Node support efficacy in Congreve & Lamsdell matrices

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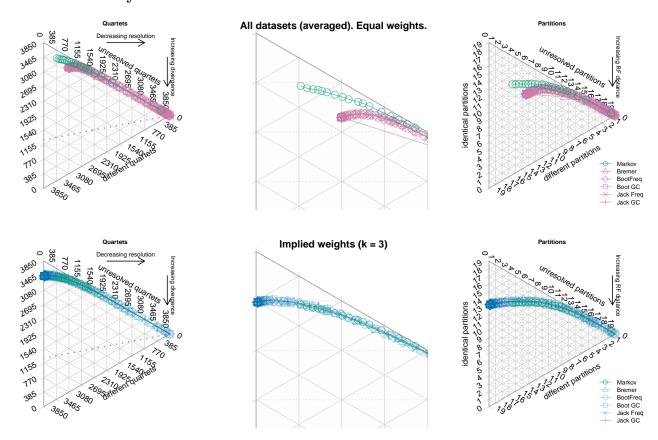
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This page depicts the analytical results of all 100 matrices generated by Congreve & Lamsdell [1] using a ternary plotting approach [2], with quartets and partitions used as distance metrics.

The most highly resolved tree is progressively reduced by collapsing nodes with a support value below an increasing threshold.

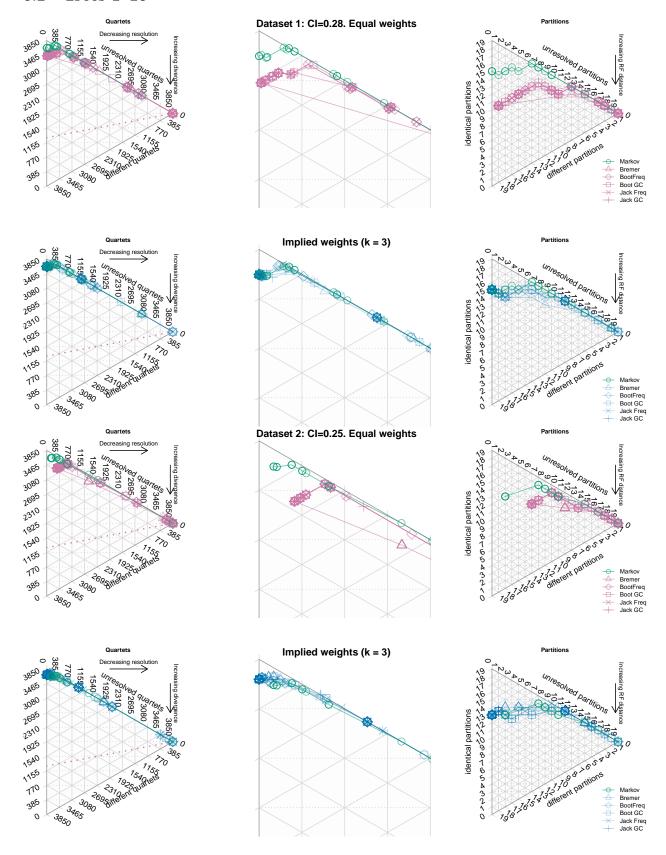
0.1 Summary

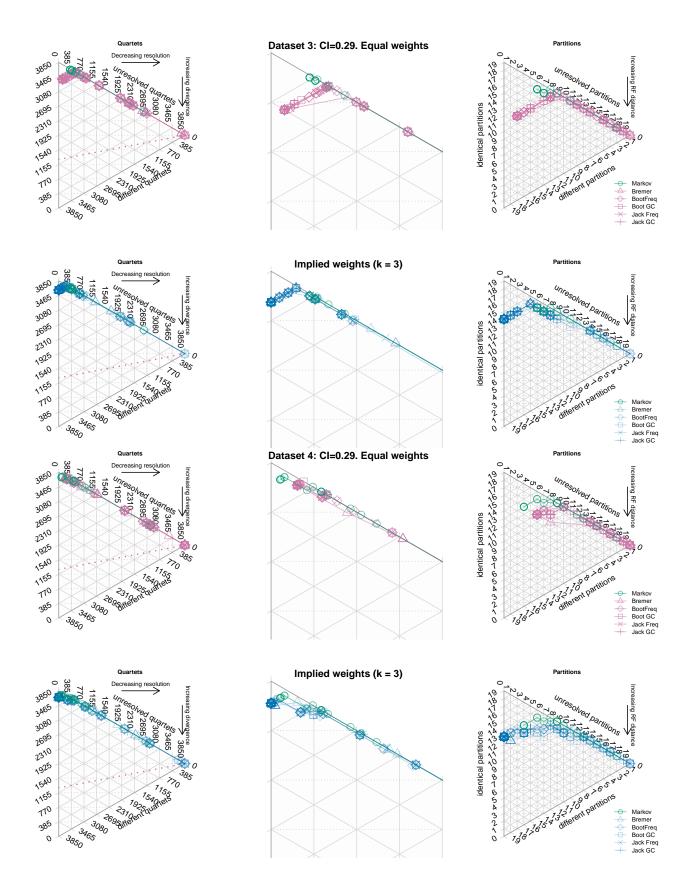


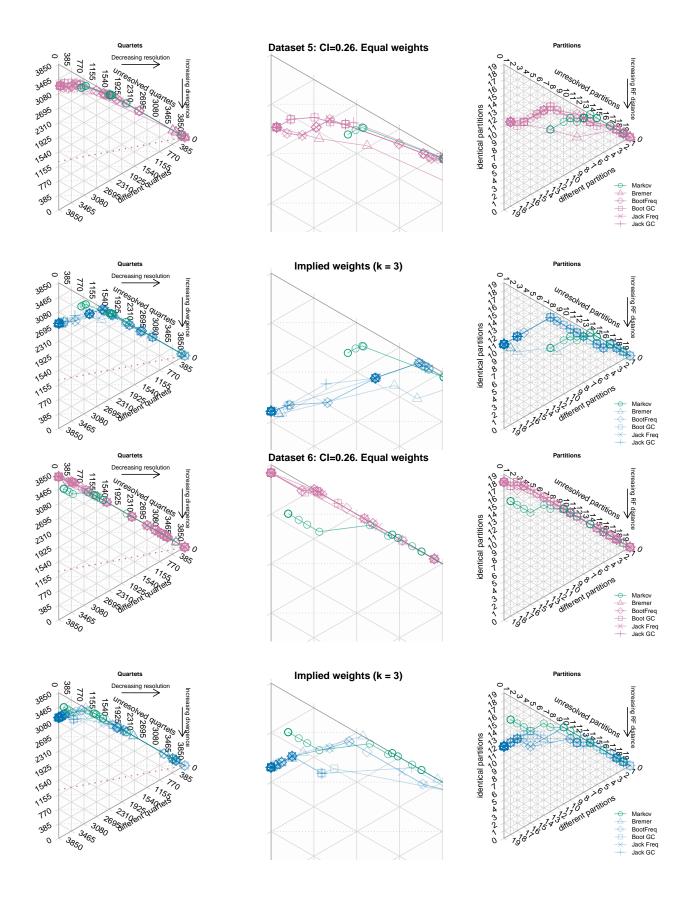
Though the Bootstrap GC metric systematically produces the lowest normalized tree distances (SD/MaxI), it is not significantly better than other methods. The following table reports P values that fail to reject the null hypothesis that the specified node support metric is equally good at ascribing incorrect nodes the lowest support values.

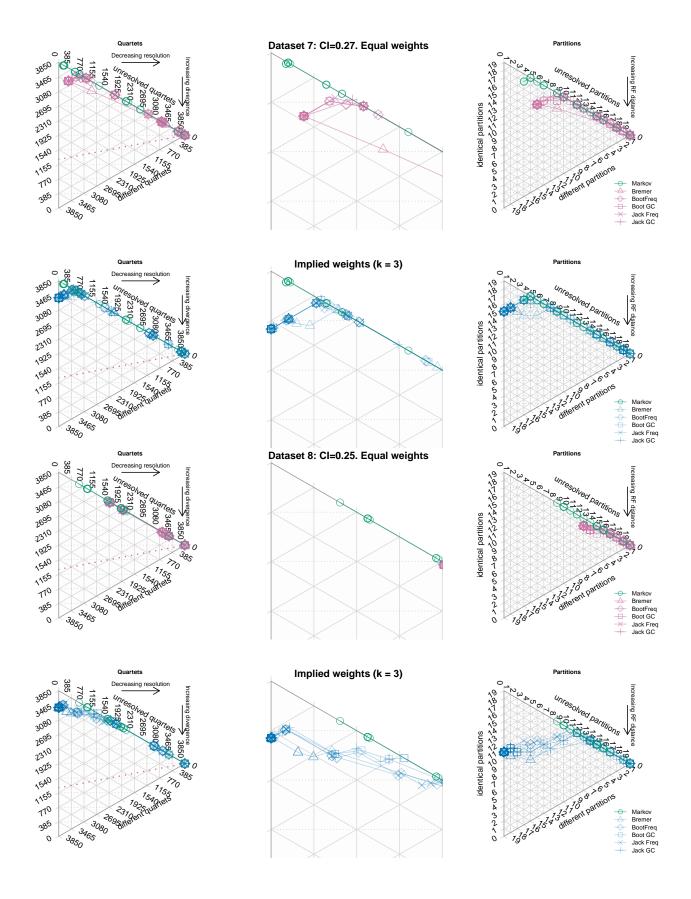
	eq	k1	k2	k3	k5	kX	kC
Bootstrap GC	1.0000000	1.0000000	1.0000000	1.0000000	1.0000000	1.0000000	1.0000000
Bootstrap Freq	0.9840650	0.9915189	0.9934145	0.9760370	0.9485781	0.9615921	0.9720185
Jackknife GC	0.9888177	0.9995312	0.9331647	0.9599348	0.9637166	0.9268107	0.9743023
Jackknife Freq	0.9942934	0.9554285	0.9509308	0.9839102	0.8639063	0.9408796	0.9723566
Bremer	0.4347916	0.3324499	0.5075762	0.4474386	0.3405988	0.2397081	0.8365157

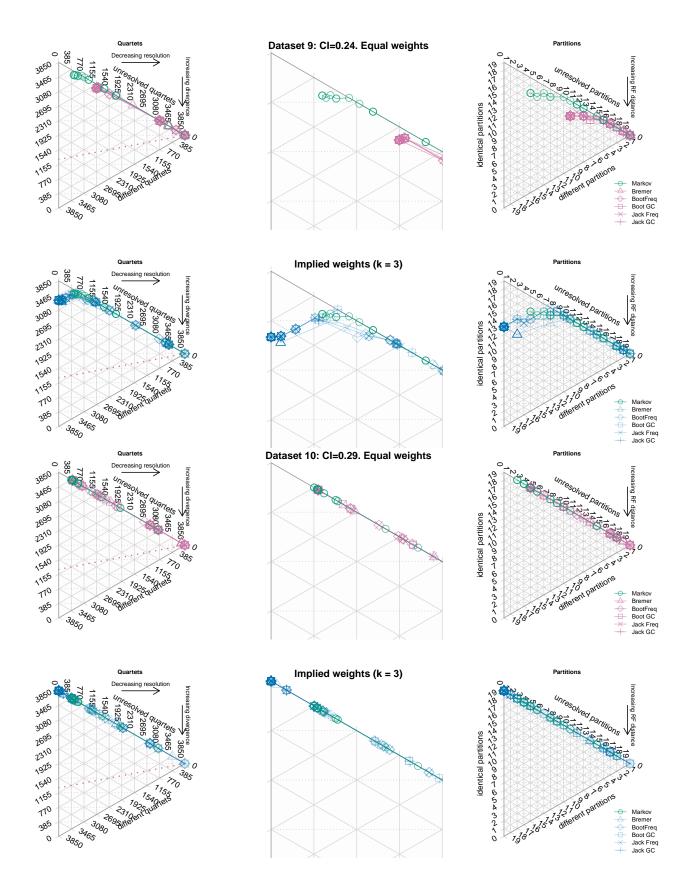
0.2 Trees 1-10



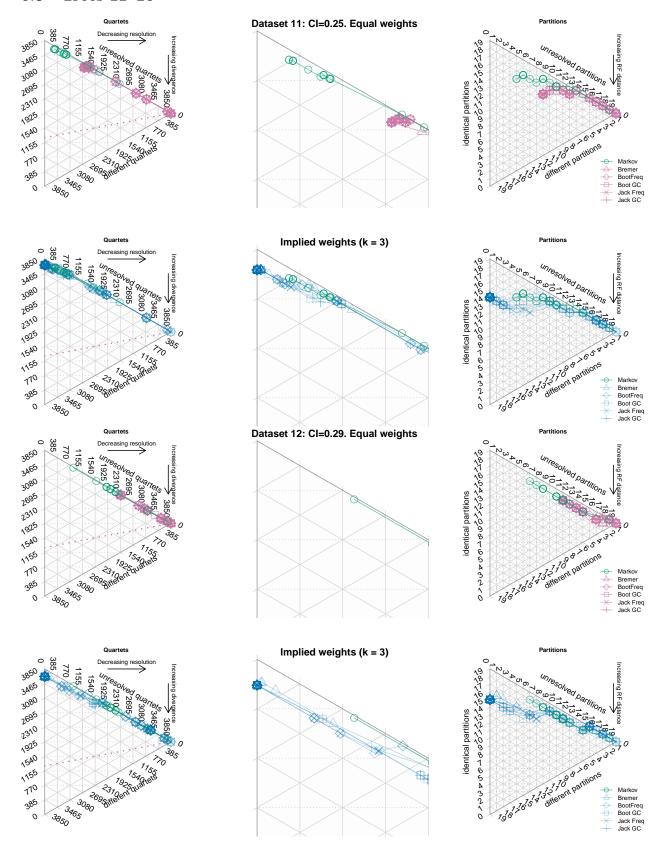


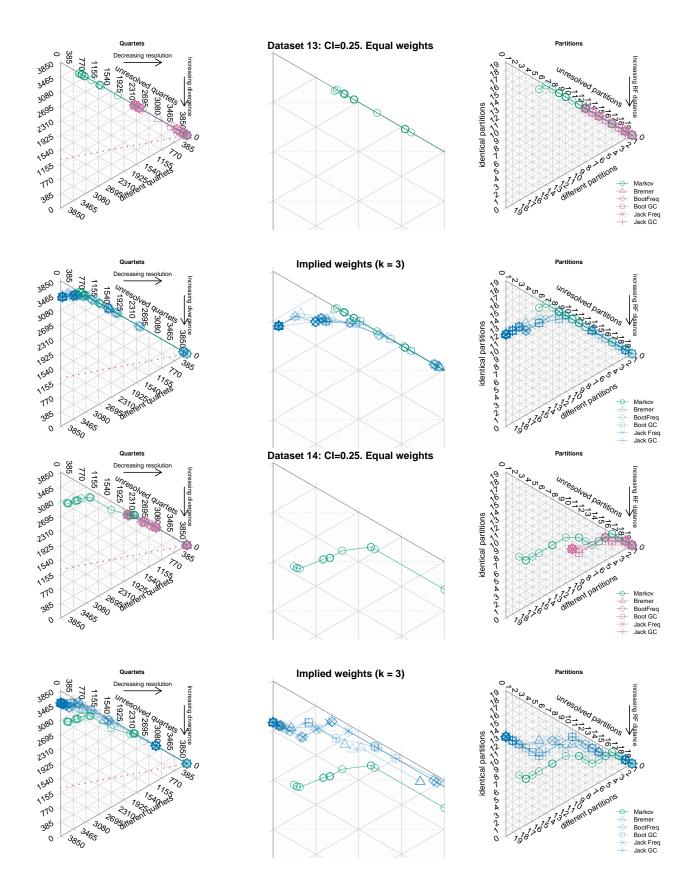


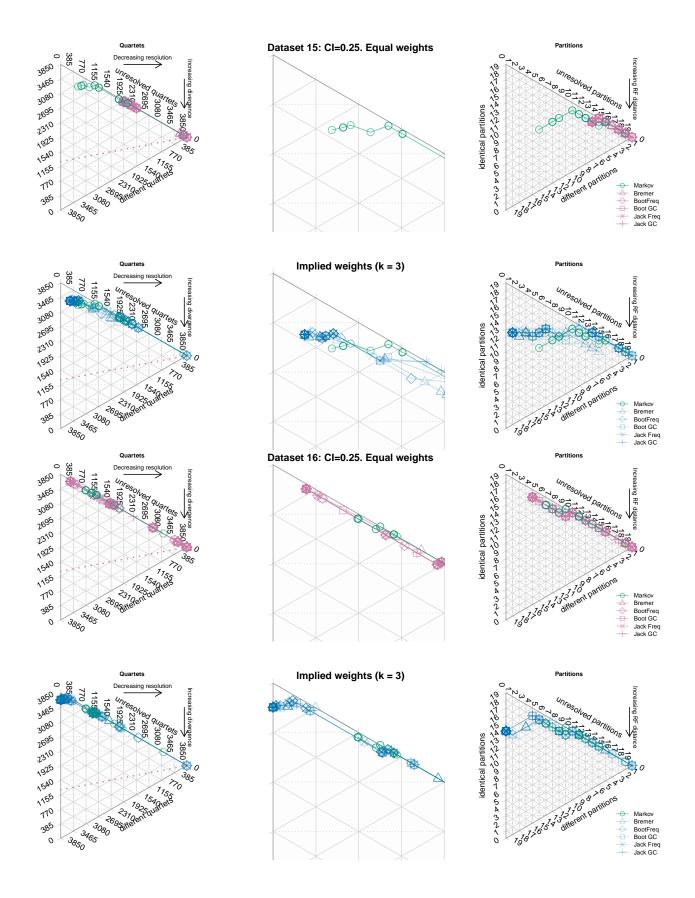


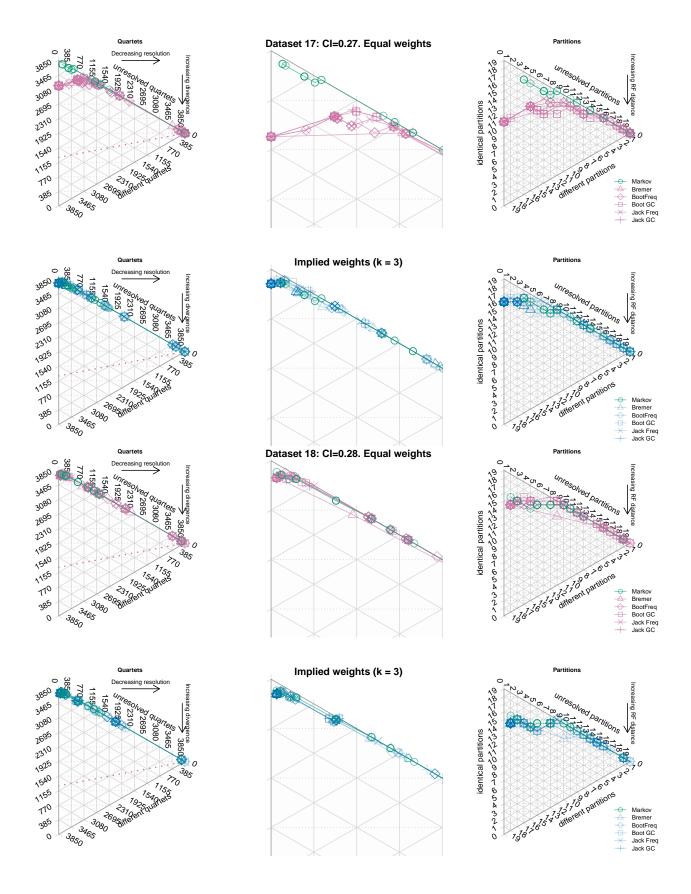


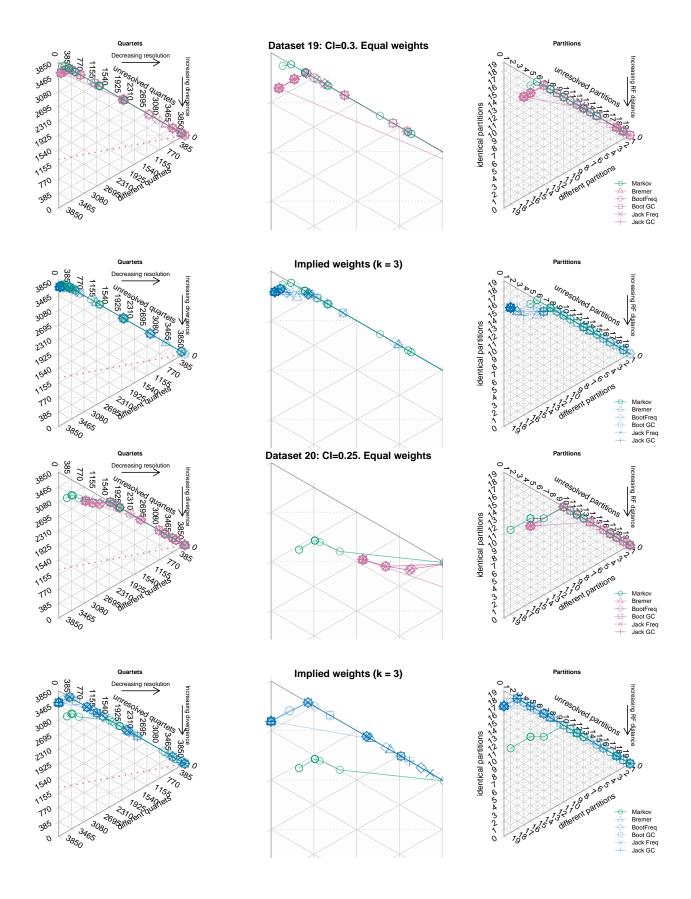
0.3 Trees 11-20



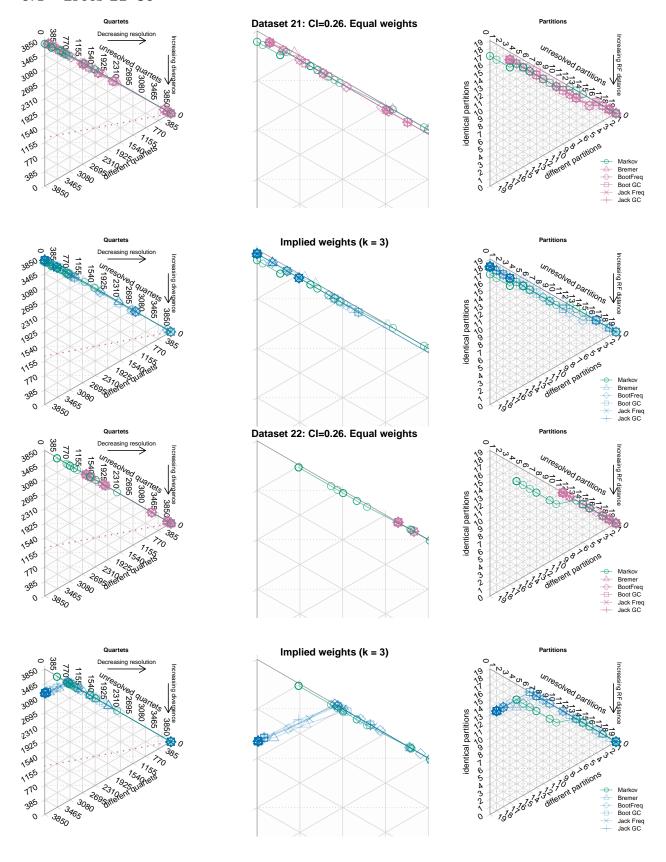


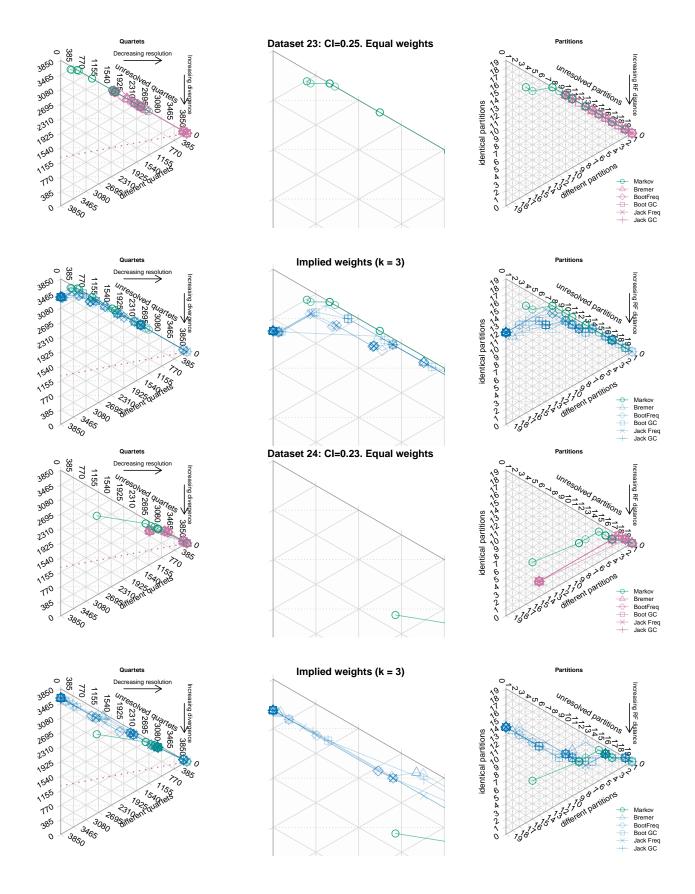


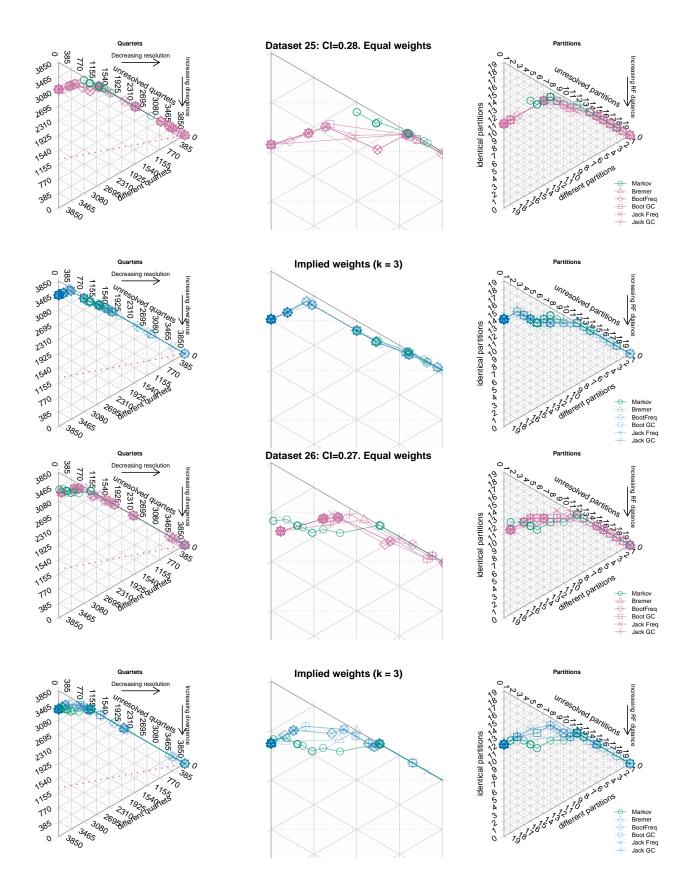


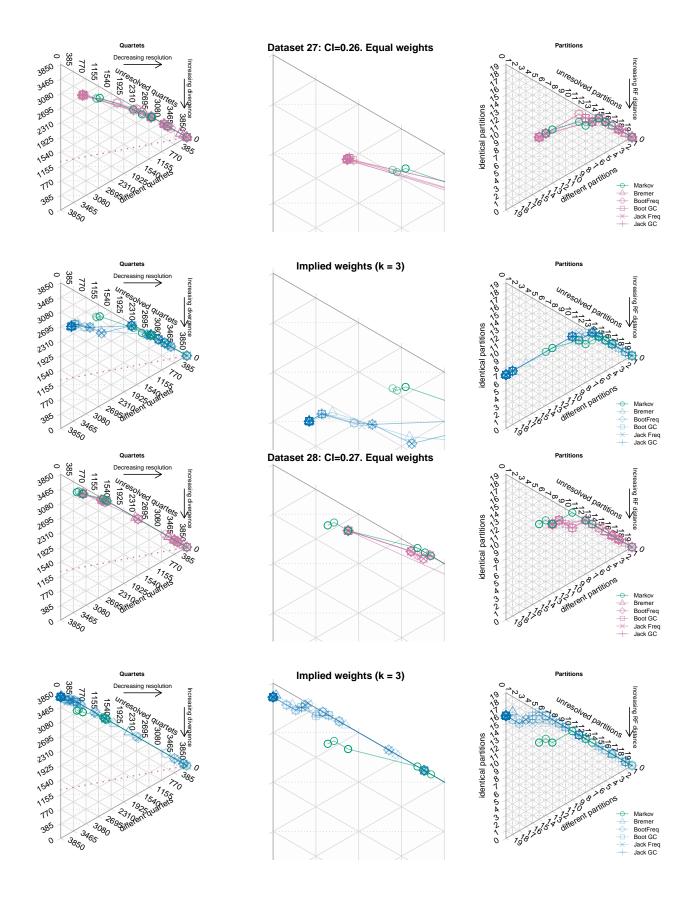


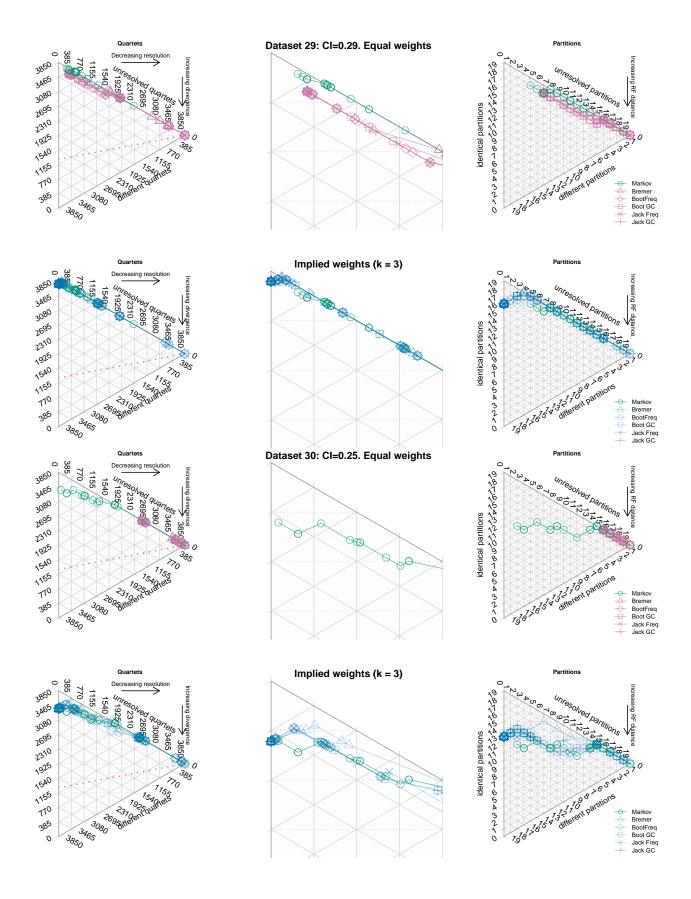
0.4 Trees 21-30



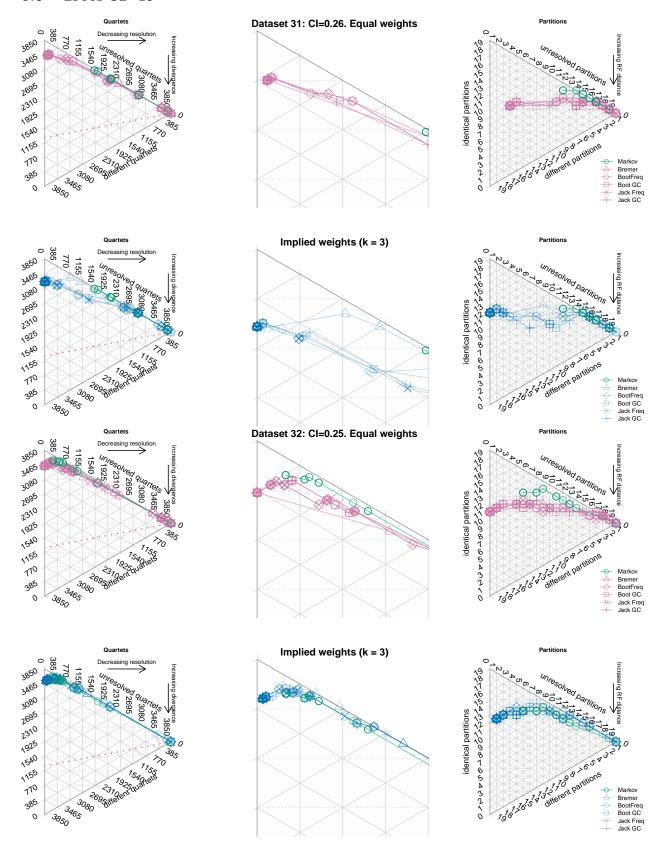


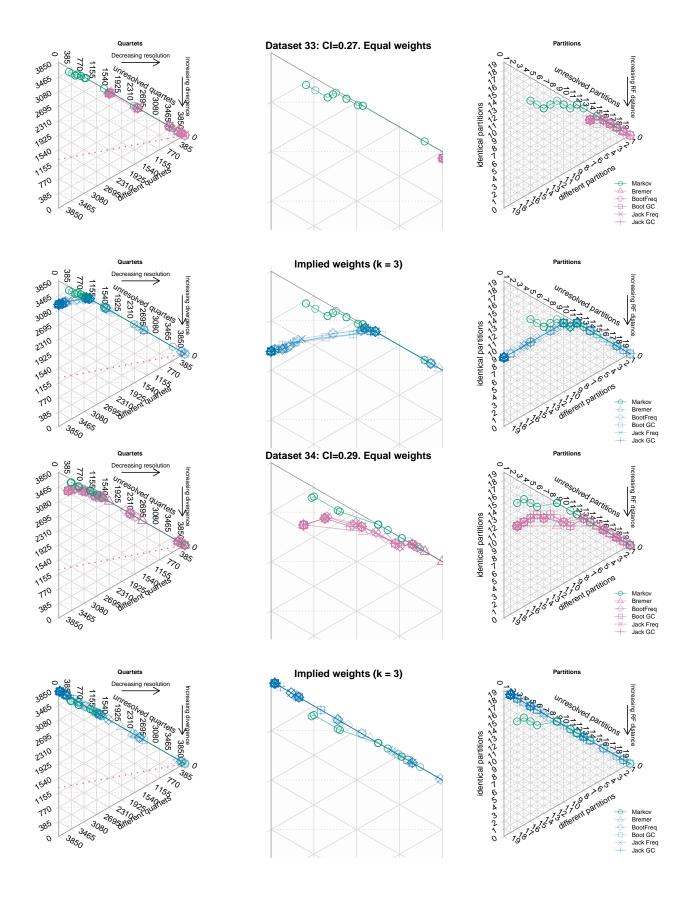


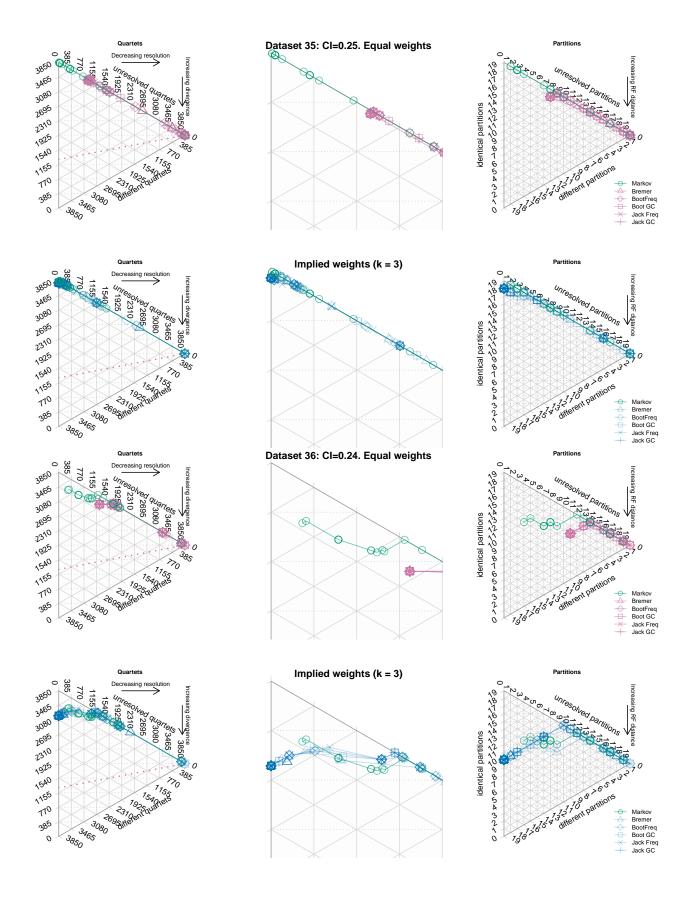


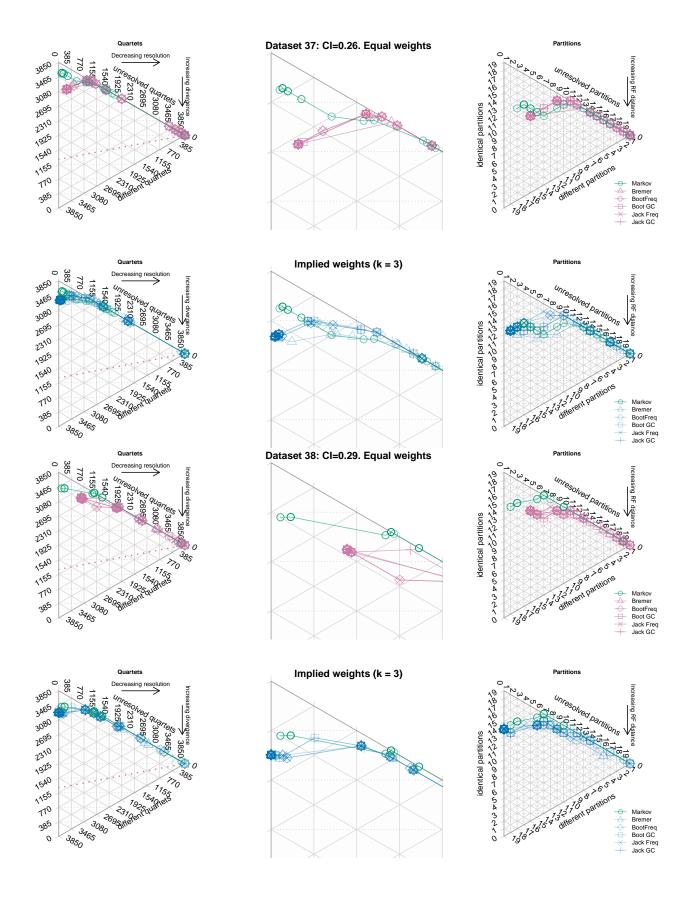


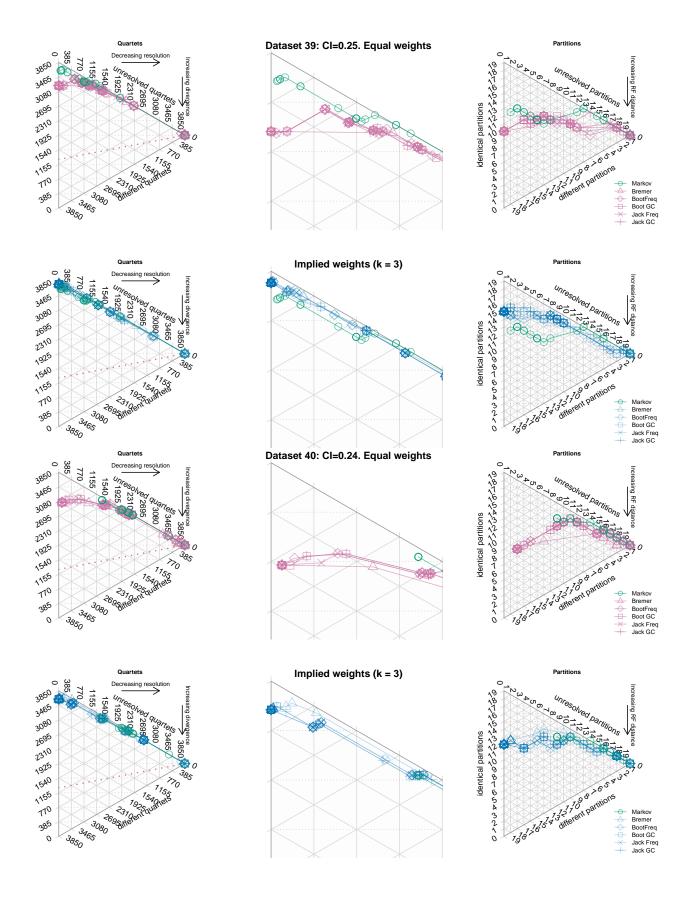
0.5 Trees 31-40



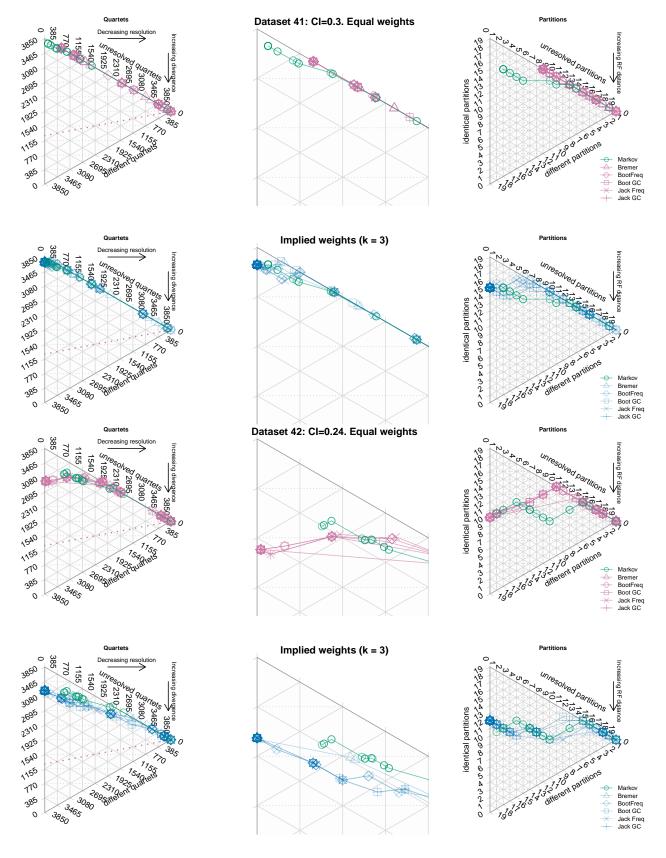


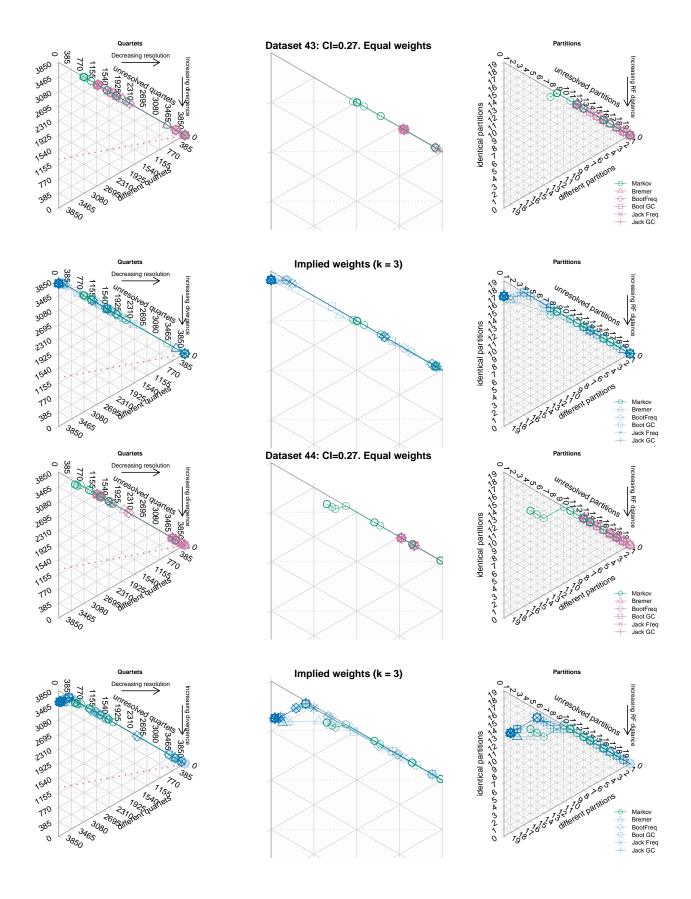


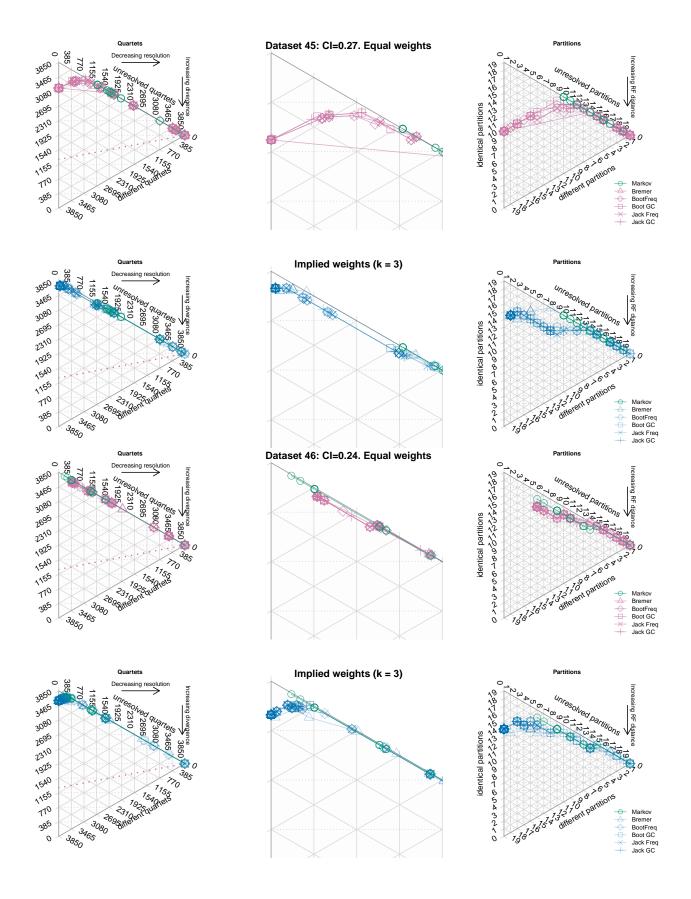


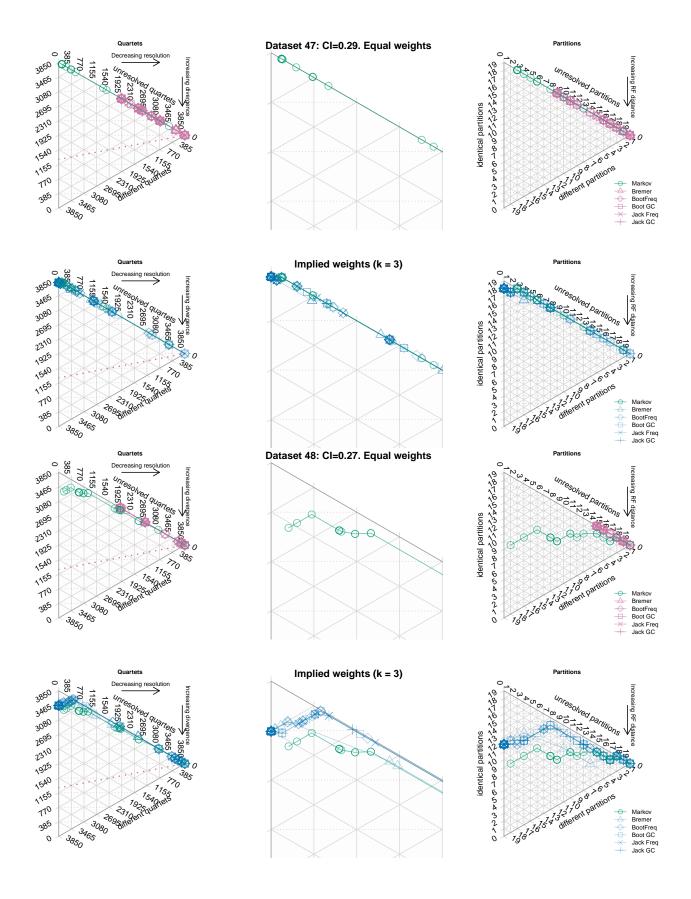


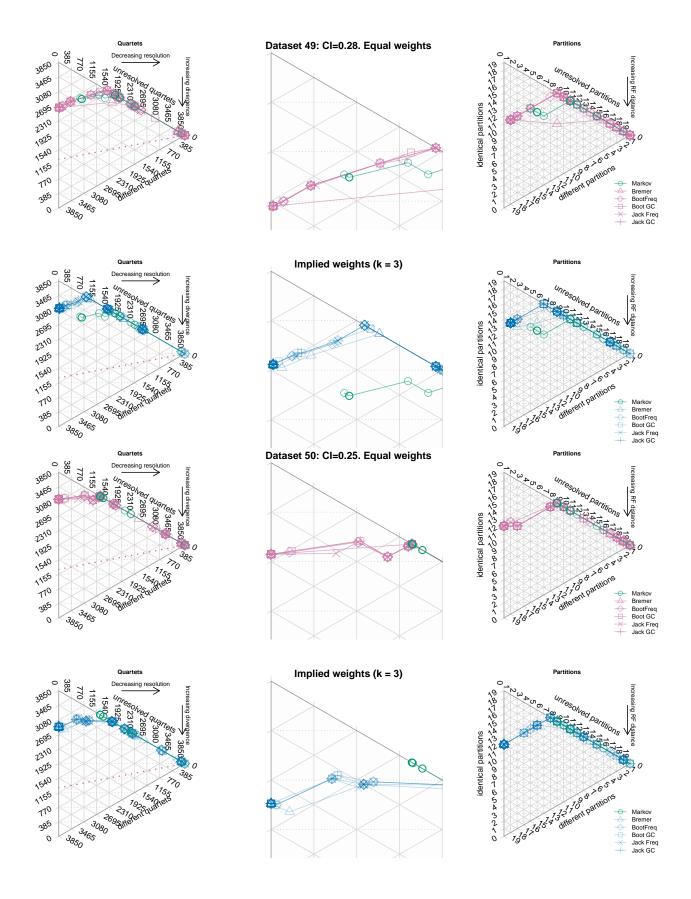
0.6 Trees 41-50



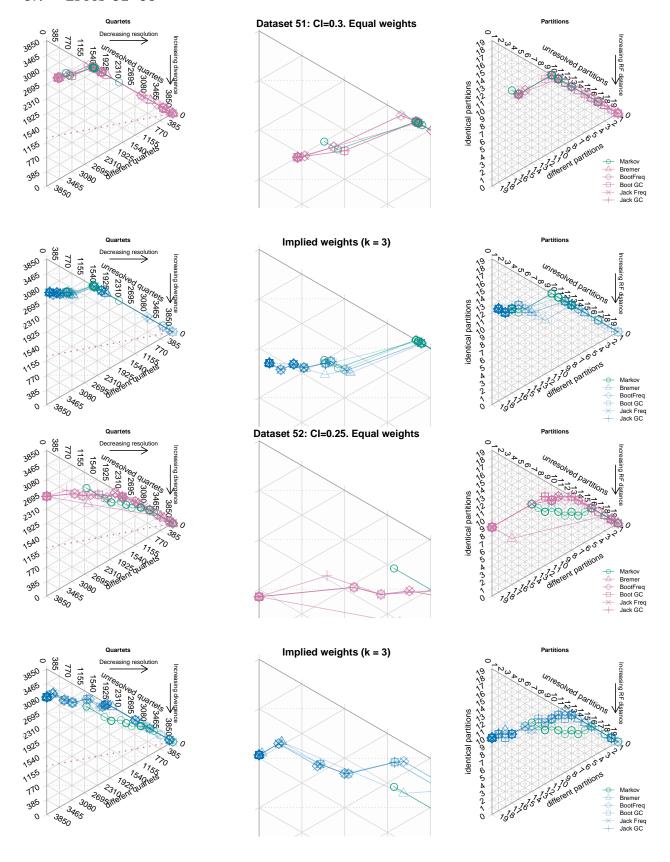


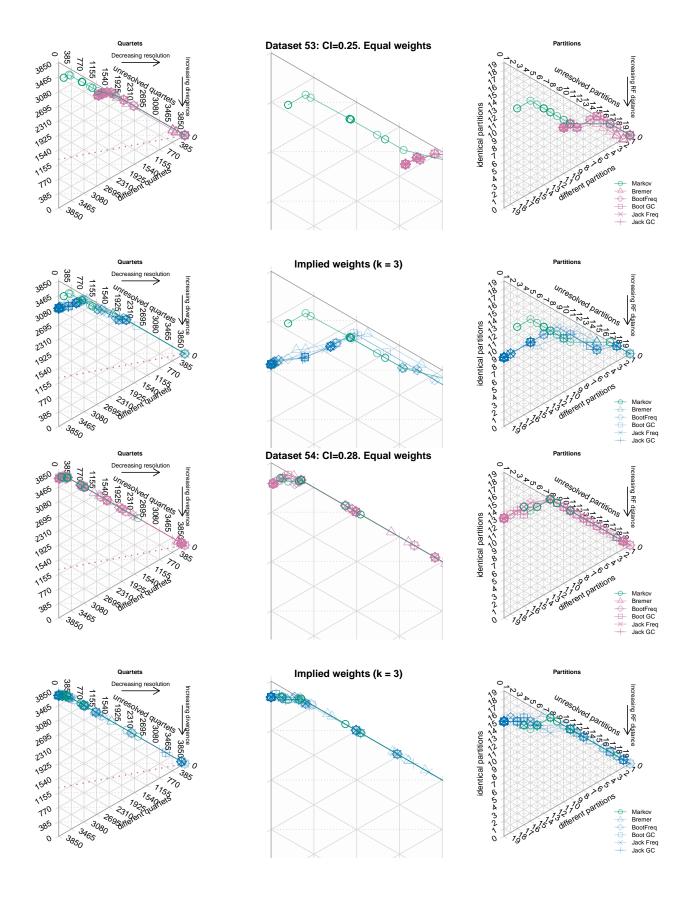


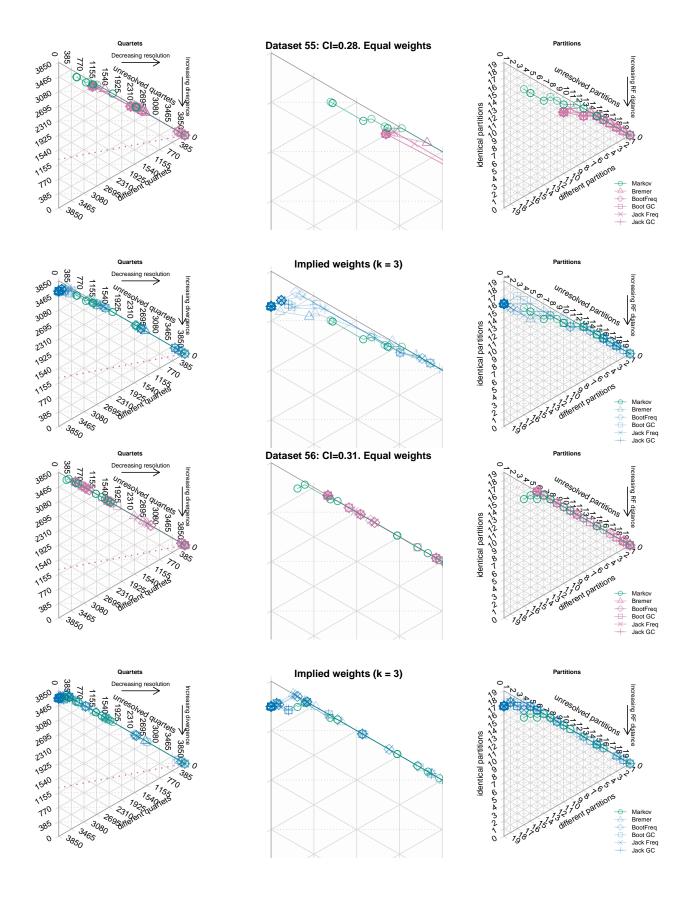


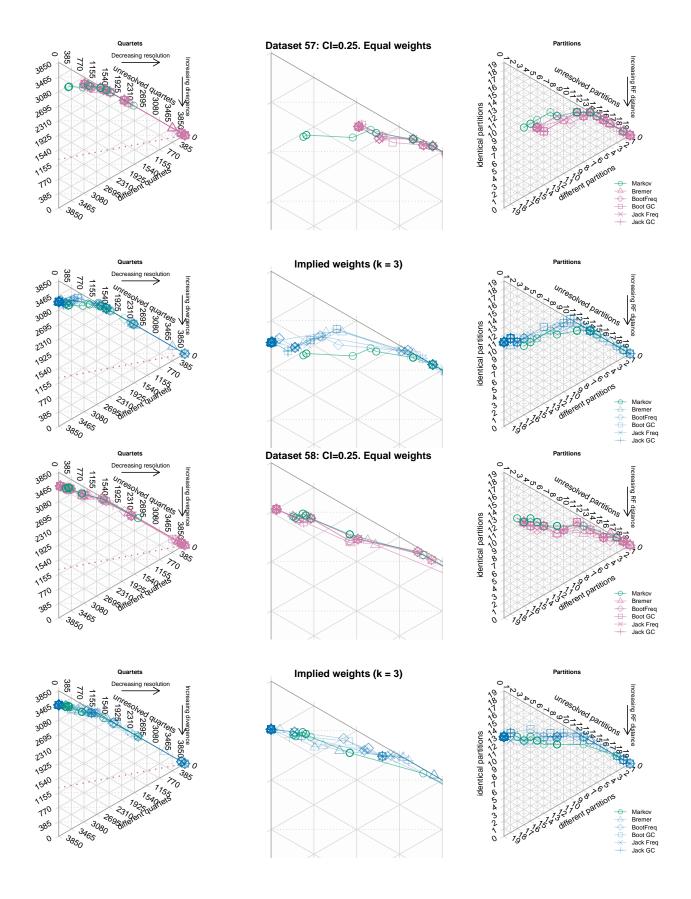


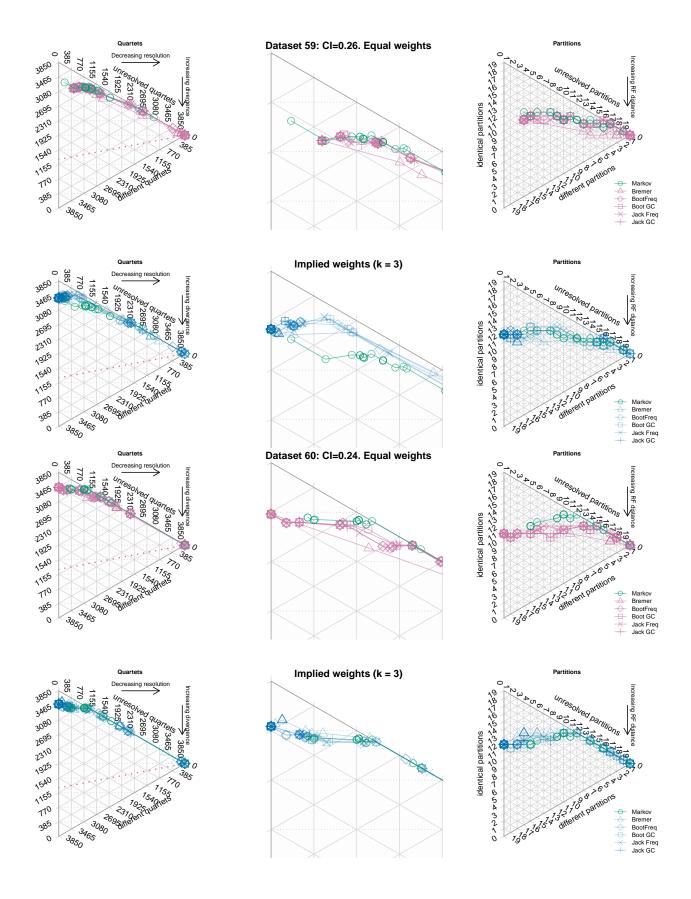
0.7 Trees 51-60



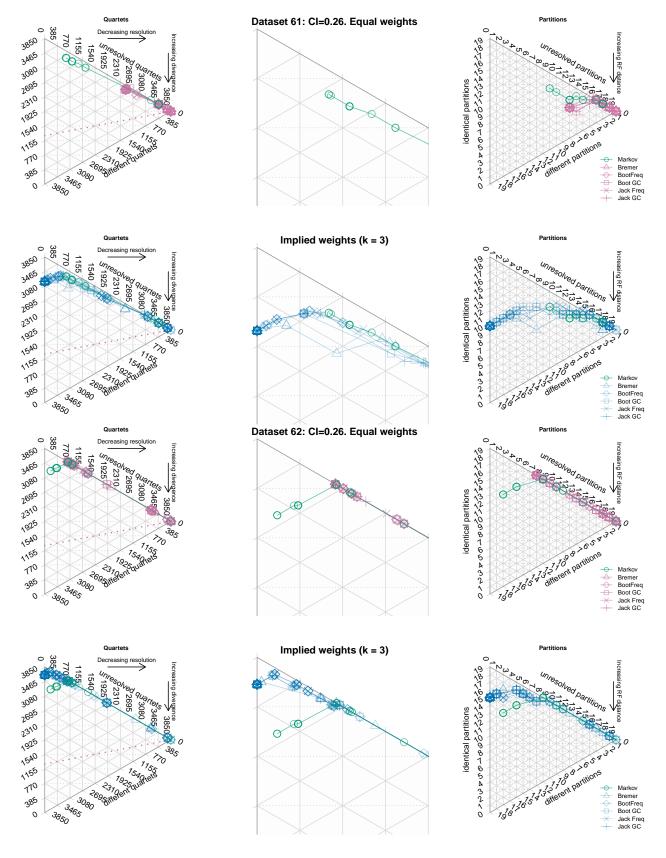


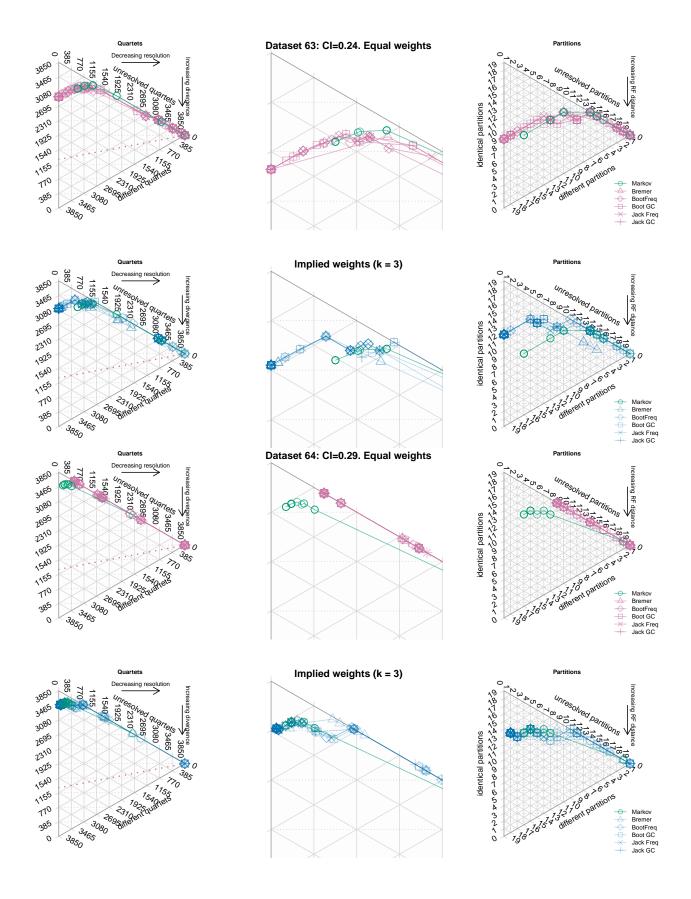


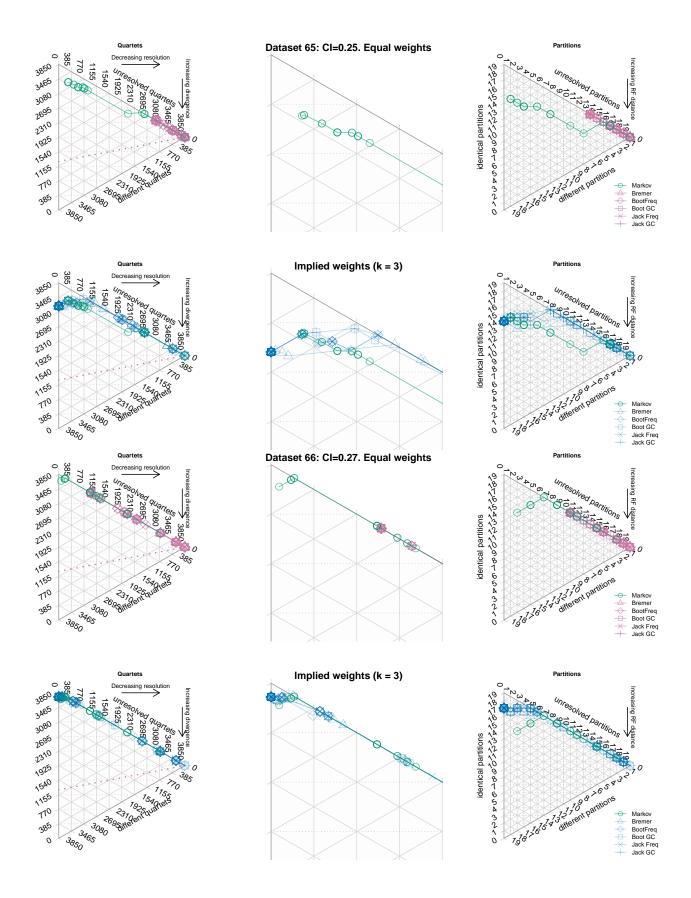


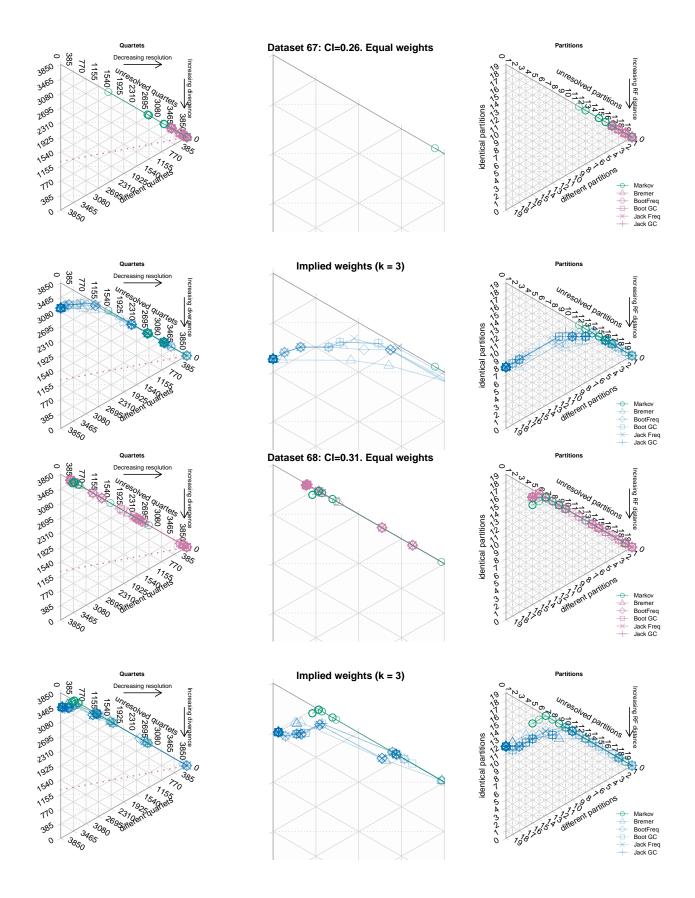


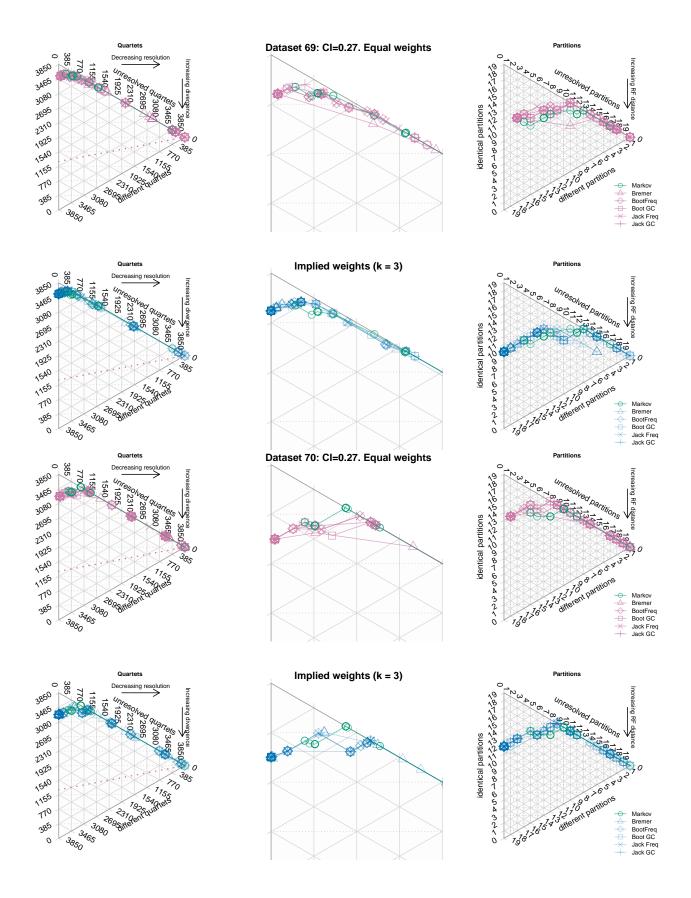
0.8 Trees 61-70



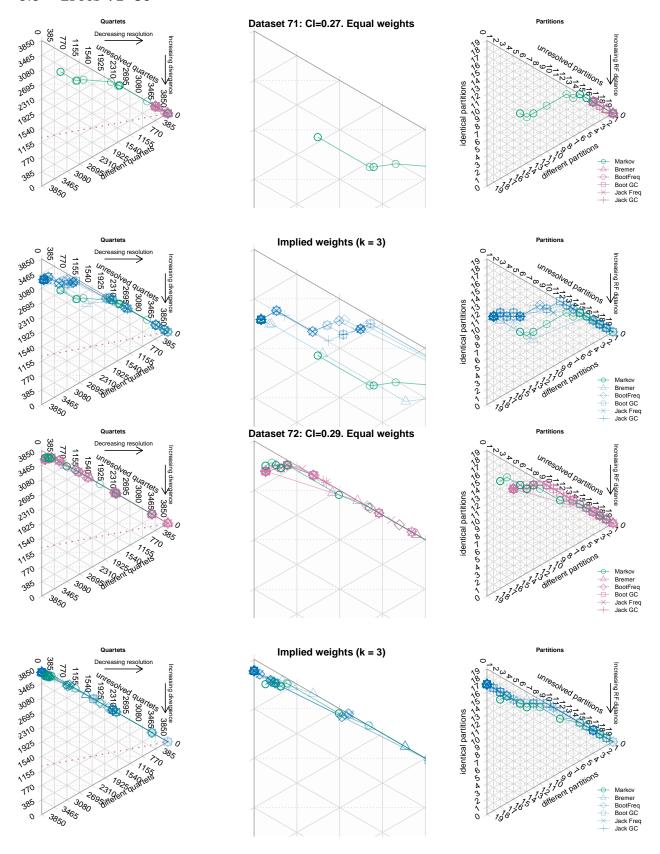


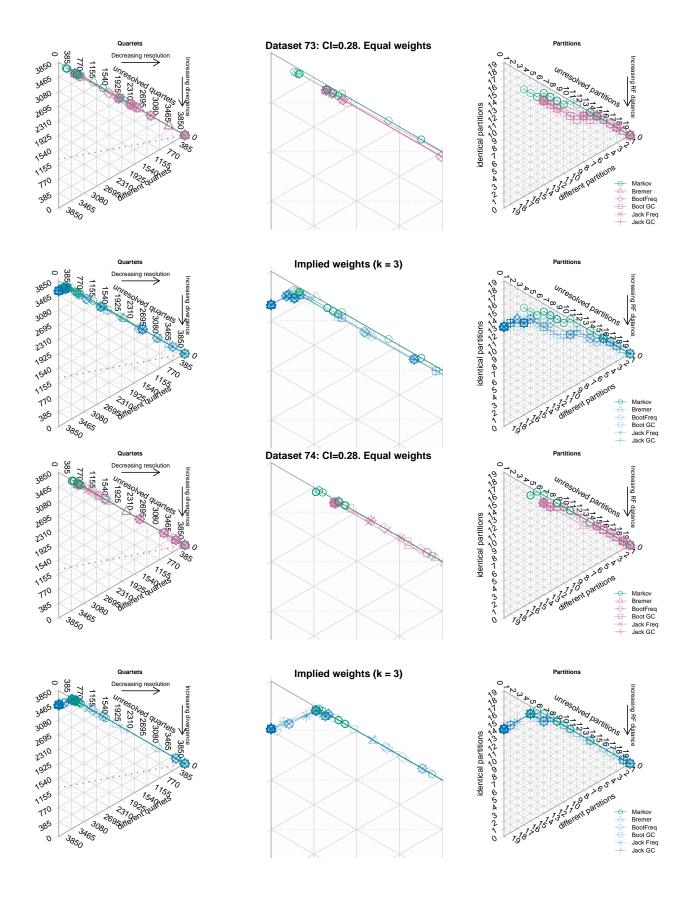


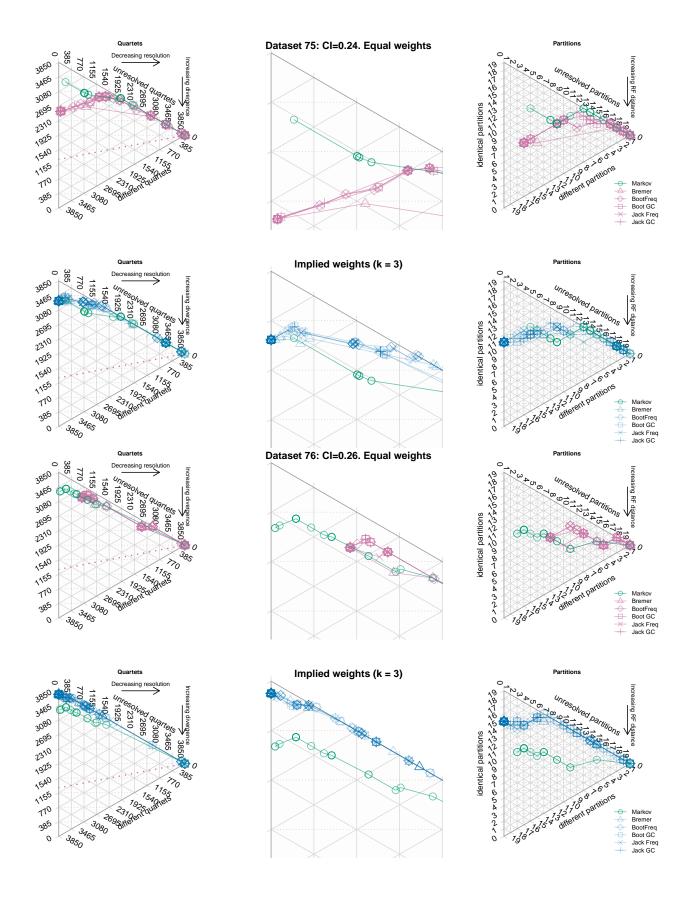


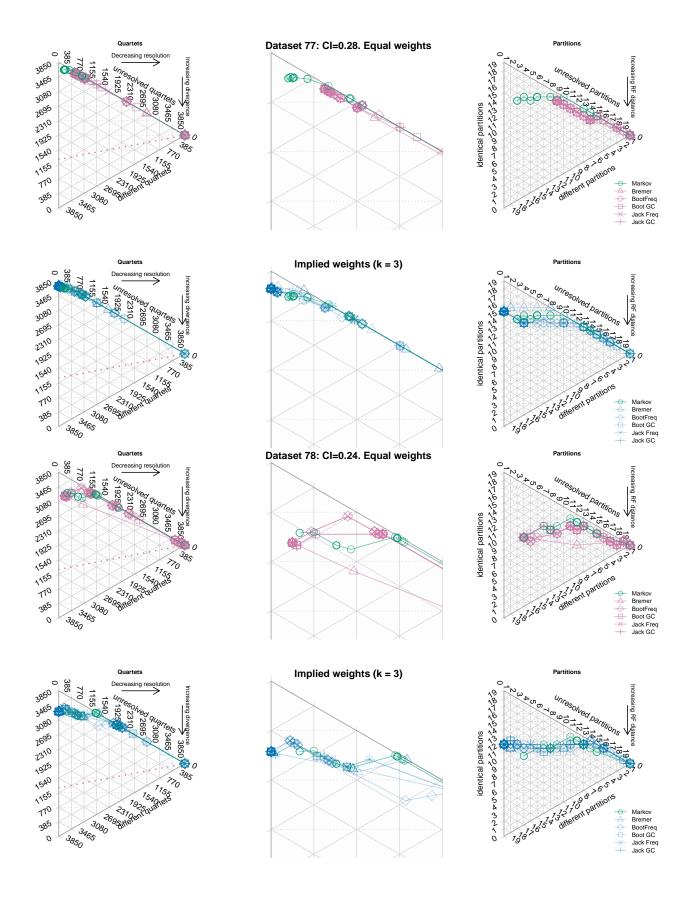


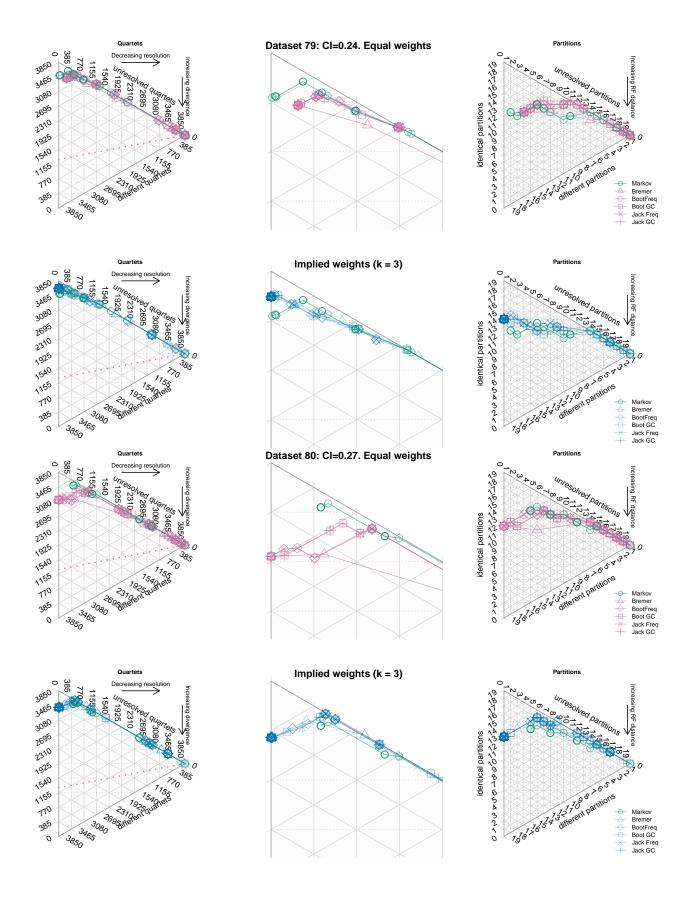
0.9 Trees 71-80



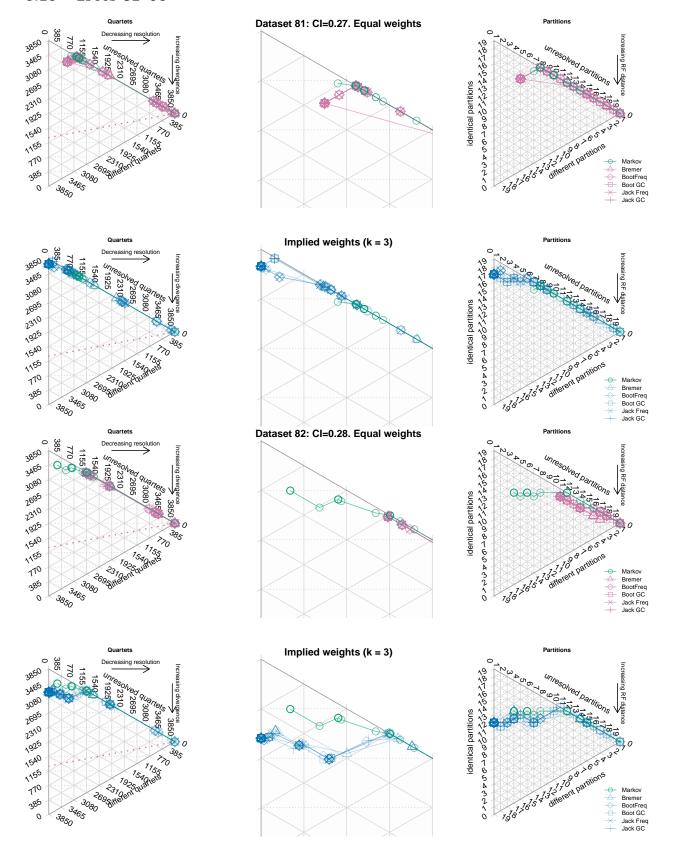


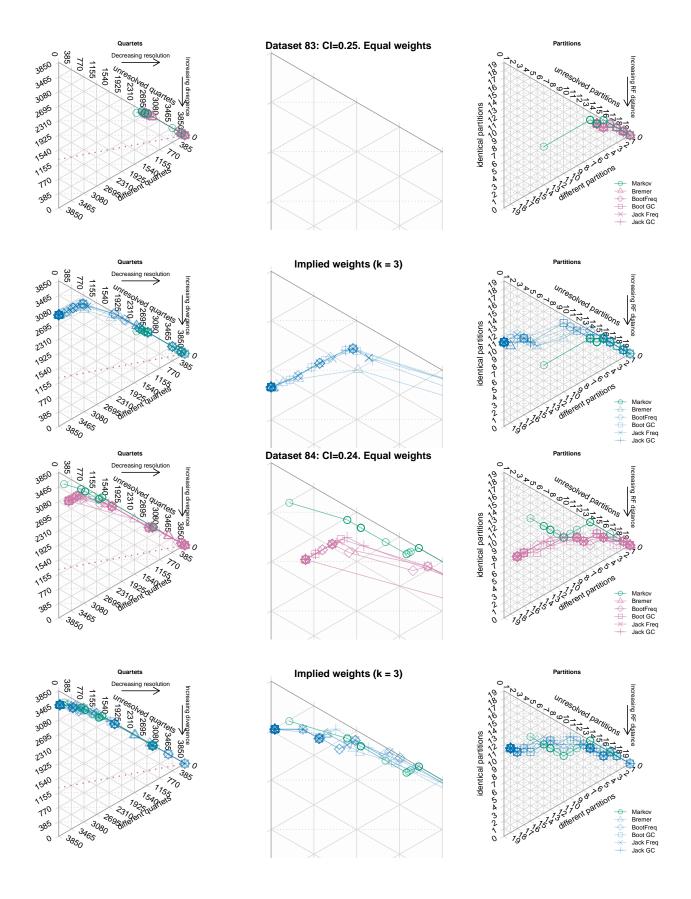


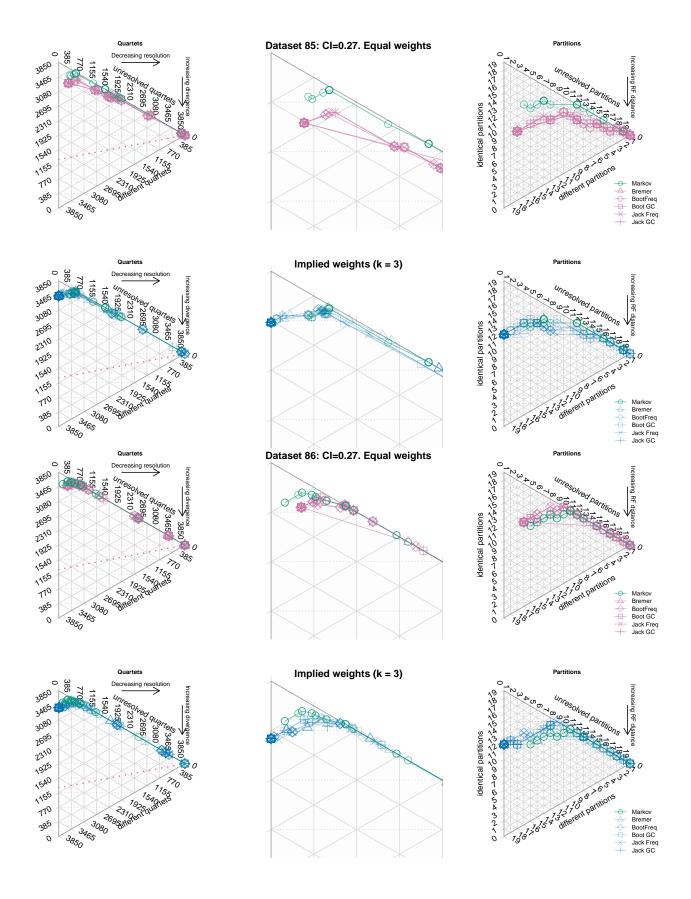


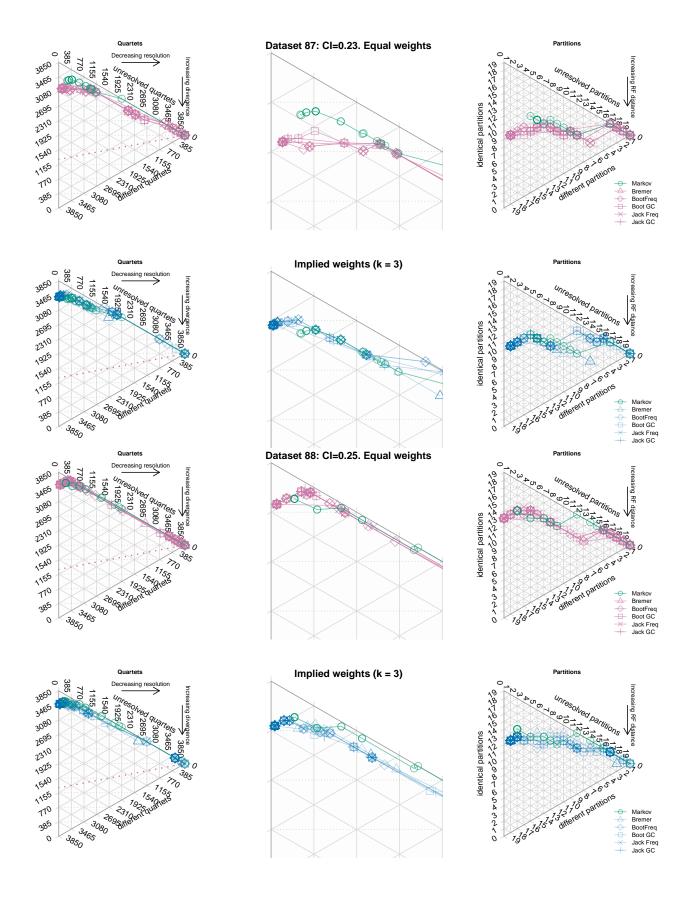


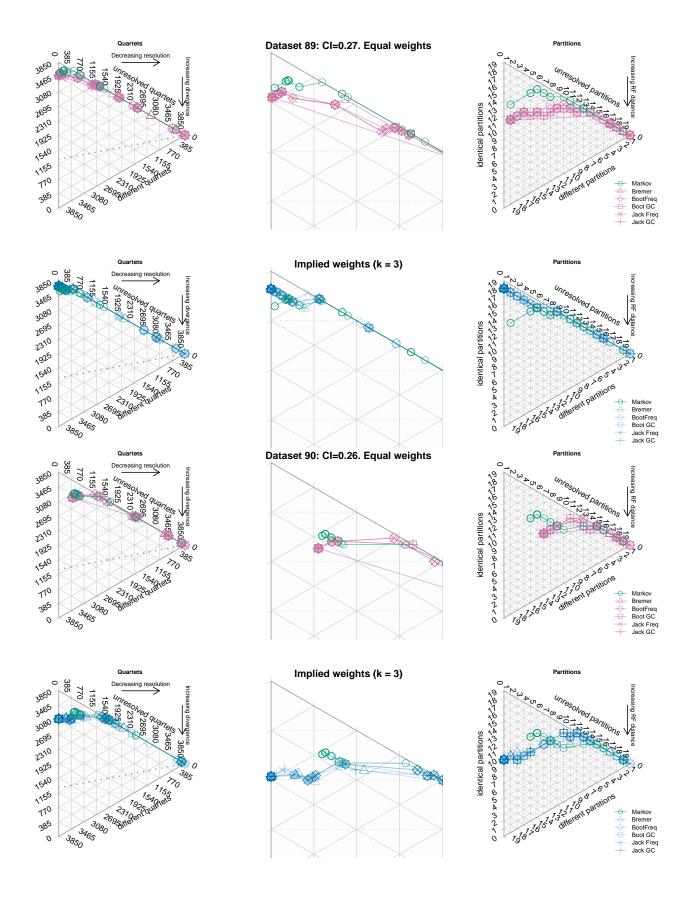
0.10 Trees 81-90



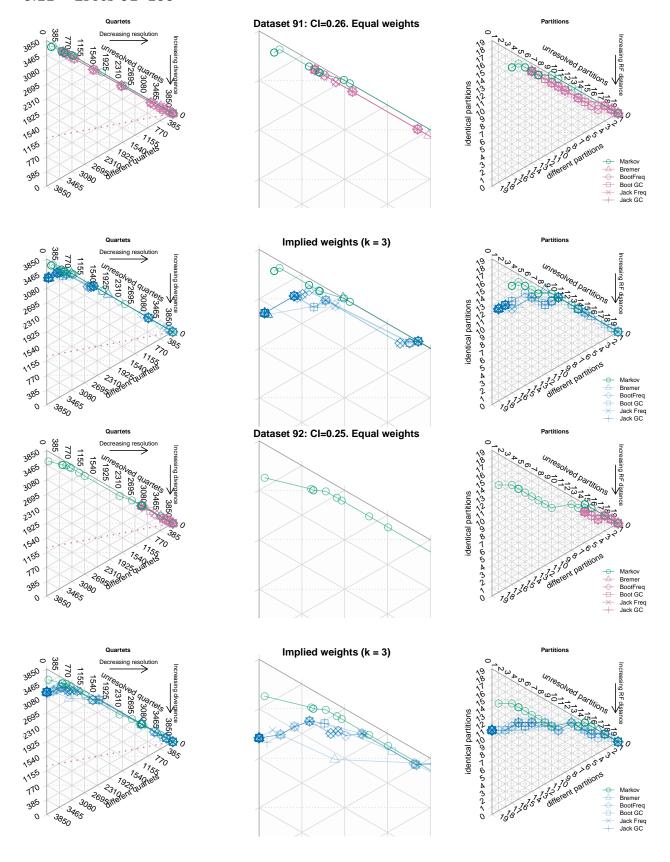


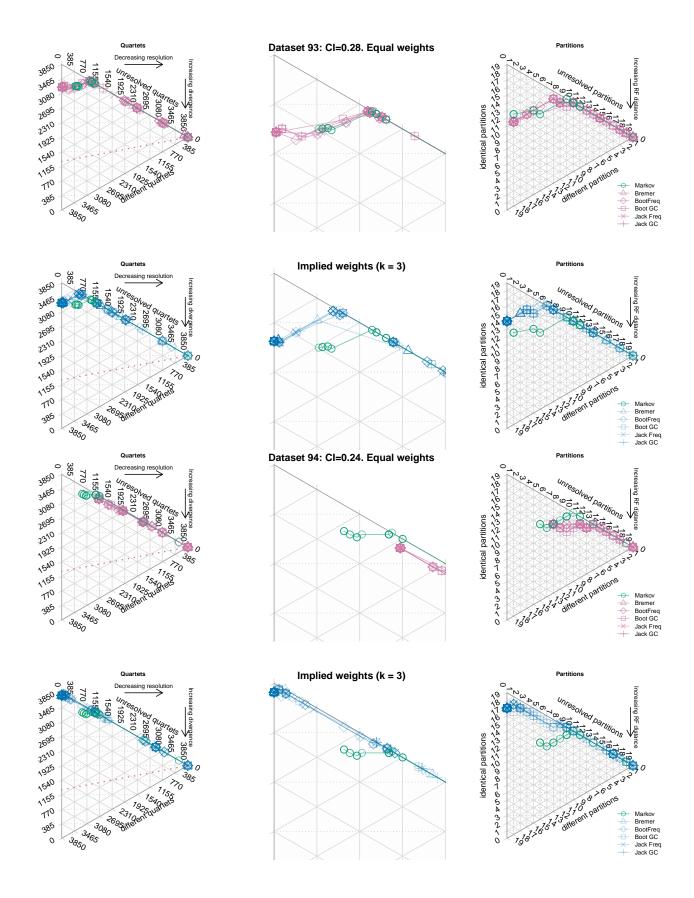


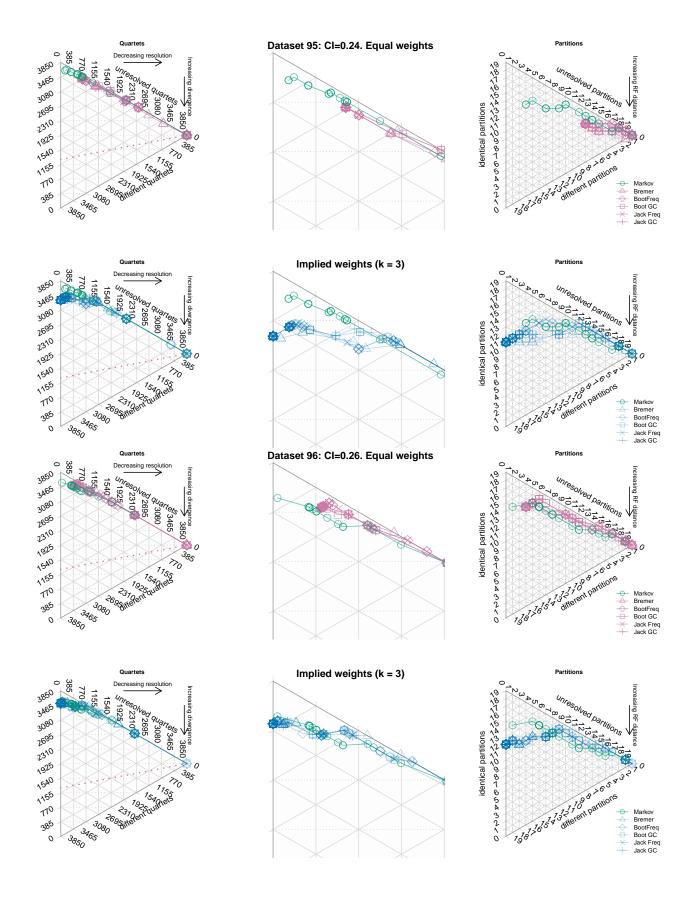


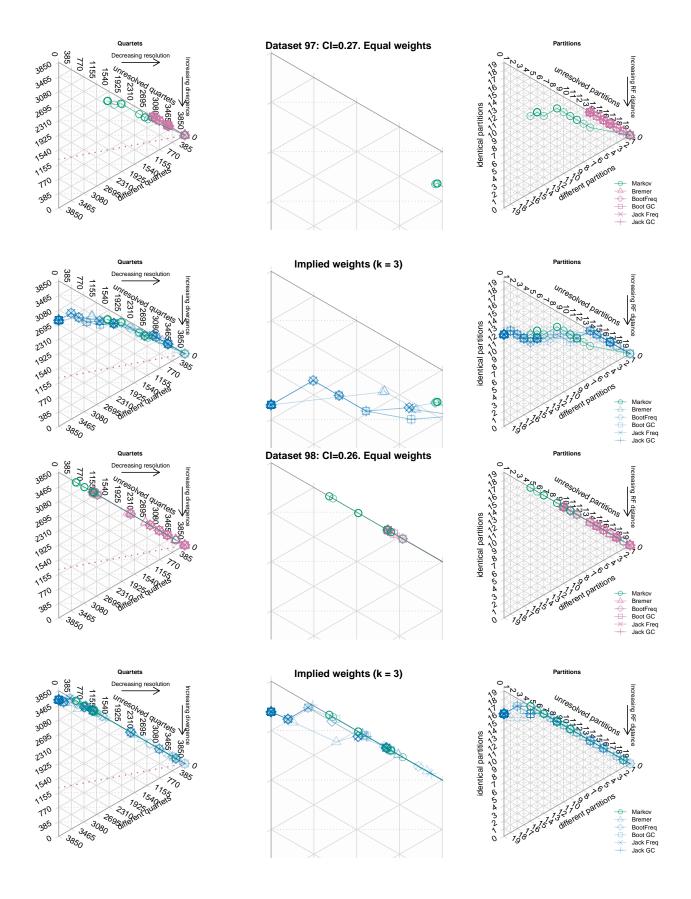


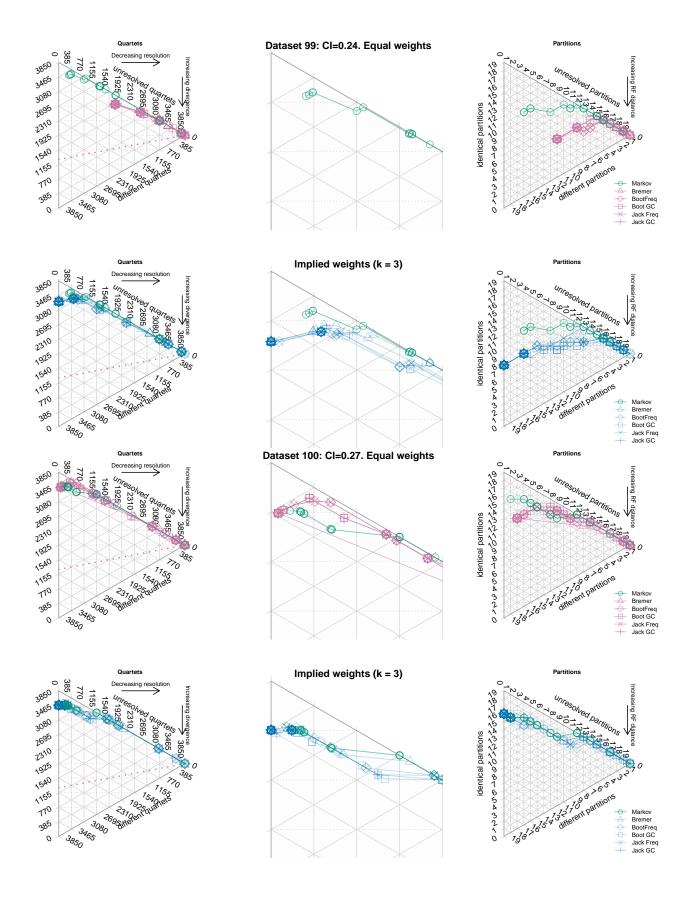
0.11 Trees 91–100











References

- 1. Congreve CR, Lamsdell JC. 2016 Implied weighting and its utility in palaeontological datasets: a study using modelled phylogenetic matrices. Palaeontology **59**, 447–465. (doi:10.1111/pala.12236)
- 2. Smith MR. 2019 Bayesian and parsimony approaches reconstruct informative trees from simulated morphological datasets. $Biology\ Letters\ {f 15},\ 20180632.$ (doi:10.1098/rsbl.2018.0632)