PREDICTION OF MALADAPTATION FROM ECOLOGICAL AND GENOMIC DATA USING GENOMIC OFFSETS

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ACRONYMS

- SNP single-nucleotide polymorphism
- QTL quantitative trait locus
- RONA risk of non-adaptednes
- RDA redundancy analysis
- FDR false-discovery ratio
- PCA principal component analysis
- LFMM latent factor mixed model
- GEA genotype × environment association