pool Spanish, French, German, and American observations into OTHER, retaining categories that would otherwise fail the minimum cell-count restriction. The result is essentially unchanged ($E = -0.5$, $C = +20.4$). The pooled category is heterogeneous, however, and this check was not repeated for the earlier contrasts.

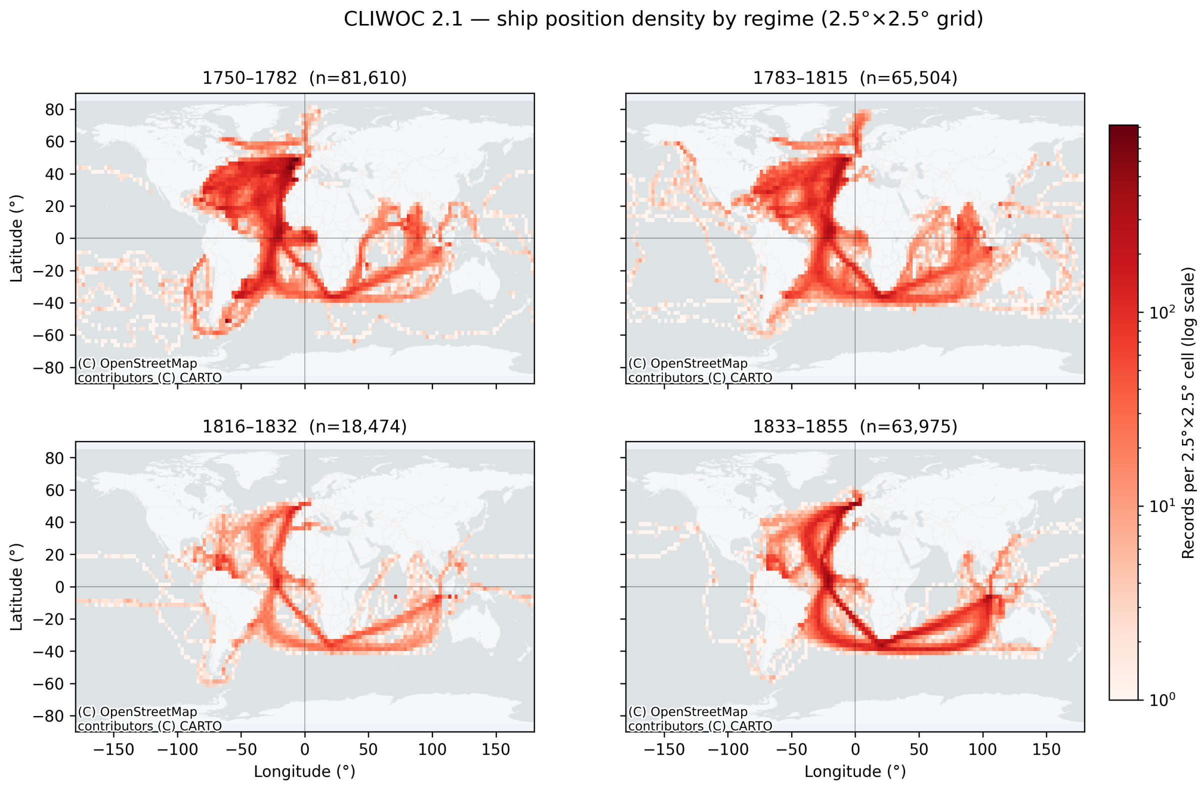

Figure 5: Positions of W-bearing records by BIC-selected working regime, all nationalities pooled. The map includes records with `LatInd` and `LonInd` codes 1, 2, or 5 [18]. Basemap: © OpenStreetMap contributors.

It should therefore be read as a limited robustness check, not as evidence that nationality composition has been exhaustively characterized.

2.7 Geographic-composition sensitivity

The 1750–1782 to 1783–1815 contrast has a large within-category component under the nationality standardization (Table 3). One possible source of that contrast is changing spatial coverage: the observed fleet shifts southward over this period (Figure 5). We therefore assess whether the contrast is sensitive to standardizing the geographic distribution of the W-bearing sample.

Using the same descriptive decomposition as in Section 2.6, we compare the two regimes after classifying observations by 10° latitude bands, 20° longitude bands, and joint $5^\circ \times 5^\circ$ grid cells. The weight-change component asks how much of the selected mean contrast would change if the geographic distribution shifted while cell-specific mean W values were held at their earlier-regime levels. A remaining within-cell component shows only that the tested geographic specification is insufficient; it does not identify the cause of the residual.

The three specifications yield the same limited conclusion. Latitude weighting contributes -0.89 of a -10.38 contrast; longitude weighting is near zero (-0.15, with an interval including zero); and the joint-grid weight component is positive ($+0.40$) while the total contrast is negative. Thus, at the tested spatial resolutions and with these multi-decade pooled regimes, spatial reweighting does not account for most of the selected contrast.

The joint grid addresses a two-dimensional redistribution of observations, but it remains a coarse standardization. It pools all nationalities and does not condition jointly on season, route, coast/open-ocean location, year within regime, ship or voyage, or observing practice. The retained grid cells cover 90.9% of regime-A and 87.9% of regime-B records. This high retention limits, but does not eliminate, loss of support through the grid restriction; it is not evidence of

Table 4: Descriptive geographic standardizations of the 1750–1782 to 1783–1815 mean-W contrast, all nationalities pooled. N is the number of records retained after the minimum cell-count restriction in regimes A and B. Bracketed values are 95% intervals from 2,000 record-level bootstrap resamples within regime; asterisks mark intervals excluding zero.

Specification	N (A/B)	Total gap	Weights	Within cell	Interaction
Latitude (10°)	68,504 / 55,893	-10.38^{*} [$-10.96, -9.78$]	-0.89^{*} [$-1.11, -0.67$]	-9.61^{*} [$-10.21, -9.00$]	$+0.11$ [$-0.13, 0.37$]
Longitude (20°)	68,582 / 55,907	-10.40^{*} [$-10.96, -9.80$]	-0.15 [$-0.32, 0.02$]	-10.18^{*} [$-10.76, -9.57$]	-0.06 [$-0.26, 0.13$]
Joint grid (5°×5°)	62,307 / 49,124	-9.93^{*} [$-10.54, -9.27$]	$+0.40^{*}$ [$0.06, 0.76$]	-9.01^{*} [$-9.65, -8.35$]	-1.32^{*} [$-1.71, -0.92$]

complete spatiotemporal common support.

Accordingly, the result narrows one class of geographic-composition explanation. It does not establish a physical cause for the residual, exclude finer-grained geographic confounding, or establish that the decline is non-compositional. The early decline begins before the Beaufort scale was devised and spans both pre- and post-1805 observations [7]. Changes in reporting vocabulary, observing practice, source survival, or conversion remain possible explanations alongside atmospheric variation. The present analysis can show only that the tested latitude, longitude, and grid standardizations are insufficient to account for the contrast.

2.8 Dutch provenance classification and the recovery contrast

The nationality-only decomposition assigns most of the 1816–1832 to 1833–1855 recovery contrast to the within-category component. We therefore examine whether the pooled Dutch category contains source streams with materially different W distributions. Following the distinction documented by Koek and Können [7, p. 84], we classify a Dutch record as "NL-Numeric" when its trimmed `AllWindForces` value matches the regular expression `^-?\d+(\.\d+)?(-\d+(\.\d+)?)?$` (positive or negative integer or float number, including from-to-values), and as "NL-Verbal" otherwise. This is a indirect operational provenance classifier: it is consistent with the historical extraction and modern-translation streams described by Koek and Können, but it is not a direct archival identifier of either pathway.

The two classes have markedly different mean W values (Table 5). NL-Numeric records average 77.18, whereas NL-Verbal records average 49.94. The classification is concentrated in the recovery window: NL-Numeric is absent before 1816, remains uncommon during 1816–1832, and becomes dominant after 1833. The refinement therefore chiefly affects the recovery contrast.

Table 5: Mean W by operational Dutch `AllWindForces` classification, 1750–1855. British observations are included only as a descriptive reference.

Subset	n	Mean W
NL-Numeric	45,468	78.85
NL-Verbal	66,937	47.60
British (reference)	83,317	85.24

We repeat the recovery standardization after replacing the pooled Dutch category with NL-Numeric and NL-Verbal, retaining the same years, minimum cell-count restriction, records, and 2,000 record-level bootstrap resamples. The total contrast remains +20.4 because only the category definition changes. The weight-change component rises from −0.5 under pooled nationality to +17.3 under the split classification, accounting for the large majority of the total

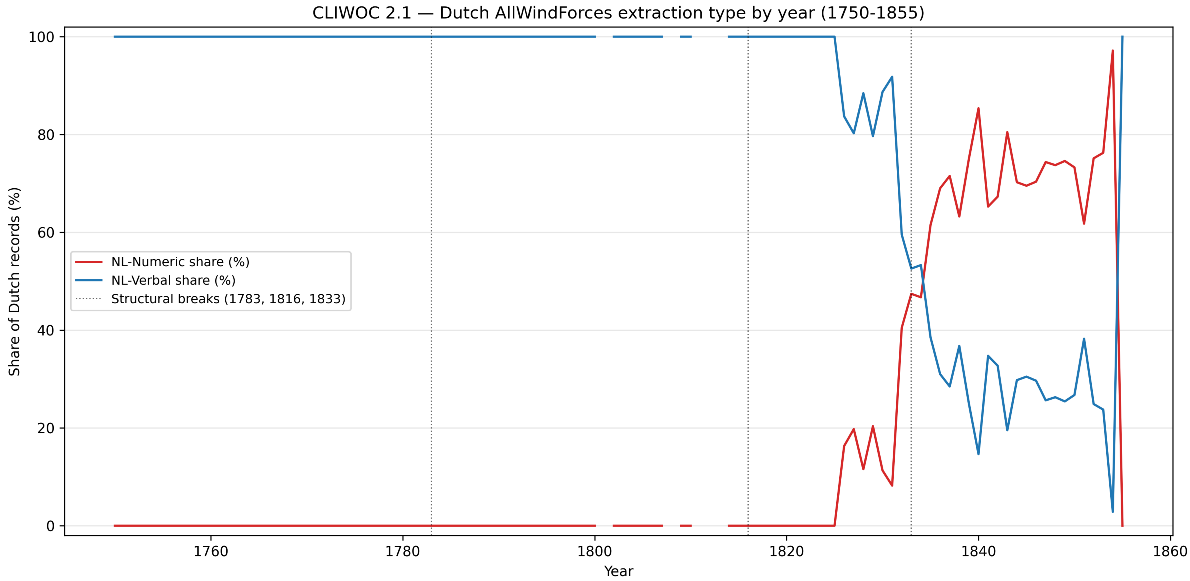

Figure 6: Share of Dutch W-bearing records by operational `AllWindForces` classification, 1750–1855. Dotted lines mark BIC-selected working boundaries.

contrast; the within-category component becomes small and *negative* (-1.1, 95% CI excluding zero), and the interaction component increases from $+0.4$ under pooled nationality to $+4.2$ under the split classification (Table 6). The two streams move in different directions: NL-Numeric's own mean rises from 73.9 to 79.0 across the two regimes, while NL-Verbal's own mean *falls* from 44.7 to 42.8. Thus, the recovery contrast is highly sensitive to whether Dutch records are pooled or classified by `AllWindForces`. Under the stated reference convention, the weight-change and interaction components are $+17.3$ and $+4.2$, respectively, while the within-category component is -1.1. Thus, the split classification reallocates most of the selected recovery contrast away from the pooled within-category component. This descriptive accounting does not identify a causal format, conversion, or extraction effect.

Table 6: Descriptive standardization of the recovery contrast (1816–1832 $\to$ 1833–1855) under pooled nationality and the Dutch `AllWindForces` classification. Both rows use the same records and minimum cell-count restriction. Asterisks mark 95% record-level bootstrap intervals excluding zero.

Treatment	N (A/B)	Total gap	Weights	Within category	Interaction
Dutch pooled	15,269 / 62,052	+20.4*	−0.5*	+20.5*	+0.4*
Dutch split by `AllWindForces`	15,269 / 62,052	+20.4*	+17.3*	−1.1*	+4.2*

It shows that the selected recovery contrast is sensitive both to nationality and to classification granularity within Dutch records. It does not show that the categories exhaust relevant source-composition differences or identify the cause of the remaining within-category component.

2.9 Within-category component at the trough onset

The nationality standardization of the 1783–1815 to 1816–1832 contrast leaves a negative within-category component ($C = -4.05$; Table 3). This component is not a residual causal effect: it may contain source composition below nationality, route and seasonal coverage, reporting practice, measurement differences, and atmospheric variation. Agreement among observers does not by itself establish that observations from different fleets or periods share a stable measurement scale [21, 22]. Here we ask two narrower descriptive questions: which nationalities contribute to

C, and are their trough-period means consistent with a specified linear extrapolation from the preceding regime?

Under the reference-weight decomposition,

$$C = \sum_{g} s_A(g) \left[\mu_B(g) - \mu_A(g)\right],$$

so each nationality has a non-overlapping contribution to the selected within-category component. British observations contribute −2.87 of the total −4.05; Spanish and Dutch observations contribute −0.80 and −0.38, respectively (Table 7). Thus, the component is dominated by British observations but is not exclusively British. The intervals shown are record-level bootstrap intervals and should not be interpreted as fully accounting for dependence within ships or voyages.

Table 7: Nationality contributions to the within-category component for the 1783–1815 → 1816–1832 contrast. Contributions sum to $C = -4.05$, subject to rounding. Bracketed values are 95% record-level bootstrap intervals (2,000 resamples).

Nationality	Share in regime A	Contribution to C	95% interval
British	0.57	−2.87	[−3.74, −2.06]
Spanish	0.17	−0.80	[−1.54, −0.11]
Dutch	0.25	−0.38	[−0.62, −0.14]
American	0.00	−0.01	[−0.03, 0.01]
Total (C)		−4.05	[−5.21, −2.98]

A two-regime comparison cannot distinguish a continuing trend from a deviation at the boundary. We therefore fit, separately for British, Dutch, and Spanish observations, a linear annual trend using only 1783–1815 and compare its extrapolated trough-period mean with the observed 1816–1832 mean. Standard errors are clustered by ship [36]. This is a test of consistency with the specified linear model, not a general test of trend continuation or a causal test of a historical break. Dutch observations have a nearly flat fitted pre-trend, and their observed trough mean is not distinguishable from the linear extrapolation. For Spanish observations, the observed trough mean does not reject the specified linear extrapolation; however, the trough period includes only nine ships, so cluster-robust inference is especially fragile [36]. British observations differ from their linear extrapolation: the fitted pre-trough decline predicts a mean of 61.4, whereas the observed trough mean is 71.7 ($p = 0.001$). The British trough sample, however, contains only 32 ships, compared with 291 ships in the fitted pre-trough period. This result is therefore evidence against this particular linear continuation model, not evidence that British observations underwent a new physical, reporting, or compositional shift.

Table 8: Comparison of observed trough-period mean W with the mean predicted by a linear trend fitted over 1783–1815. Standard errors are clustered by ship. The comparison tests the stated linear extrapolation only.

Nationality	Pre-trend (units/yr)	Predicted	Observed	p	Ships (fit / trough)
Dutch	$+0.01 \pm 0.12$	49.6	47.6	0.61	128 / 87
Spanish	−0.35	68.3	75.1	0.45	153 / 9
British	−0.64	61.4	71.7	0.001	291 / 32

Taken together, these results do not resolve the within-category component. But they show that British observations contribute most to it and are inconsistent with one linear extrapolation from 1783–1815. Dutch observations, and Spanish observations subject to limited trough-period support, are consistent with their corresponding linear extrapolations. Alternative pre-trend windows, nonlinear trends, and direct descriptions of ship, route, company, archive, and seasonal composition would be needed before assigning a mechanism to the British result.

3 Results

The analyses identify four BIC-selected working regimes in the annual CLIWOC W aggregate (Table 1). The three contrasts between adjacent-regime contrast do not share a single empirical structure. For the 1783–1815 to 1816–1832 contrast, the descriptive Oaxaca–Blinder accounting assigns a large share of the observed decline to changing nationality weights under the stated reference convention (Table 3). A smaller within-nationality component remains, however.

For the 1816–1832 to 1833–1855 contrast, the accounting is highly sensitive to disaggregating Dutch observations by the `AllWindForces` format classification. Under pooled nationality, the weight component is -0.5; under the split classification, it is $+17.3$, with a further $+4.2$ interaction component and a -1.1 within-category component (Table 6). This reallocation shows that the selected recovery contrast depends materially on the category definition used for Dutch records. It does not identify a causal format, conversion, or extraction effect.

The earlier 1750–1782 to 1783–1815 contrast has a different structure. Nationality weights account for little of the decline, and the latitude, longitude, and joint $5° \times 5°$ spatial specifications do not materially reduce the within-stratum component (Table 3; Section 2.7). This is a negative result rather than a causal explanation: the tested composition and geographic specifications are insufficient to account for the contrast, but they do not identify its source.

The reported components are descriptive accountings under their stated reference distributions and category definitions. They should not be combined as components of one fixed estimand: the nationality, geographic, and Dutch-format analyses use different classifications and, where applicable, different support restrictions. The estimates should also be read in light of uneven coverage. The trough regime contains fewer annual observations than the regimes on either side, and the British extrapolation analysis contains substantially fewer British clusters after 1815. The British trough mean differs from the specified linear 1783–1815 extrapolation, but that result does not distinguish among nonlinear pre-trend behaviour, changing sample composition, reporting changes, and atmospheric variation.

4 Discussion

The central implication is methodological. A record-weighted annual mean is not automatically an estimate of a stable historical or climatic quantity; it is first an aggregate of the observations that happen to enter the dataset. In CLIWOC, those observations vary over time in nationality, archival coverage, and, within the Dutch material examined here, the form and apparent provenance of wind-force values. Consequently, a change in the pooled annual mean cannot by itself be interpreted as a change in global atmospheric circulation.

The decompositions make this problem visible, but they do not solve it causally. They are descriptive standardizations under specified categories and reference weights. Their weight-change components show how much a selected regime contrast would change if category shares changed while category-specific means were held fixed. They do not estimate the effects of nationality, the end of the Napoleonic Wars, archival practice, or a particular conversion pathway. The remaining within-category and interaction components may include residual source composition below the chosen classification, route and season mix, reporting practice, measurement conversion, and atmospheric variation. The Dutch split should therefore be interpreted as evidence that pooled Dutch records combine source streams with materially different distributions of W, not as proof that a particular extraction process caused the observed recovery.

The unresolved early decline is equally important. Its persistence after the tested nationality and spatial standardizations does not validate a climatic explanation. It establishes only that those specifications do not account for the contrast. Source survival, voyage and route structure, observing and transcription practice, and changes in pre-standardised wind-force vocabulary remain plausible candidates. More generally, a global-atmospheric interpretation would require an explicit target population, comparisons within demonstrable spatiotemporal and source-level common support, uncertainty that respects ship or voyage clustering, documentary validation of provenance classifications, and external validation using observations independent of the analysed CLIWOC material. ICOADS may assist with the last task [37], but only after CLIWOC records and duplicates or overlaps have been removed.

The post-1815 reduction in British records should not be interpreted as evidence of a collapse in British maritime observation. Previous work identifies several non-exclusive mechanisms that could reduce the number of surviving or digitized logbooks, including the nineteenth-century shift from multiple officer logbooks toward a general ship logbook, event-focused digitization priorities, and the continued existence of substantial but undigitized British collections [38, 39]. Independent work on English East India Company records also identifies at least 30 contributing ships in every year from 1794 to 1833, including the post-1815 period [40]. These findings make simple source scarcity unlikely, but they do not establish which archival or sampling mechanism produced the British decline in CLIWOC.

This lesson applies to conventional and AI-assisted analysis alike. Computational tools can efficiently reconstruct, visualize, and interrogate historical datasets. They do not, however, supply the source criticism needed to establish what an aggregate represents, whether its inputs are comparable over time, or what substantive inference its movement can support.

5 Conclusion

This study reproduces the principal annual CLIWOC W aggregate analysed by Degroot, but finds that the aggregate is composition-sensitive across the period in which it is used to support a claim about global atmospheric circulation. The selected 1816 onset and 1833 recovery contrasts are highly sensitive, respectively, to nationality weighting and to the treatment of Dutch source streams. The earlier decline remains unresolved under the specifications examined here.

The appropriate conclusion is therefore narrower than either a global climate reconstruction or a complete archival explanation. The CLIWOC aggregate cannot, by itself, identify a planetary shift in atmospheric circulation. Before such an interpretation can be entertained, the analysis must define the quantity to be estimated, establish comparability and common support among contributing observations, quantify uncertainty at the relevant source level, validate provenance classifications, and test the result against genuinely independent evidence. Historical source criticism is not an optional supplement to this work; it determines the inferential meaning of the aggregate itself.

6 Data Availability

The CLIWOC database is available from PANGEA [3]. All source code used for this study is available from Zenodo (`https://doi.org/10.5281/zenodo.21951457`).

7 Competing Interests

The author declares no competing interests.

8 Use of Generative AI

Generative AI was used in this study for coding assistance (Anthropic Claude), research, forumulation, and translation of German notes (Elicit), and review (Undermind). The author takes full responsibility for all arguments, analyses, and conclusions.

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A Breakpoint Detection: Sensitivity Analysis

Section 2.3 reports a suite of robustness checks on the primary BIC-based breakpoint detection (unweighted yearly means, level-change model), motivated by the fact that annual means pool unequal numbers of contributing records and that adjacent years may be serially dependent. Table 9 reports the full results: three alternative year-level aggregations (median, 10% trimmed mean, and ship-year/cluster mean, in which each ship's own yearly mean is computed before averaging across ships), an effective-cluster-weighted specification (each year weighted by its number of distinct contributing ships), and a slope-permitting (piecewise-linear) alternative to the primary level-change model described in Section 2.3.

Table 9: Breakpoint-detection sensitivity: alternative aggregations, weighting, and model specifications, against the primary result ($m = 3$; 1783, 1816, 1833).

Specification	Best m	Breakpoint years	Matches primary
Primary (yearly mean, unweighted, level-change)	3	1783, 1816, 1833	—
Annual median	2	1815, 1834	No
Annual trimmed mean (10%)	3	1783, 1816, 1833	Yes
Ship-year (cluster) mean	3	1783, 1816, 1833	Yes
Ship-count-weighted segmentation	3	1783, 1816, 1833	Yes
Slope-change (piecewise-linear)	2	1816, 1833	No (drops 1783)

Three of the four alternative specifications — trimmed mean, ship-year aggregation, and ship-count weighting — recover the identical breakpoint set. The median-based specification does not: it selects a coarser two-breakpoint segmentation (1815, 1834) rather than three, though both of its breakpoints fall within one to two years of two of the three primary dates. The slope-change alternative selects only two breakpoints (1816, 1833), dropping 1783 specifically; this is consistent with, rather than contradicting, the primary analysis, since the 1750–1782-to-1783–1815 transition is characterised elsewhere in this report (Section 2.6) as an almost entirely gradual, trend-like change rather than an abrupt level shift, which a piecewise-linear model can partly absorb into a single sloped segment. BIC nonetheless favours the level-change model overall (390.2 vs. 407.5 for the slope-change model at their respective optimal segmentations), so the primary level-change specification is retained throughout the main text.

Breakpoint-location uncertainty was quantified with 500 ship-cluster block-bootstrap replicates: within each year, ships (not individual daily rows) were resampled with replacement, preserving each ship's full set of daily entries as a block, and the segmentation rerun on each resulting series. The bootstrap selected $m = 3$ in 486 of 500 replicates (97.2%), $m = 4$ in 12, and $m = 5$ in 2. Breakpoint-year mass is concentrated tightly around each primary date rather than spread diffusely: 1783 itself accounts for 76.6% of first-breakpoint replicates, with a further 8.8% at 1781 and the remainder scattered across nearby years; 1816 and its immediate neighbour

1815 jointly account for 96.4% of second-breakpoint replicates; 1833 and 1832 jointly account for 77.6% of third-breakpoint replicates. Leave-one-year-out sensitivity, in which each year is removed in turn and the segmentation rerun on the remaining 105, reproduces the identical three-breakpoint set for 105 of 106 years; the sole exception is the removal of 1782 itself, which shifts the first breakpoint to 1781, immediately adjacent to the primary result.

B Candidate Set and Preprocessing

This appendix documents the random-forest screening (Section 2.4) used to prioritize metadata variables for descriptive follow-up. The screen is a candidate-ranking exercise, not a causal model and not an exhaustive adjustment procedure. Its target is the record-level CLIWOC wind-force field W; the analysis uses the same 1750–1855, non-missing-W replication sample described in Section 2.1.

The primary screen draws a random subsample of 50,000 records using seed 42. It evaluates 48 metadata columns after excluding the outcome and its immediate derivation chain (`W`, `WI`, `AllWindForces`, and `WindScale`), the time index, free-text and near-identifier fields, and raw latitude and longitude. Raw coordinates are omitted from this screen because geographic composition is examined separately in Section 2.7. Table 10 lists every candidate field, its data type, missingness rate, and treatment in the screening pipeline.

Categorical fields are encoded by alphabetical factor order (the primary specification) or by mean-target order (a sensitivity check; Section 2.4); numerical and encoded missing values are median-imputed. A binary missingness indicator is added for each candidate field. The same fixed seed governs subsampling, train/test splitting, forest fitting, and permutation; the forest is fit single-threaded ($n_{\text{jobs}} = 1$) for full reproducibility.

Table 10: Candidate fields included in the random-forest screen. Missingness is the % of records with a null value for that field. Complete field definitions follow the CLIWOC documentation.

Field	Type	Missing	Preprocessing
`AT`	Numeric	80.8%	Numeric; median-imputed
`AirPressureReadingUnits`	Categorical	81.9%	Ordinal-encoded (alphabetical); median-imputed
`AirThermReadingUnits`	Categorical	80.8%	Ordinal-encoded (alphabetical); median-imputed
`Anchored`	Numeric	0.0%	Numeric; median-imputed
`BaroReading`	Numeric	81.9%	Numeric; median-imputed
`C1`	Categorical	0.0%	Grouped: NationalityFamily
`Calendar`	Numeric	0.0%	Numeric; median-imputed
`Company`	Categorical	40.3%	Grouped: NationalityFamily
`D`	Numeric	3.6%	Numeric; median-imputed
`Day`	Numeric	0.0%	Numeric; median-imputed
`DayOfTheWeek`	Categorical	67.3%	Ordinal-encoded (alphabetical); median-imputed
`Decl`	Numeric	9.6%	Numeric; median-imputed
`DistToLandmarkUnits`	Categorical	69.3%	Ordinal-encoded (alphabetical); median-imputed
`DistTravelledUnits`	Categorical	39.1%	Ordinal-encoded (alphabetical); median-imputed
`Distance`	Numeric	39.1%	Numeric; median-imputed
`Fog`	Numeric	0.0%	Numeric; median-imputed
`Glasses`	Numeric	65.1%	Numeric; median-imputed

(Table 10 continued)

Field	Type	Missing	Preprocessing
`Gusts`	Numeric	0.0%	Numeric; median-imputed
`HR`	Numeric	9.2%	Numeric; median-imputed
`Hail`	Numeric	0.0%	Numeric; median-imputed
`IT`	Numeric	80.8%	Numeric; median-imputed
`Illustr`	Numeric	0.0%	Numeric; median-imputed
`InstAbbr`	Categorical	0.2%	Grouped: NationalityFamily
`InstLand`	Categorical	0.0%	Grouped: NationalityFamily
`InstName`	Categorical	0.2%	Grouped: NationalityFamily
`InstPlace`	Categorical	0.2%	Grouped: NationalityFamily
`LMdistance1`	Numeric	69.5%	Numeric; median-imputed
`LatInd`	Numeric	0.0%	Numeric; median-imputed
`LogbookLanguage`	Categorical	0.0%	Grouped: NationalityFamily
`LonInd`	Numeric	0.0%	Numeric; median-imputed
`LongitudeUnits`	Categorical	10.9%	Ordinal-encoded (alphabetical); median-imputed
`Month`	Numeric	0.0%	Numeric; median-imputed
`PartDay`	Numeric	64.0%	Numeric; median-imputed
`PosCoastal`	Numeric	0.0%	Numeric; median-imputed
`Rain`	Numeric	0.0%	Numeric; median-imputed
`Rank2`	Categorical	83.3%	Ordinal-encoded (alphabetical); median-imputed
`RefenceCourse`	Categorical	42.9%	Ordinal-encoded (alphabetical); median-imputed
`ReferenceWindDirection`	Categorical	3.4%	Ordinal-encoded (alphabetical); median-imputed
`Release`	Categorical	0.0%	Ordinal-encoded (alphabetical); median-imputed
`SLP`	Numeric	81.9%	Numeric; median-imputed
`SeaIce`	Numeric	0.0%	Numeric; median-imputed
`Snow`	Numeric	0.0%	Numeric; median-imputed
`StartDay`	Categorical	0.0%	Grouped: NationalityFamily
`TairReading`	Numeric	80.8%	Numeric; median-imputed
`Thunder`	Numeric	0.0%	Numeric; median-imputed
`TimeOB`	Numeric	0.0%	Numeric; median-imputed
`TrivialCorrection`	Numeric	0.0%	Numeric; median-imputed
`Watch`	Categorical	65.1%	Ordinal-encoded (alphabetical); median-imputed

C Grouped Permutation Importance

Permutation importance is calculated as the reduction in held-out predictive performance after permuting a candidate while leaving all other model inputs unchanged. Several fields are near-total proxies for nationality: `C1`, `InstAbbr`, `InstName`, `InstPlace`, `InstLand`, `Company`, `LogbookLanguage`, and `StartDay`. We therefore score them jointly as **NationalityFamily**. In each permutation repeat, the eight columns are relocated to a common randomly permuted row index. This preserves each record's observed combination of nationality-proxy values while breaking its association with W.

Table 11 documents the proxy relationship in full, reporting, for every category of every constituent field, its modal nationality and the share of that category's records attributable to it. `StartDay` is included in the grouped permutation because its apparent signal is driven partly by language-specific placeholder values, including `UNKNOWN` and `ONBEKEND`; unlike the other seven fields, however, `StartDay`'s categories are not uniformly near-total proxies (modal shares range from 61.8% to 100%, against 93.7–100% for every other constituent field), and `UNKNOWN` specifically is majority-Dutch (61.8%) rather than majority-English, a more mixed pattern than the language-placeholder account alone would suggest. One further category, `InstAbbr`'s `NIWI`, is the weakest link in the entire table at 70.5% modal share; every other category across all eight fields exceeds 93%.

Table 11: Nationality-proxy diagnostics. For each category, the table reports its modal nationality the share of records assigned to that nationality.

Field	Category	Modal nat
`C1`	DE	DE
`C1`	DK	DK
`C1`	ES	ES
`C1`	FR	FR
`C1`	N	N
`C1`	NL	NL
`C1`	RA	RA
`C1`	SE	SE
`C1`	UK	UK
`C1`	US	US
`InstAbbr`	AGI	ES
`InstAbbr`	AGMAB	ES
`InstAbbr`	BL	UK
`InstAbbr`	CARAN	FR
`InstAbbr`	GAA	NL
`InstAbbr`	GAD	NL
`InstAbbr`	GAS	NL
`InstAbbr`	GUL	SE
`InstAbbr`	HUA	NL
`InstAbbr`	KNMI	NL
`InstAbbr`	KVABS	SE
`InstAbbr`	MMR	NL
`InstAbbr`	MNL	NL
`InstAbbr`	MNM	ES
`InstAbbr`	NAN	NL
`InstAbbr`	NIWI	FR
`InstAbbr`	NMM	UK
`InstAbbr`	NSA	NL
`InstAbbr`	NSG	NL
`InstAbbr`	PRO	UK
`InstAbbr`	RAZ	NL
`InstName`	ARCHIVO DEL MUSEO NAVAL MADRID	ES
`InstName`	ARCHIVO GENERAL DE INDIAS	ES
`InstName`	ARCHIVO GENERAL DE MARINA ALVARO DE BAZÁN	ES
`InstName`	ARCHIVO MUSEO NAVAL MADRID	ES
`InstName`	BRITISH LIBRARY	UK
`InstName`	CENTRE D'ACCUEIL ET DE RECHERCHE DES ARCH. NATION.	FR

(Table 11 continued)

Field	Category	Modal nat
InstName	GEMEENTEARCHIEF AMSTERDAM	NL
InstName	GEMEENTEARCHIEF DORDRECHT	NL
InstName	GEMEENTEARCHIEF SCHIEDAM	NL
InstName	GOTHENBURG UNIVERSITY LIBRARY	SE
InstName	HET UTRECHTS ARCHIEF	NL
InstName	KONINKLIJK NEDERLANDS METEOROLOGISCH INSTITUUT	NL
InstName	MARITIEM MUSEUM ROTTERDAM	NL
InstName	MUSEUM NATURALIS LEIDEN	NL
InstName	NATIONAAL ARCHIEF OF THE NETHERLANDS	NL
InstName	NATIONAL MARITIME MUSEUM	UK
InstName	NEDERLANDS INSTITUUT VOOR WETENSCHAPPELIJKE INFORM	FR
InstName	NEDERLANDS SCHEEPVAARTMUSEUM AMSTERDAM	NL
InstName	NOORDELIJK SCHEEPVAARTMUSEUM GRONINGEN	NL
InstName	PUBLIC RECORD OFFICE	UK
InstName	RIJKSARCHIEF ZEELAND	NL
InstName	ROYAL SOCIETY OF SCIENCES	SE
InstPlace	AMSTERDAM	NL
InstPlace	DE BILT	NL
InstPlace	DEN HAAG	NL
InstPlace	DORDRECHT	NL
InstPlace	GOTHENBURG	SE
InstPlace	GREENWICH	UK
InstPlace	GRONINGEN	NL
InstPlace	KEW	UK
InstPlace	LEIDEN	NL
InstPlace	LONDON	UK
InstPlace	MADRID	ES
InstPlace	MIDDELBURG	NL
InstPlace	PARIS	FR
InstPlace	ROTTERDAM	NL
InstPlace	SCHIEDAM	NL
InstPlace	SEVILLE	ES
InstPlace	STOCKHOLM	SE
InstPlace	UTRECHT	NL
InstPlace	VISO DEL M	ES
InstLand	FRANCE	FR
InstLand	NEDERLAND	NL
InstLand	SPAIN	ES
InstLand	SWEDEN	SE
InstLand	UNITED KINGDOM	UK
Company	A. HOBOKEN, ROTTERDAM	NL
Company	A. VAN HOBOKEN & ZN. TE ROTTERDAM.	NL
Company	ADM	NL
Company	EIC	UK
Company	H. V. RIJCKEVORSEL, ROTTERDAM	NL
Company	HUDSON BAY COMPANY	UK
Company	MAR	NL
Company	MCC	NL
Company	MER	NL

(*Table 11 continued*)

Field	Category	Modal nat
`Company`	MERCHANT NAVY	UK
`Company`	OIC	DK
`Company`	PARTICULIER	NL
`Company`	RN	UK
`Company`	ROYAL NAVY	UK
`Company`	SWEDISH EAST INDIA COMPANY	SE
`Company`	THOMAS BROUW EN ZN.	NL
`Company`	VOC	NL
`Company`	VOC-Z	NL
`Company`	WHA	NL
`Company`	WIC	NL
`LogbookLanguage`	DUTCH	NL
`LogbookLanguage`	ENGLISH	UK
`LogbookLanguage`	FRENCH	FR
`LogbookLanguage`	SPANISH	ES
`StartDay`	0	NL
`StartDay`	12	UK
`StartDay`	ONBEKEND	NL
`StartDay`	UNKNOWN	NL

D Full predictive metadata-screening results: ID-level split sensitivity checks

This appendix reports two sensitivity analyses for the metadata screen described in Section 2.4. Both use a train/test split grouped by `ID`, so that no `ID` appears in both samples (1,460 `ID`s in training and 487 in testing). The first retains alphabetical categorical encoding; the second orders categories by their training-sample mean W. The latter is a directional encoding sensitivity check only, because the training observations contribute to the category means used to encode themselves.

Across both ID-level runs, **NationalityFamily** remains the second-ranked predictor after `Distance`. This result supports its use as a prioritized source-composition candidate, but does not establish that it is the only relevant compositional variable or that its importance is causal. Tables 12 and 13 give the full results for all 48 candidate columns.

Rows ending in `__missing` are missingness indicators rather than substantive variables. Fields labelled "negligible importance; not examined" fall below the threshold for descriptive follow-up in this study; the label does not establish that they are irrelevant in other specifications or analyses.

Table 12: Complete permutation-importance results, alphabetical encoding, `ID`-level split (train $R^2 = 0.289$, test $R^2 = 0.220$).

Field / group	Importance
`Distance`	0.2301
NationalityFamily	**0.0605**
`Decl`	0.0532
`D`	0.0231
`Rain`	0.0208

(Table 12 continued)

Field / group	Importance
Release	0.0146
Gusts	0.0086
HR	0.0050
LatInd	0.0031
Anchored	0.0030
AT	0.0024
TairReading	0.0022
ReferenceWindDirection__missing	0.0021
SLP	0.0016
Distance__missing	0.0016
Month	0.0014
D__missing	0.0013
LonInd	0.0012
DayOfTheWeek__missing	0.0011
DistTravelledUnits__missing	0.0010
LongitudeUnits	0.0010
Rank2__missing	0.0006
BaroReading	0.0006
RefenceCourse__missing	0.0006
AirPressureReadingUnits	0.0005
Rank2	0.0004
Hail	0.0001
DistTravelledUnits	0.0001
HR__missing	0.0001
Decl__missing	0.0000
LongitudeUnits__missing	0.0000
Watch__missing	0.0000
TimeOB	0.0000
PartDay	0.0000
Watch	0.0000
PosCoastal	0.0000
TairReading__missing	0.0000
Anchored__missing	0.0000
TrivialCorrection__missing	0.0000
PosCoastal__missing	0.0000
LatInd__missing	0.0000
LonInd__missing	0.0000
Illustr	0.0000
Release__missing	0.0000
TrivialCorrection	0.0000
Rain__missing	0.0000
Illustr__missing	0.0000
TimeOB__missing	0.0000
Day__missing	0.0000
IT	0.0000
AirThermReadingUnits	0.0000
Glasses	0.0000
ReferenceWindDirection	0.0000
Calendar__missing	0.0000

(Table 12 continued)

Field / group	Importance
SeaIce__missing	0.0000
SeaIce	0.0000
Gusts__missing	0.0000
Snow	0.0000
Snow__missing	0.0000
Fog__missing	0.0000
Fog	0.0000
Thunder__missing	0.0000
Month__missing	0.0000
Hail__missing	0.0000
RefenceCourse	0.0000
Calendar	-0.0000
AT__missing	-0.0000
Glasses__missing	-0.0000
LMdistance1__missing	-0.0000
DistToLandmarkUnits__missing	-0.0000
IT__missing	-0.0000
SLP__missing	-0.0000
Thunder	-0.0000
AirThermReadingUnits__missing	-0.0000
DistToLandmarkUnits	-0.0000
BaroReading__missing	-0.0001
PartDay__missing	-0.0001
AirPressureReadingUnits__missing	-0.0001
Day	-0.0001
DayOfTheWeek	-0.0002
LMdistance1	-0.0004

Table 13: Complete permutation-importance results, mean-target encoding, ID-level split (train $R^2 = 0.285$, test $R^2 = 0.219$).

Field / group	Importance
Distance	0.1798
NationalityFamily	**0.0872**
Decl	0.0469
D	0.0288
Rain	0.0203
Release	0.0146
Gusts	0.0127
SLP	0.0046
HR	0.0043
LongitudeUnits	0.0035
AT	0.0035
Month	0.0018
D__missing	0.0017
Rank2	0.0015
LatInd	0.0015

(Table 13 continued)

Field / group	Importance
DistTravelledUnits	0.0010
DayOfTheWeek	0.0009
TairReading	0.0008
Anchored	0.0008
LonInd	0.0007
BaroReading	0.0006
ReferenceWindDirection	0.0005
Day	0.0005
ReferenceWindDirection__missing	0.0004
LMdistance1	0.0003
RefenceCourse__missing	0.0003
Rank2__missing	0.0002
DistTravelledUnits__missing	0.0002
RefenceCourse	0.0002
Distance__missing	0.0002
LMdistance1__missing	0.0001
Watch	0.0001
Hail	0.0001
DistToLandmarkUnits	0.0001
AirPressureReadingUnits	0.0001
AirThermReadingUnits	0.0000
LongitudeUnits__missing	0.0000
DistToLandmarkUnits__missing	0.0000
PosCoastal	0.0000
HR__missing	0.0000
TrivialCorrection__missing	0.0000
Illustr__missing	0.0000
LonInd__missing	0.0000
Illustr	0.0000
TrivialCorrection	0.0000
Rain__missing	0.0000
Release__missing	0.0000
PosCoastal__missing	0.0000
LatInd__missing	0.0000
Glasses	0.0000
Anchored__missing	0.0000
IT	0.0000
SeaIce__missing	0.0000
Day__missing	0.0000
Month__missing	0.0000
Gusts__missing	0.0000
SeaIce	0.0000
Snow	0.0000
Hail__missing	0.0000
Fog__missing	0.0000
Fog	0.0000
Thunder__missing	0.0000
Snow__missing	0.0000
Calendar__missing	0.0000

(Table 13 continued)

Field / group	Importance
`TimeOB__missing`	0.0000
`AirThermReadingUnits__missing`	-0.0000
`PartDay`	-0.0000
`Thunder`	-0.0000
`AT__missing`	-0.0000
`TairReading__missing`	-0.0000
`Glasses__missing`	-0.0000
`TimeOB`	-0.0000
`IT__missing`	-0.0000
`Decl__missing`	-0.0000
`Watch__missing`	-0.0000
`SLP__missing`	-0.0000
`Calendar`	-0.0000
`DayOfTheWeek__missing`	-0.0000
`AirPressureReadingUnits__missing`	-0.0000
`BaroReading__missing`	-0.0001
`PartDay__missing`	-0.0002

787 # E Diagnostics for the operational Dutch provenance classifier

Table 14: Diagnostics for the operational Dutch provenance classifier: institution, extraction group, record and distinct ship/logbook (`ID`) values, physical extract-logbook count derived from `LogbookIdent` (KNMI only, see text), date range, and `Company`-field missingness, restricted to the 1750–1855 study period (N=112,398; 9 Dutch records overall do not have `AllWindForces` entries).

Institution	Group	n records	n distinct `ID`-values	n physical logbooks (`LogbookIdent`)	Years	`Company` mis
KNMI	NL-Numeric	42,503	263	16	1826–1854	
NAN	NL-Numeric	1	1	—	1853	
NAN	NL-Verbal	43,099	279	—	1750–1855	
KNMI	NL-Verbal	10,751	247	16	1826–1854	
RAZ	NL-Verbal	9,300	61	—	1750–1794	
NSA	NL-Verbal	1,863	9	—	1785–1829	
MMR	NL-Verbal	1,734	16	—	1755–1838	
GAA	NL-Verbal	1,475	13	—	1750–1778	
HUA	NL-Verbal	544	4	—	1754–1841	
GAS	NL-Verbal	412	5	—	1788–1793	
GAD	NL-Verbal	372	4	—	1769–1798	
MNL	NL-Verbal	176	2	—	1778–1779	
NSG	NL-Verbal	168	1	—	1835–1836	1