

Evaluation of microbiome association models under realistic and confounded conditions



Morgan Essex*, Jakob Wirbel*,
Sofia Forslund, Georg Zeller

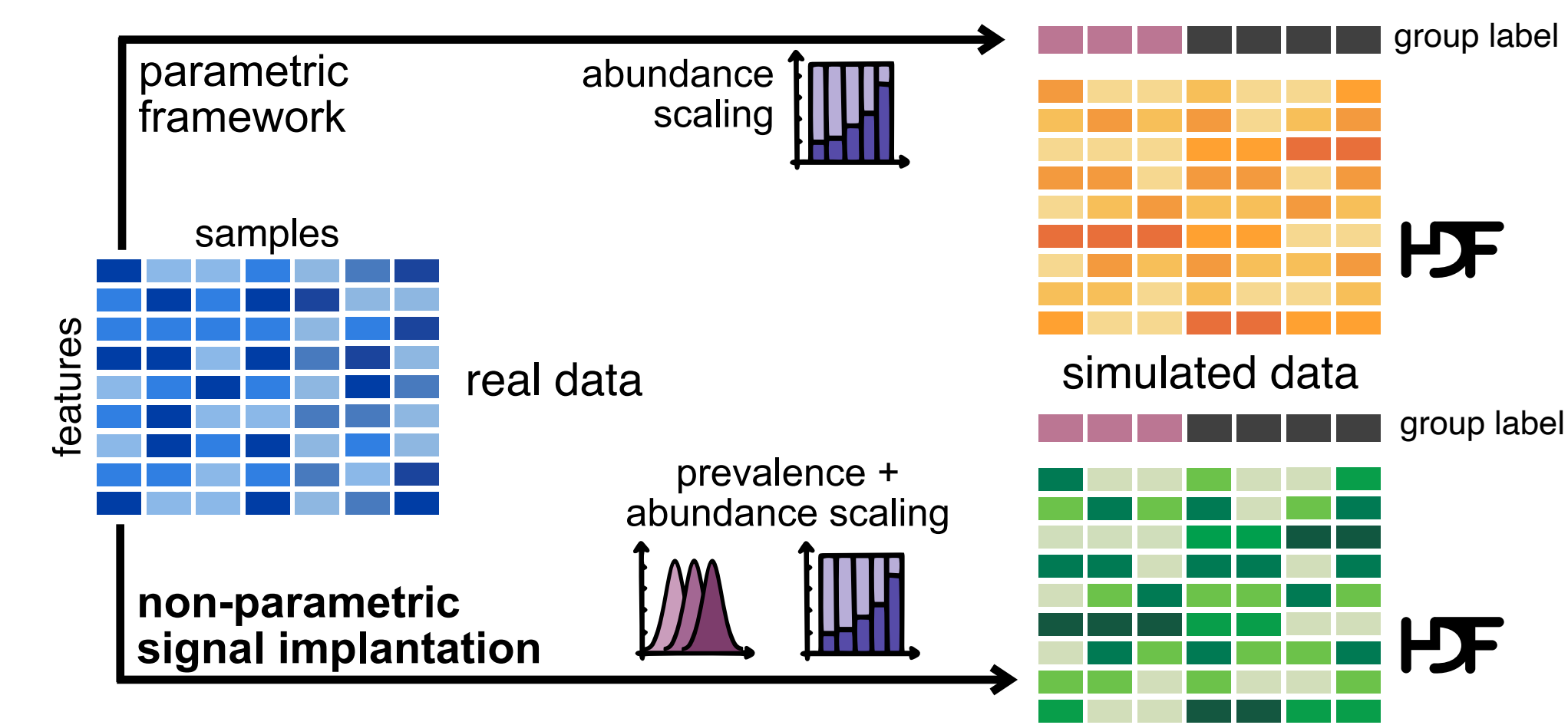
*both authors contributed equally

1. Introduction

- ▶ Testing for differential abundance is a fundamental task in metagenome-wide association studies, yet **there is no consensus on statistical methodology**
- ▶ Benchmarks typically use reshuffled real data, which lacks a ground truth, or **simulated data** generated by parametric methods, which **lacks evaluation** on its resemblance to real metagenomic data
- ▶ **Technical or biological confounders** further hamper reliability and reproducibility of findings in clinical applications of differential abundance testing, yet have thus far been largely ignored in benchmarks

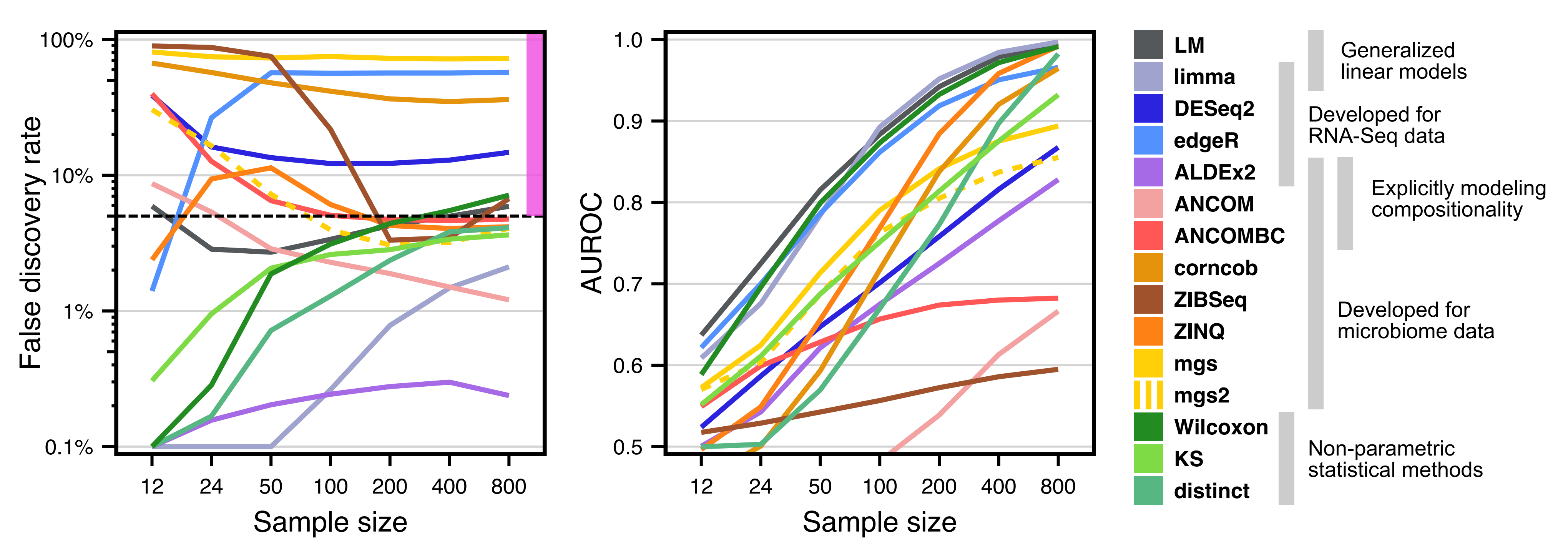
2. Methods and Study Design

- ▶ We developed and validated a **novel simulation framework** mimicking case-control study designs that implants signals into **real metagenomic data**¹



- ▶ We performed a large **benchmarking study**, including 6 simulation frameworks (5 parametric + ours) with varying effect sizes, and 15 differential abundance methods with different normalization techniques
- ▶ We extended our framework to simulate known **patterns of confounding**, mimicking e.g. technical batch effects or medication intake in disease cohorts
- ▶ We further benchmarked methods that performed well in our first evaluation on their ability to detect differentially abundant features under **varying strengths of confounding effects**
- ▶ Our code is **open source** to facilitate community development of e.g. other study designs, method benchmarks, or power analysis applications

Many **differential abundance methods** applied in metagenome-wide association studies **fail to control the false discovery rate** or **offer limited sensitivity** to detect potential biomarkers

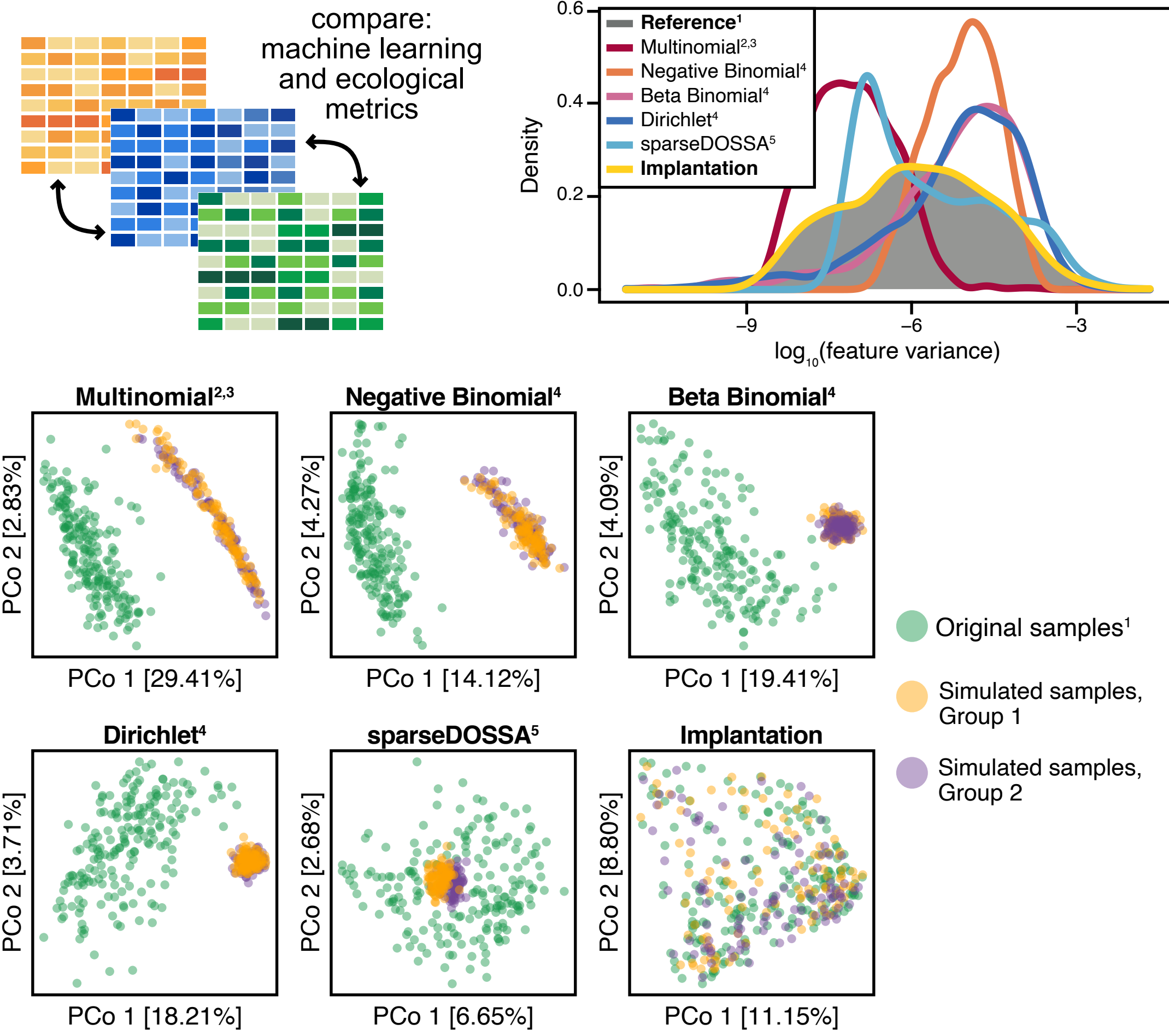


These issues are **exacerbated in the presence of confounding factors** known to plague real-world studies

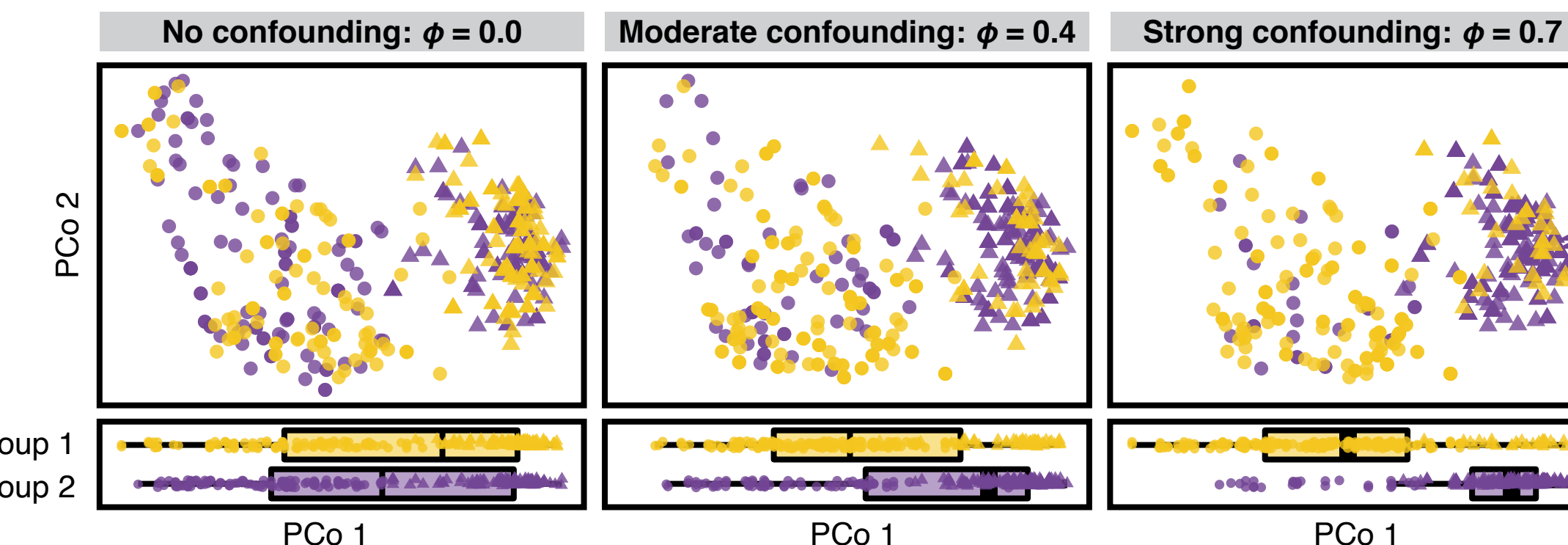
Linear models and the **Wilcoxon test** suffer the least from these issues, can be **adjusted for covariates**, and **should be preferred** over other statistical methods for robust differential abundance analysis of **microbiome data**

3. Main Findings and Implications

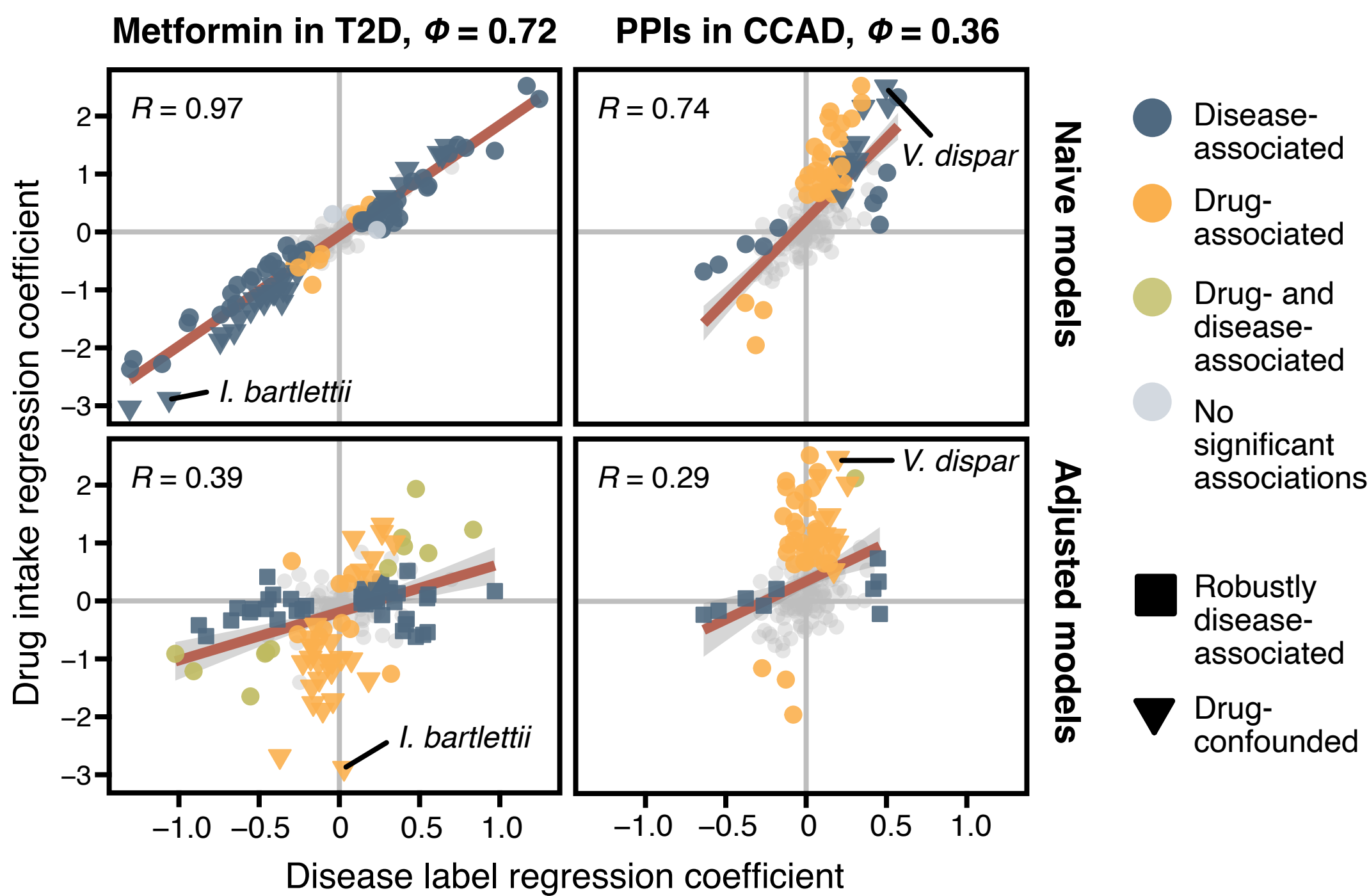
- ▶ Signal implantation, but not parametric simulations, can reproduce key characteristics of metagenomic data critical for robust method benchmarking



- ▶ Biased resampling produces simulated case-control groups aligned with a secondary variable to a pre-calibrated degree (below: study of origin, left: simulated confounder group)



- ▶ Linear mixed-effect models offer the most flexibility and scalability in their implementation, and are capable of disentangling drug- and disease-associated microbial features in real clinical data⁷



References

1) Zeevi et al., Personalized nutrition by prediction of glycemic responses. *Cell* (2015). 2) McMurdie and Holmes, Waste not, want not: why rarefying microbiome data is inadmissible. *PLoS Computational Biology* (2014). 3) Weiss et al., Normalization and microbial differential abundance strategies depend upon data characteristics. *Microbiome* (2017). 4) Hawinkel et al., A broken promise: microbiome differential abundance methods do not control the false discovery rate. *Briefings in Bioinformatics* (2019). 5) Ma et al., A statistical model for describing and simulating microbial community profiles. *bioRxiv* (2021). 6) Xie et al., Shotgun metagenomics of 250 adult twins reveals genetic and environmental impacts on the gut microbiome. *Cell Systems* (2016). 7) Forslund et al., Combinatorial, additive, and dose-dependent drug-microbiome associations. *Nature* (2021).