

Methods note · Observation and data

The missing peak: a worked missing-not-at-random example

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ABSTRACT

An apparently complete environmental record can underestimate its target when high values are less likely to be retained. This methods note presents a wholly fictional 100-value index series whose response-dependent missingness lowers the observed mean. It compares zero replacement, complete-case averaging, mean imputation, interpolation, and model-based assumptions, then expresses the complete-period mean as a function of the unknown missing-value mean. A sensitivity table and an educational tipping point make the unidentifiable component explicit. Seaman and colleagues' missingness definitions, CF conventions, and observing-network context frame the analysis. No empirical correction, safety threshold, or acceptable completeness percentage is proposed. The note argues for preserving failure information and reporting assumption-dependent conclusions rather than allowing a smooth completed series to conceal selection.

Keywords: missing not at random · sensitivity analysis · missingness mechanisms · observation gaps

A source-based editorial text, not a report of original Still North research. Examples and imagery are illustrative.

The missing values may be the values that matter most

An incomplete environmental series can have a plausible average and the wrong target. If an instrument becomes less likely to retain a reading when the measured quantity is high, the observed mean describes successful recording, not necessarily the full scheduled period. More careful arithmetic on the observed values cannot by itself reconstruct the unobserved ones. The missingness mechanism has become part of the scientific problem.

This methods note develops one fully fictional missing-not-at-random example, then compares simple analyses and an explicit sensitivity calculation. It uses Seaman and colleagues' methodological account of missing-at-random assumptions, CF metadata conventions, and the Arctic observing-network assessment. It reports no observations, fitted model, or tested correction. The index and comparison boundary are educational inventions, not environmental-health or operational safety thresholds.

What the terms mean in this example

Missing completely at random means, in the simplified setting here, that recording does not depend on the scheduled values. Missing at random permits dependence on observed information, while assuming that, conditional on the information used, missingness does not further depend on the missing values. Missing not at random describes the remaining dependence on values that are not observed. These are assumptions about a process or model, not labels assigned by looking at the shape of a gap.

Seaman and colleagues explain that the terms have been used inconsistently and distinguish definitions appropriate to different inferential frameworks. Their central caution is important for applied work: ignoring the

missingness mechanism is justified only under specified conditions. “Missing at random” does not mean that the missing positions look scattered, and it does not mean that every incomplete-data method is automatically valid.

The classification also depends on which observed variables are available and included. Failure linked entirely to a well-recorded environmental covariate could support a conditional missing-at-random analysis under a suitable model. Failure that still depends on the unrecorded response after that conditioning does not. Logging an explanation such as “rough conditions” is useful evidence, but does not prove that the available covariates capture everything needed.

Fictional case: a logger loses high readings

Suppose a logger is scheduled to record 100 equally spaced index values. In the invented complete series, 80 values equal two units and 20 equal ten units. All 80 low values are retained. Only five of the high values are retained; the remaining 15 are missing. For teaching purposes, the complete series is known to the author of the example. An analyst opening the incomplete file would not know the missing values.

The target is the mean of all 100 scheduled values, not the mean conditional on successful recording. With the complete invented series, it is (80 times two plus 20 times ten) divided by 100, or 3.60 units. The observed sum is 210 over 85 recorded values, giving approximately 2.47 units. The 85% completion rate sounds substantial, but the missing 15% is concentrated exactly where the response is high.

The example specifies a response-dependent recording process, with no additional observed variable that removes that dependence. It is therefore missing not at random under the stated model. A random loss of 15

Invented state	Scheduled values	Recorded values	Unrecorded values
Index equals two	80	80	0
Index equals ten	20	5	15
Total	100	85	15

Assumed mean of missing values	Resulting complete-period mean	Interpretation
About 2.47 units	About 2.47 units	Missing values resemble the observed mean
5.00 units	2.85 units	Missing values are moderately higher
10.00 units	3.60 units	The complete fictional case specified above

values would be a different example, even if it produced the same completion percentage. Completeness is a count; representativeness depends on how the count arose.

Three tempting calculations

Replacing missing values by zero gives 210 divided by 100, or 2.10 units. That invents low measurements where none were retained. Dividing by 85 gives 2.47, a correct mean for the observed subset but a misleading estimate of the intended complete-period mean under this mechanism. Filling every gap with 2.47 reproduces the same mean, while potentially making subsequent uncertainty calculations falsely resemble a complete record.

Linear interpolation is not a general solution either. If high values occur in sustained unobserved episodes, interpolation between low endpoints can erase them. Carrying the last observation forward makes a different unverified assumption. Neither operation becomes evidence about a peak merely because the resulting line looks smooth. If a model estimates missing values, the public record should distinguish those estimates from retained observations.

More sophisticated imputation also needs an assumption. Drawing missing values from a model learned only from successful readings can reproduce the selection already present. Multiple imputation can represent uncertainty under its model, but does not make an unjustified missing-at-random assumption true. A narrow interval around the wrong target is not repaired by generating more imputed datasets.

A transparent sensitivity calculation

Let m denote the unknown mean of the 15 missing index values. Holding the observed sum fixed, the complete-period mean would be (210 plus 15 times m) divided by 100. This simple expression exposes the unobserved quantity on which the result depends. It does not estimate m . The following scenarios are assumptions chosen to display sensitivity, not observations or probabilities assigned to competing explanations.

Suppose a purely educational summary distinguishes means above and below three index units. The complete-period mean exceeds three only when m exceeds six. This is a tipping-point statement: the classification depends on whether the missing mean is above six. It is not evidence that six is likely, nor advice to select whichever assumption yields a preferred category. A real analysis would need substantive evidence to justify a plausible range for m .

If defensible physical bounds were available, they could constrain the mean without identifying it exactly. But bounds should not be invented to narrow an inconvenient interval. A detection limit, sensor range, or theoretical maximum may describe different things. Failure beyond an instrument's range can be evidence of censoring or saturation rather than ordinary missingness, and the analysis should preserve that distinction.

Improve the record of failure

The CF conventions specify ways to encode undefined or missing values and provide flags for quality and instrument state. Such metadata prevent blanks from being mistaken for zero and help separate sensor failure, rejected readings, and other states. They do not, by themselves, identify the missingness mechanism or supply the missing response.

Useful supporting information can include a known observation schedule, local status logs, saturation flags, battery history, independent covariates, and recoverable onboard storage. Collect it where appropriate without creating new privacy or governance exposures. If an independent measurement helps characterise unrecorded periods, explain its own uncertainty and comparability. A nearby record is not automatically an exact substitute.

The 2025 Arctic observing-network assessment describes uneven coverage and limitations associated with observing conditions and platforms. That context reinforces the need to inspect when and where data are available. It does not establish that any particular environmental series is missing not at random. Mechanism claims require evidence about that series and its collection process.

Limits and implication

The worked series assumes two exact index levels, equal scheduling intervals, and no measurement error. Real records can involve autocorrelation, irregular sampling, uncertain schedules, and several kinds of missingness simultaneously. The example cannot determine a general correction or an acceptable completeness percentage. It also cannot show that missing values are high merely because high values would change the conclusion.

Its implication is narrower and useful: state the target, retain the missingness information, calculate what the observed subset actually describes, and expose how conclusions depend on unobserved values. Where data cannot identify the missing mean, a sensitivity analysis is more honest than a completed-looking series. The gap

then remains a quantified limit on knowledge rather than a quiet source of false certainty.

References

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