DRISEE overestimates errors in metagenomic sequencing data

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Abstract
The extremely high error rates reported by Keegan et al. in 'A platform-independent method for detecting errors in metagenomic sequencing data: DRISEE' (PLoS Comput Biol 2012;8:e1002541) for many next-generation sequencing datasets prompted us to re-examine their results. Our analysis reveals that the presence of conserved artificial sequences, e.g. Illumina adapters, and other naturally occurring sequence motifs accounts for most of the reported errors. We conclude that DRISEE reports inflated levels of sequencing error, particularly for Illumina data. Tools offered for evaluating large datasets need scrupulous review before they are implemented.

Keywords: next-generation sequencing; sequencing error; adapter ligation; PCR; quality score

INTRODUCTION
Error identification and correction in high-throughput sequencing datasets, especially at the single read level, have been addressed by many investigators [1–18]. Many approaches use platform-dependent quality scores, read consensus or k-mer analysis. Recently, Keegan et al. [19] described DRISEE, a method to assess quality of genomic and metagenomic next-generation sequencing runs. The authors analysed numerous publicly available datasets with DRISEE and reported widely variable levels of sequencing errors, generally far higher than other published estimates [1, 20–22].

DRISEE bases its error estimates on variation from a consensus sequence in bins of artificially duplicated reads (ADRs). DRISEE assumes that prior to sequencing, over-amplification from a given start point in the template leads to formation of ADRs, and that sequencing error, not naturally occurring sequence diversity, accounts for sequence variation within an ADR bin. An ADR bin consists of all reads starting with an identical prefix, by default the first 50 nt of the read.

DRISEE as described might provide an improved method for estimating sequencing errors than the platform-based quality scores; however, the authors failed to carefully examine the origins of ADR bins. DRISEE analyses all reads except those that contain ambiguous bases. The authors correctly note, ‘Bins can be screened for eukaryotic content, sequences with low complexity, and/or known sequences that may exhibit an unusually high level of biological repetition (16s rRNA-based, sequences with low complexity, eukaryotic sequences etc.). Bins that contain such sequences should be excluded from further consideration’. However, the Supplemental Methods in the DRISEE manuscript reveal that the authors did not exclude such reads.

Widespread Illumina adapter contamination
We obtained from the NCBI Sequence Read Archive (SRA) the 12 metagenomic datasets that were used in the original publication to generate Figure 4b. DRISEE error estimation demonstrated...
a significant discrepancy from the quality scores reported by the Illumina platform. Our analysis of DRISEE-generated ADR bins with ≥20 reads showed that Illumina adapter sequences drive the formation of these bins. This 65-nt adaptor sequence usually occurs upstream of the sequencing primer-binding site. Unfortunately, Illumina adapter artifacts sometimes contaminate libraries. Unless they are filtered out or trimmed, reads starting with Illumina adapters will present identical 65-nt prefixes at the start of the read and create a spurious ADR bin. DRISEE interprets the actual biological variation that follows the adapter sequences in these bins as extensive sequencing error.

With DRISEE (version 1.2), we re-analysed the 12 datasets, identifying reads as ‘adapter contaminated’ if they presented at least 15 nt perfect identity to the Illumina adapter sequences in the first 50 nt (see Supplemental Methods). Figure 1 shows the marked difference in error estimation for reads with and without Illumina adapters. Although Keegan et al.’s [19] claim that the true error rates are higher than reported in the quality scores may be correct, the exceedingly high error rates presented in Figure 4b from the original publication reflect the presence of untrimmed Illumina adapter sequences and do not support their claims.

Spurious ADR bins caused by adaptor sequences differ markedly from valid bins in the magnitude of errors and their distribution by nucleotide position. Figure 2 shows DRISEE output from individual large bins from dataset SRR061459. The adapter-generated bin exhibits error greater than zero at all positions following the prefix and the average error greatly exceeds that of the valid ADR bin.

Low-complexity and conserved gene reads
Analysis of all 10 Illumina genomic datasets, as well as 10 randomly chosen Illumina metagenomic runs from Keegan et al.’s Figure 3 [19], detected significant Illumina adapter contamination and a high proportion of low-complexity reads in all datasets, both of which generated spurious bins that inflated DRISEE error drastically. Table 1 demonstrates the inflation of DRISEE error for one of these datasets chosen randomly (SRA accession SRR061488). Genes with conserved regions followed by biological variation that commonly occurs in both bacterial and eukaryotic genomes can create bins large enough

![Diagram](image-url)
Figure 2: DRISEE error by position. The largest bin contained 15,264 reads and the prefix appeared to be a true ADR (bacterial genomic sequence). The per cent error at each position is plotted on the y-axis (light blue). Scores for an adapter-generated bin with 8177 reads are shown for comparison (dark red).

Figure 3: Some of the motifs that generated invalid bins for dataset 4441625.3. The first 20 largest bins are shown. The first column is bin size and the second is the 50-nt prefix. Similar motifs are shown using the same font colour.
adds a layer of complexity and might result in too few bins to reach a robust error estimate. The minimum number of bins necessary to reach a reliable estimate and the impact of the sub-sampling necessary to complete the analysis in a reasonable time were not adequately addressed by the authors.

Although DRISEE may eventually have the potential to identify problematic datasets and assess the sequencing quality of next-generation sequencing runs based on ADRs, the current version of the software is inadequate and its results are unrealistic.

**SUPPLEMENTARY DATA**

Supplementary data are available online at http://bib.oxfordjournals.org/.

**Key points**

- DRISEE is proposed as a method for detecting errors in metagenomic sequencing data by binning reads that contain the same prefix and investigating their divergence.
- DRISEE does not eliminate bins created by adapter contamination or that arise from closely related or low-complexity sequences, which results in inflated error estimates.
- DRISEE in its current implementation is inaccurate, and error rates reported in the DRISEE publication regarding Illumina and 454 technologies are misleading.

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**Table I:** Change in DRISEE error estimation for SRR061488 after removing adapter-contaminated and low-complexity bins from the analysis

| Category                  | Number | DRISEE error (%) |
|---------------------------|--------|------------------|
| All bins                  | 4766   | 39.9             |
| Adapter-contaminated bins | 1645   | 45.1             |
| Low-complexity bins       | 2718   | 34.8             |
| Remaining bins            | 403    | 6.6              |

*Number of bins containing ≥20 reads and no ambiguous bases in their prefixes.
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