Source-composition sensitivity in historical marine wind observations: a CLIWOC case study, 1750–1855

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Source-composition sensitivity in historical marine wind observations: a CLIWOC case study, 1750–1855

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Abstract.

Historical ship-logbook observations are widely used to reconstruct pre-instrumental marine climate, but aggregate trends can be sensitive to changes in the source composition of the underlying archive. We reproduce a recent 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—format and documented processing history 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 are pooled or classified by the operational numeric-versus-verbal `AllWindForces` rule. 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. The analysis provides a source-comparability diagnosis for this CLIWOC aggregate; it does not provide a replacement reconstruction of atmospheric circulation.

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 (García-Herrera et al., 2001; García-Herrera et al., 2005; García-Herrera, 2007). Its main value is that it provides rare, high-frequency observations for the pre-instrumental oceans, although coverage is biased toward surviving

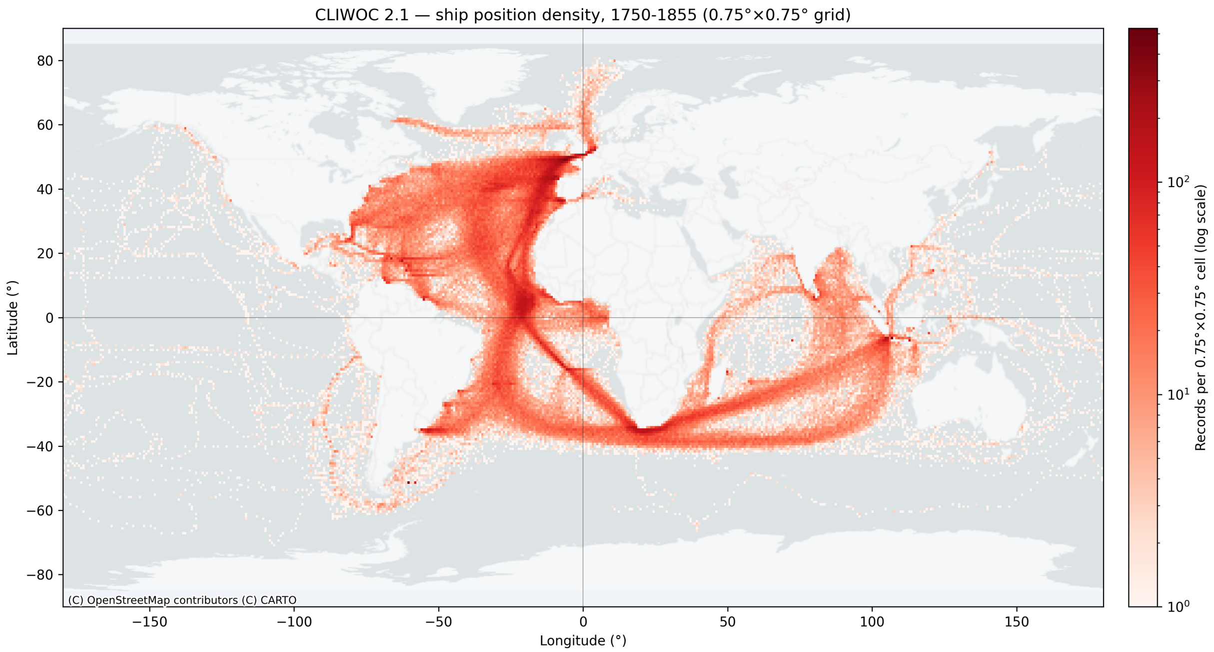

Figure 1. Positions of W-bearing wind records (N=225,326) from the CLIWOC database. Only data coded as reliable are used (`LatInd`, `LonInd` = 1,2, or 5). Basemap: © OpenStreetMap contributors.

archives and heavily travelled European shipping routes (García-Herrera et al., 2006) (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 (García-Herrera et al., 2006, 2018).

A recent analysis of CLIWOC interpreted the annual aggregate as evidence of a large late-eighteenth- to early-nineteenth-century shift in atmospheric circulation (Degroot, 2026, pp. 573, 576–577). That interpretation provides a concrete test case for a broader reconstruction problem: whether a changing aggregate of historical marine observations can be interpreted as a change in the climate system rather than a change in the observations contributing to the aggregate:

> Overall, global wind speeds seemed to gradually decline beginning in about 1780, and then undergo a profound slump between 1816 and 1831 [...] 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 (Degroot, 2026, pp. 576–577).

This interpretation turns on whether the annual record-weighted series represents a sufficiently stable and comparable observation population over time. We reproduce the principal aggregate and evaluate that requirement directly, asking whether selected regime contrasts are sensitive to observed changes in source composition, geographic coverage, and the format of Dutch wind-force entries.

This study does not provide a replacement reconstruction of atmospheric circulation or estimate the causal effect of nationality, archival practice, war, or data conversion on CLIWOC. Instead, it evaluates whether an unstandardized annual CLIWOC aggregate satisfies basic comparability conditions for physical interpretation. We first reproduce the published annual pattern and define BIC-selected working comparison windows. We then assess the sensitivity of adjacent-regime contrasts to nationality composition, geographic coverage, and an operational numeric-versus-verbal classification of Dutch `AllWindForces` values. A contrast that changes materially under these documented source classifications cannot be interpreted as invariant evidence of a shared atmospheric change.

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. (García-Herrera et al., 2001; Koek and Können, 2005; Garcia-Herrera et al., 2003):

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 (Oliver and Kington, 1970; Barrett et al., 2018; Luterbacher et al., 2024), and new data-rescue efforts like Teleti et al. (2026) continue to expand historical ship-logbook coverage. Also, CLIWOC data have supported research on historical mobility, maritime trade, economic history, invasion biology, and genomic biogeography (Heblich et al., 2022; Hudson et al., 2022; Litvine et al., 2024; Roberts et al., 2023; Kelly and Ó Gráda, 2019).

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 study evaluates those comparability conditions in the reproduced CLIWOC series. Even a composition-stable sample does not automatically identify a wider climatic quantity: physical interpretation additionally requires a defined target population, appropriate spatiotemporal support, and validation against independent evidence. The present analysis addresses the source-composition requirement, not those further reconstruction steps.

2 Material and methods

2.1 Data, outcome, and replication sample

We work with version 2.1 of the CLIWOC dataset, obtained as a tab-separated conversion of the original fixed-width release from PANGEA (García-Herrera, 2007). 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 (García Herrera et al., 2003).

The 180 fields fall into two large sections ((Können and Koek, 2005); see (CLI) for a summarized documentation of the IMMA-format). The first, roughly 53 fields, follows the standardized IMMA (International Maritime Meteorological Archive) core format (Smith et al., 2022): 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 motivating analysis reports 244,553 “weather and journey data” entries and 244,039 “wind force measurements” (Degroot, 2026, p. 574). In CLIWOC 2.1, the first count corresponds to records with a numerical value in field `W`; the second corresponds to the same set restricted to 1750–1855 by field `YR`. We therefore use this date-restricted `W` subset ($N = 244{,}039$) throughout.

Figure 2 reproduces the annual record-weighted `W` aggregate used in the motivating analysis, including the annual maximum of 34.00 km/h in 1758 and minimum of 16.29 km/h in 1830 (Degroot, 2026, p. 577). The annual record-count series shown in the published figure, however, counts all CLIWOC records rather than only records carrying `W`. Reporting both series here distinguishes the observation count from the wind-force analysis sample. The analyses that follow concern the reproducible CLIWOC 2.1 `W` aggregate and its source composition.

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,

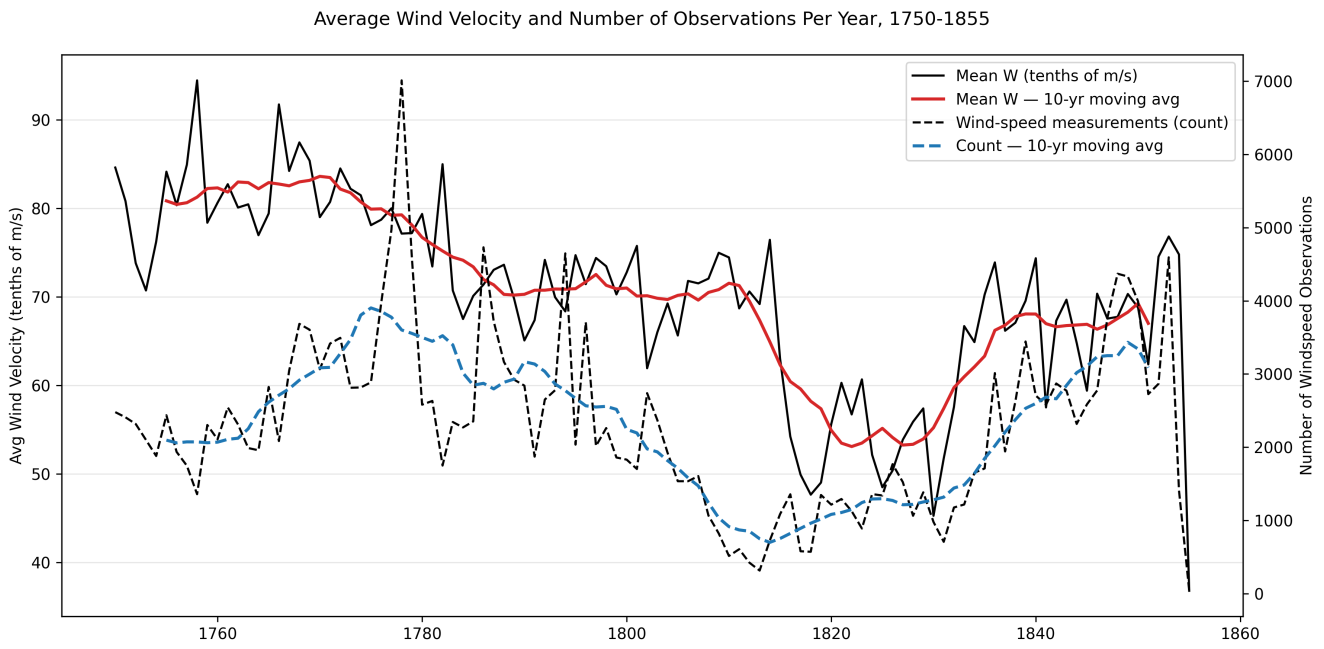

Figure 2. Reproduced annual record-weighted CLIWOC `W` series and annual CLIWOC record count, 1750–1855. Lines show moving averages. The wind-force analysis sample contains records with non-missing `W`; the count series includes all CLIWOC records.

Dutch, Spanish, and French sources (Garcia-Herrera et al., 2003; Wheeler, 2005; Wheeler and Wilkinson, 2005; Koek and Können, 2005; Prieto et al., 2005). These studies document the work required to harmonize national vocabularies, but they do not by themselves establish temporal or cross-source equivalence of the resulting numerical values: 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 (Wheeler and Wilkinson, 2005). 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 (Wheeler, 2005).

2.2 Analytical design and estimands

The motivating study interpreted the annual CLIWOC aggregate as showing a long decline, then a trough beginning around 1816, and a subsequent recovery (Degroot, 2026, 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 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 (1988),

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

For the level-change model, this penalty corresponds to $m+1$ segment means, m selected breakpoint locations, and one pooled variance parameter (Bai and Perron, 2003; Yao, 1988).

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 SA1 reports the selected number and location of changes for every specification.

Breakpoint-location uncertainty is assessed using 500 *year-stratified ship-cluster bootstrap* replicates (Welsh, 2006). 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 SA1 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

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

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 SA1, 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.

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

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 SA1.

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

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 (Breiman, 2001; Strobl et al., 2007, 2008). 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 (Strobl et al., 2008; Gregorutti et al., 2017).

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 (Roberts et al., 2017). 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. 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.

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

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.

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

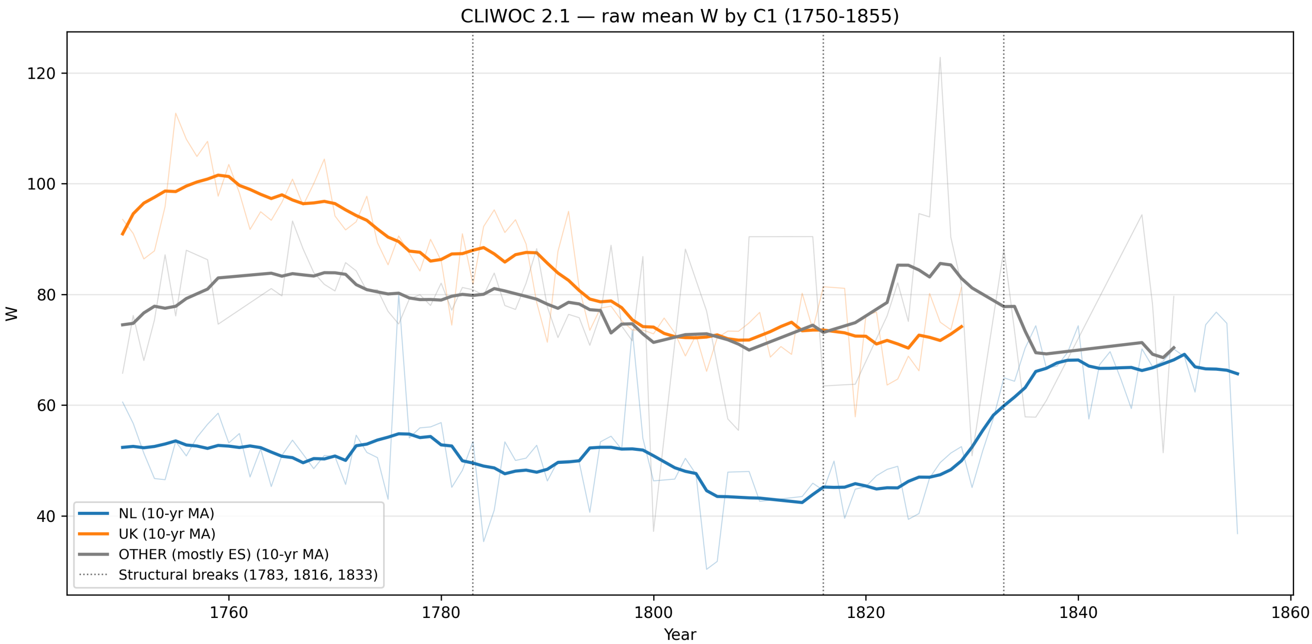

Figure 3. Raw yearly mean W by nationality (`C1`), 1750–1855. Thin lines show yearly means; heavy lines show 10-year moving averages. The pooled OTHER category is dominated by Spanish records. Dotted lines mark BIC-selected working boundaries (1783, 1816, and 1833).

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

a within-category component,

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

and their interaction,

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

such that $\Delta = E + C + I$ exactly (Kitagawa, 1955; Blinder, 1973; Oaxaca, 1973; Jann, 2008). 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.

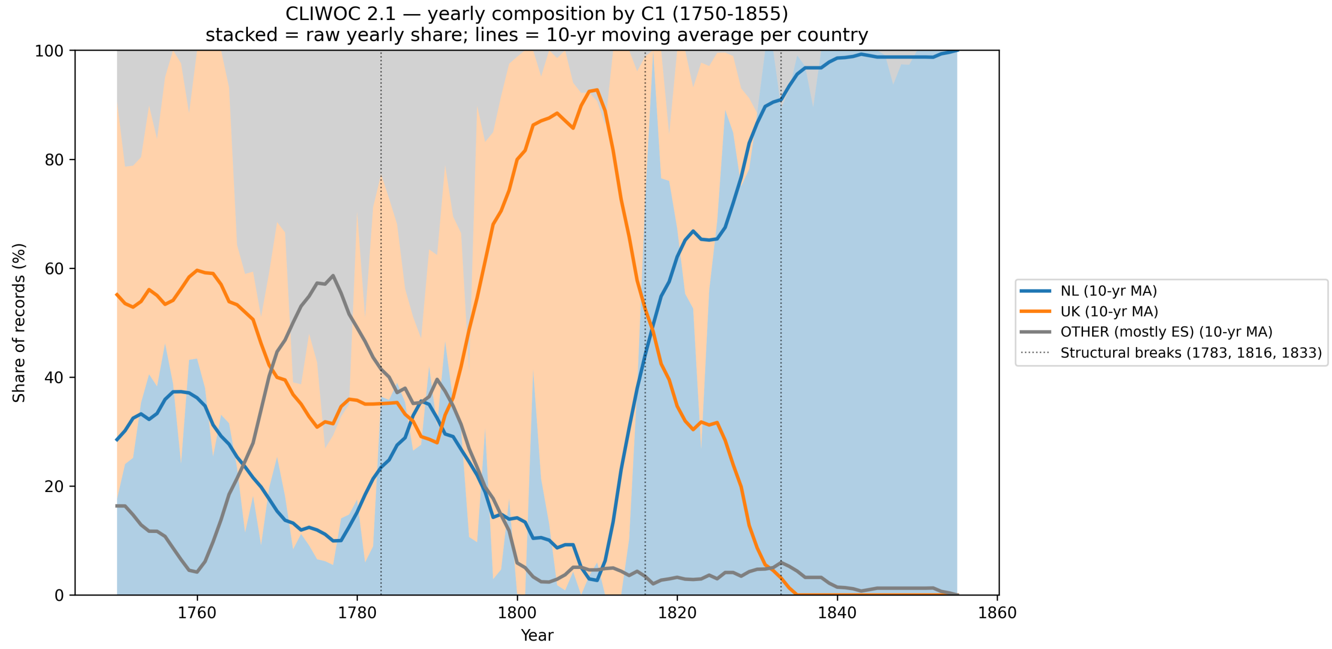

Figure 4. Composition of the W-bearing CLIWOC sample by nationality (`C1`), 1750–1855. Stacked areas show raw yearly shares; lines show 10-year moving averages. Dotted lines mark BIC-selected working boundaries (1783, 1816, and 1833).

We 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.

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

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 $[-0.6, -0.4]$	$+20.5$ $[19.8, 21.3]$	$+0.4$ $[0.3, 0.5]$

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 $5° \times 5°$ 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.

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* $[-1.71, -0.92]$

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.

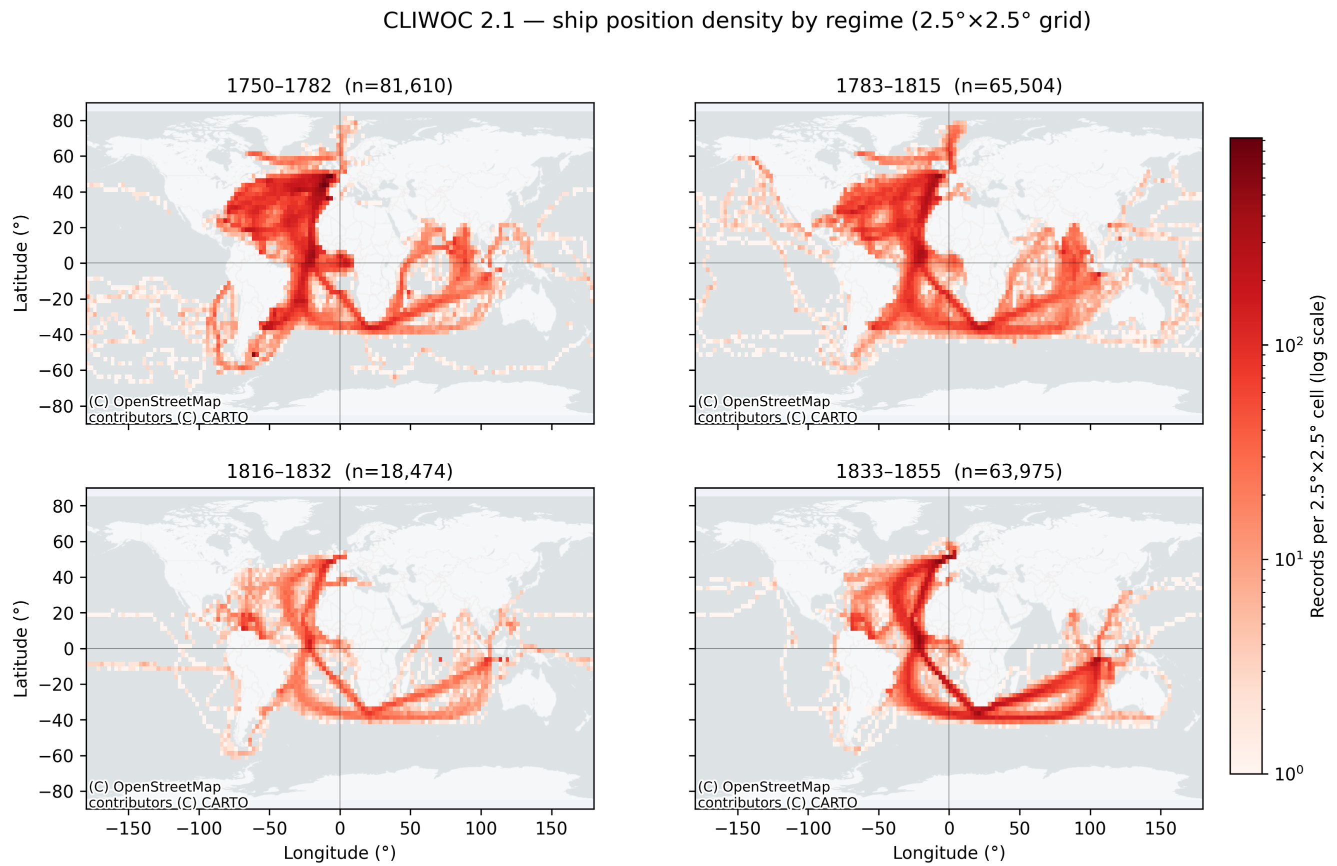

Figure 5. Positions of W-bearing records by BIC-selected working regime, all nationalities pooled. The map includes records with `LatInd` and `LonInd` codes 1, 2, or 5 (Können and Koek, 2005). Basemap: © OpenStreetMap contributors.

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 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 (Koek and Können, 2005). 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 conversion provenances with materially different W distributions. Following the distinction documented by Koek and Können (2005, 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 an operational format classifier. It is consistent with differences in historical extraction and later translation described by Koek and Können, but it does not identify the archival or conversion pathway of an individual record.

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 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.

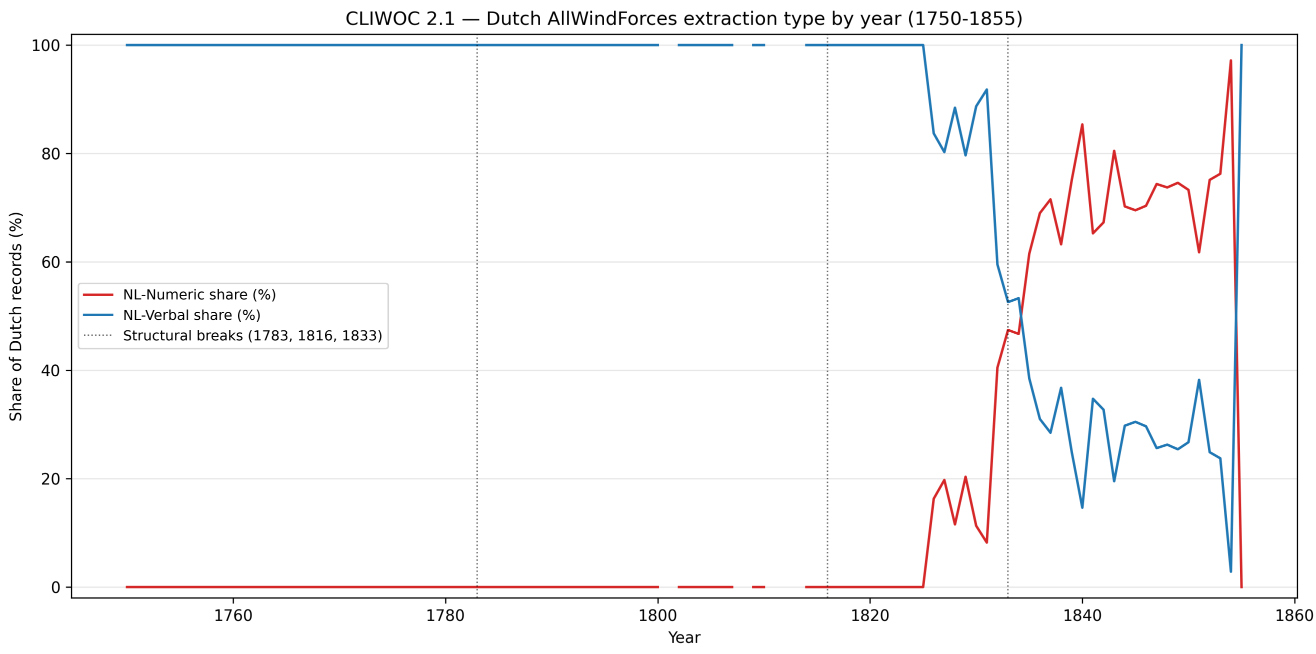

Figure 6. Share of Dutch W-bearing records by operational `AllWindForces` classification, 1750–1855. Dotted lines mark BIC-selected working boundaries.

Table 6. Descriptive standardization of the recovery contrast (1816–1832 $\rightarrow$ 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 (Wheeler and Wilkinson, 2005; Wheeler, 2005). 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,

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

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 $\rightarrow$ 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 (Cameron and Miller, 2015). 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 (Cameron and Miller, 2015). 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 annual record-weighted CLIWOC W series is not invariant to documented changes in the composition of the observations contributing to it. The 1783–1815 to 1816–1832 contrast has a large nationality-weight component under the stated reference convention. The 1816–1832 to 1833–1855 contrast changes materially when Dutch records are classified by the operational numeric-versus-verbal `AllWindForces` rule. These results do not show that nationality or field format caused either aggregate transition. They show that the physical interpretation of a pooled annual series depends on source categories that change over time.

The decompositions make that dependence visible but do not resolve it causally. They are descriptive standardizations under specified categories and reference weights. A weight-change component gives the change in a selected regime contrast implied by replacing reference-period category shares with later-period shares while holding category-specific means fixed. It is not an estimate of the effects of nationality, the end of the Napoleonic Wars, archival practice, or a particular conversion process. The within-category and interaction components may still contain source composition below the selected category grain, route and seasonal coverage, reporting practice, measurement conversion, and atmospheric variation. Likewise, the Dutch split demonstrates that pooling Dutch records with different `AllWindForces` formats materially changes the accounting of the recovery contrast. It does not identify the archival or conversion pathway of an individual record, or establish that a particular processing history caused the recovery.

The earlier 1750–1782 to 1783–1815 decline remains unresolved. Its persistence after the nationality and spatial standardizations tested here does not validate a climatic explanation; it shows only that those specifications do not account for the contrast. Source survival, voyage and route structure, observing and transcription practice, and changes in pre-standardized wind-force vocabulary remain plausible candidates (Woodruff et al., 2005). The post-1815 reduction in British CLIWOC records should likewise not be interpreted as a collapse in British maritime observation. Several mechanisms can reduce the number of surviving or digitized logbooks, including the nineteenth-century movement from multiple officer logs toward a general ship log, event-focused digitization, and the continued existence of substantial undigitized British holdings (Brohan et al., 2009; Gallego et al., 2005). English East India Company material, for example, includes at least 30 contributing ships in every year from 1794 to 1833 (Brohan et al., 2012). These observations make a simple scarcity account unlikely, but they do not identify the archival or sampling process responsible for the British pattern in CLIWOC.

For historical marine climate reconstruction, the implication is practical. A record-weighted annual mean is first a description of the observations that enter the database; it becomes evidence about a wider climatic quantity only under additional comparability assumptions. Analyses seeking that interpretation should define the target population, document source and spatiotemporal coverage, restrict comparisons to demonstrable common support, quantify uncertainty at an appropriate ship, voyage, or logbook level, and assess sensitivity to plausible source classifications. They should also compare any proposed climate signal with observations genuinely independent of the analysed CLIWOC material. ICOADS may assist with such a comparison only after CLIWOC records and duplicates or overlaps have been identified and removed (Woodruff et al., 2005). These checks do not diminish the value of ship-logbook observations; they specify the evidence needed to translate a changing historical archive into a defensible climate reconstruction.

5 Conclusions

This study reproduced the principal annual record-weighted CLIWOC W aggregate used to support a recent interpretation of global atmospheric change and assessed the source-comparability conditions required for that interpretation. The aggregate is sensitive to documented changes in the observations contributing to it. Under the stated reference convention, the 1783–1815 to 1816–1832 contrast has a large nationality-weight component. The 1816–1832 to 1833–1855 recovery contrast changes materially when Dutch observations are pooled or classified by the operational numeric-versus-verbal `AllWindForces` rule. The earlier 1750–1782 to 1783–1815 decline remains unresolved under the nationality and geographic specifications examined here.

These findings do not establish that nationality, archival practice, or any particular conversion process caused the observed regime contrasts. They show that the unstandardized annual aggregate is not, by itself, a stable estimator of a global atmospheric quantity. The unresolved early decline does not supply affirmative evidence for a climatic interpretation; it identifies the limits of the source-composition and spatial standardizations tested here.

Historical ship-logbook observations remain valuable evidence for climate reconstruction. However, analyses that interpret their aggregates physically should define the target population, document source-level and spatiotemporal coverage, establish comparison within demonstrable common support, quantify uncertainty at the relevant ship, voyage, or logbook level, assess sensitivity to plausible source classifications, and evaluate the resulting signal against genuinely independent observations. Historical source criticism is therefore not an ancillary step after aggregation; it is part of defining what an historical-observation aggregate can represent.

Code availability. All source code used for this study is available from Zenodo (https://doi.org/10.5281/zenodo.21951457).

Data availability. The CLIWOC database is available from PANGEA (García-Herrera, 2007).

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Appendix 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 A1 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 A1. 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.

Appendix 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 B1 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 B1: 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

(Table B1 continued)

Field	Type	Missing	Preprocessing
`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
`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

(Table B1 continued)

Field	Type	Missing	Preprocessing
`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

Appendix 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 C1 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 C1: Nationality-proxy diagnostics. For each category, the table reports its modal nationality and the share of records assigned to that nationality.

Field	Category	Modal nationality	Modal share
`C1`	DE	DE	100.0%
`C1`	DK	DK	100.0%
`C1`	ES	ES	100.0%
`C1`	FR	FR	100.0%
`C1`	N	N	100.0%
`C1`	NL	NL	100.0%
`C1`	RA	RA	100.0%
`C1`	SE	SE	100.0%
`C1`	UK	UK	100.0%
`C1`	US	US	100.0%
`InstAbbr`	AGI	ES	100.0%
`InstAbbr`	AGMAB	ES	100.0%
`InstAbbr`	BL	UK	100.0%
`InstAbbr`	CARAN	FR	100.0%
`InstAbbr`	GAA	NL	100.0%
`InstAbbr`	GAD	NL	100.0%
`InstAbbr`	GAS	NL	100.0%
`InstAbbr`	GUL	SE	100.0%
`InstAbbr`	HUA	NL	100.0%
`InstAbbr`	KNMI	NL	100.0%
`InstAbbr`	KVABS	SE	100.0%
`InstAbbr`	MMR	NL	93.7%

(Table C1 continued)

Field	Category	Modal nationality	Modal share
InstAbbr	MNL	NL	100.0%
InstAbbr	MNM	ES	100.0%
InstAbbr	NAN	NL	99.2%
InstAbbr	NIWI	FR	70.5%
InstAbbr	NMM	UK	100.0%
InstAbbr	NSA	NL	97.1%
InstAbbr	NSG	NL	100.0%
InstAbbr	PRO	UK	100.0%
InstAbbr	RAZ	NL	100.0%
InstName	ARCHIVO DEL MUSEO NAVAL MADRID	ES	100.0%
InstName	ARCHIVO GENERAL DE INDIAS	ES	100.0%
InstName	ARCHIVO GENERAL DE MARINA ALVARO DE BAZÁN	ES	100.0%
InstName	ARCHIVO MUSEO NAVAL MADRID	ES	100.0%
InstName	BRITISH LIBRARY	UK	100.0%
InstName	CENTRE D'ACCUEIL ET DE RECHERCHE DES ARCH. NATION.	FR	100.0%
InstName	GEMEENTEARCHIEF AMSTERDAM	NL	100.0%
InstName	GEMEENTEARCHIEF DORDRECHT	NL	100.0%
InstName	GEMEENTEARCHIEF SCHIEDAM	NL	100.0%
InstName	GOTHENBURG UNIVERSITY LIBRARY	SE	100.0%
InstName	HET UTRECHTS ARCHIEF	NL	100.0%
InstName	KONINKLIJK NEDERLANDS METEOROLOGISCH INSTITUUT	NL	100.0%
InstName	MARITIEM MUSEUM ROTTERDAM	NL	93.7%
InstName	MUSEUM NATURALIS LEIDEN	NL	100.0%
InstName	NATIONAAL ARCHIEF OF THE NETHERLANDS	NL	99.2%
InstName	NATIONAL MARITIME MUSEUM	UK	100.0%
InstName	NEDERLANDS INSTITUUT VOOR WETENSCHAPPELIJKE INFORM	FR	70.5%
InstName	NEDERLANDS SCHEEPVAARTMUSEUM AMSTERDAM	NL	97.1%
InstName	NOORDELIJK SCHEEPVAARTMUSEUM GRONINGEN	NL	100.0%
InstName	PUBLIC RECORD OFFICE	UK	100.0%
InstName	RIJKSARCHIEF ZEELAND	NL	100.0%
InstName	ROYAL SOCIETY OF SCIENCES	SE	100.0%
InstPlace	AMSTERDAM	NL	63.7%

(Table C1 continued)

Field	Category	Modal nationality	Modal share
InstPlace	DE BILT	NL	100.0%
InstPlace	DEN HAAG	NL	99.2%
InstPlace	DORDRECHT	NL	100.0%
InstPlace	GOTHENBURG	SE	100.0%
InstPlace	GREENWICH	UK	100.0%
InstPlace	GRONINGEN	NL	100.0%
InstPlace	KEW	UK	100.0%
InstPlace	LEIDEN	NL	100.0%
InstPlace	LONDON	UK	100.0%
InstPlace	MADRID	ES	100.0%
InstPlace	MIDDELBURG	NL	100.0%
InstPlace	PARIS	FR	100.0%
InstPlace	ROTTERDAM	NL	93.7%
InstPlace	SCHIEDAM	NL	100.0%
InstPlace	SEVILLE	ES	100.0%
InstPlace	STOCKHOLM	SE	100.0%
InstPlace	UTRECHT	NL	100.0%
InstPlace	VISO DEL M	ES	100.0%
InstLand	FRANCE	FR	100.0%
InstLand	NEDERLAND	NL	97.8%
InstLand	SPAIN	ES	100.0%
InstLand	SWEDEN	SE	100.0%
InstLand	UNITED KINGDOM	UK	100.0%
Company	A. HOBOKEN, ROTTERDAM	NL	100.0%
Company	A. VAN HOBOKEN & ZN. TE ROTTERDAM.	NL	100.0%
Company	ADM	NL	96.2%
Company	EIC	UK	100.0%
Company	H. V. RIJCKEVORSEL, ROTTERDAM	NL	100.0%
Company	HUDSON BAY COMPANY	UK	100.0%
Company	MAR	NL	99.7%
Company	MCC	NL	100.0%
Company	MER	NL	100.0%

(Table C1 continued)

Field	Category	Modal nationality	Modal shar
`Company`	MERCHANT NAVY	UK	100.0%
`Company`	OIC	DK	100.0%
`Company`	PARTICULIER	NL	100.0%
`Company`	RN	UK	100.0%
`Company`	ROYAL NAVY	UK	100.0%
`Company`	SWEDISH EAST INDIA COMPANY	SE	100.0%
`Company`	THOMAS BROUW EN ZN.	NL	100.0%
`Company`	VOC	NL	100.0%
`Company`	VOC-Z	NL	100.0%
`Company`	WHA	NL	100.0%
`Company`	WIC	NL	100.0%
`LogbookLanguage`	DUTCH	NL	99.5%
`LogbookLanguage`	ENGLISH	UK	99.3%
`LogbookLanguage`	FRENCH	FR	99.0%
`LogbookLanguage`	SPANISH	ES	100.0%
`StartDay`	0	NL	73.4%
`StartDay`	12	UK	86.5%
`StartDay`	ONBEKEND	NL	100.0%
`StartDay`	UNKNOWN	NL	61.8%

Appendix 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 D1 and D2 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 D1: 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
`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

(Table D1 continued)

Field / group	Importance
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
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

(Table D1 continued)

Field / group	Importance
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 D2: 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

(Table D2 continued)

Field / group	Importance
LongitudeUnits	0.0035
AT	0.0035
Month	0.0018
D__missing	0.0017
Rank2	0.0015
LatInd	0.0015
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

(Table D2 continued)

Field / group	Importance
`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
`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

(Table D2 continued)

Field / group	Importance
`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

Appendix E: Diagnostics for the operational Dutch provenance classifier

Table E1. 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` miss. %
KNMI	NL-Numeric	42,503	263	16	1826–1854	82.6
NAN	NL-Numeric	1	1	—	1853	0.0
NAN	NL-Verbal	43,099	279	—	1750–1855	2.3
KNMI	NL-Verbal	10,751	247	16	1826–1854	68.7
RAZ	NL-Verbal	9,300	61	—	1750–1794	0.0
NSA	NL-Verbal	1,863	9	—	1785–1829	6.7
MMR	NL-Verbal	1,734	16	—	1755–1838	8.2
GAA	NL-Verbal	1,475	13	—	1750–1778	0.0
HUA	NL-Verbal	544	4	—	1754–1841	0.0
GAS	NL-Verbal	412	5	—	1788–1793	0.0
GAD	NL-Verbal	372	4	—	1769–1798	0.0
MNL	NL-Verbal	176	2	—	1778–1779	0.0
NSG	NL-Verbal	168	1	—	1835–1836	100.0