

# 1 **Neglecting model selection alters phylogenetic inference**

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## 5 **ABSTRACT**

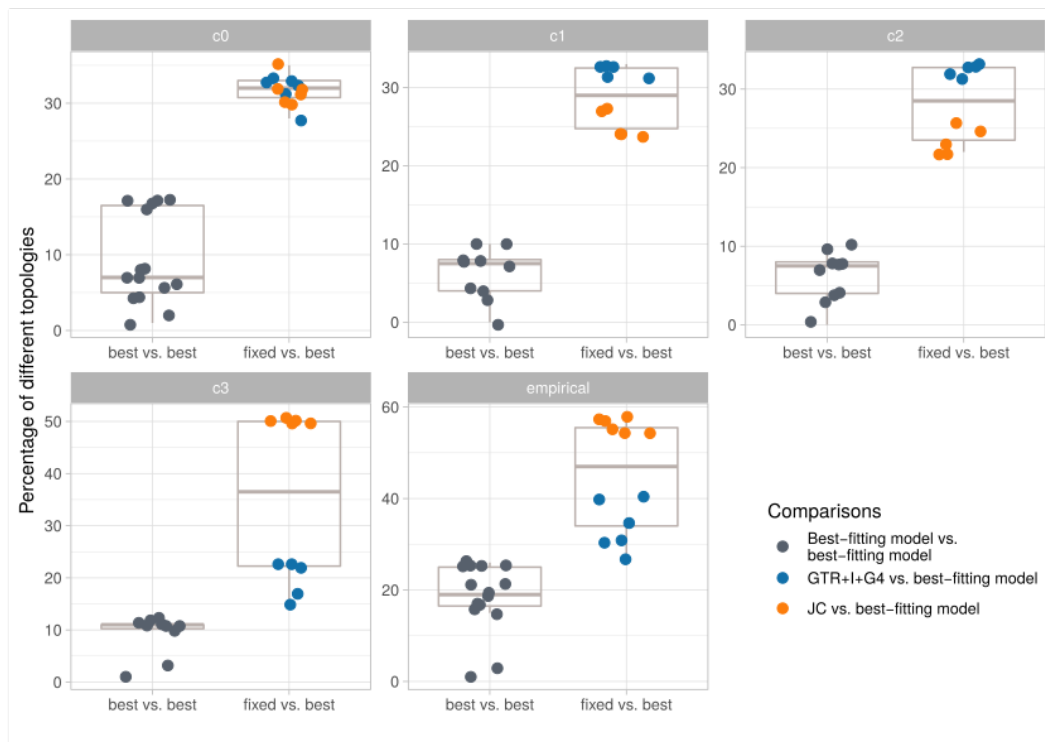
6 Molecular phylogenetics is a standard tool in modern biology that informs the evolutionary history  
7 of genes, organisms, and traits, and as such is important in a wide range of disciplines from  
8 medicine to palaeontology. Maximum likelihood phylogenetic reconstruction involves assumptions  
9 about the evolutionary processes that underlie the dataset to be analysed. These assumptions must  
10 be specified in forms of an evolutionary model, and a number of criteria may be used to identify the  
11 best-fitting from a plethora of available models of DNA evolution. Using many empirical and  
12 simulated nucleotide sequence alignments, Abadi et al.<sup>1</sup> have recently found that phylogenetic  
13 inferences using best models identified by six different model selection criteria are, on average,  
14 very similar to each other. They further claimed that using the model GTR+I+G4 without prior  
15 model-fitting results in similarly accurate phylogenetic estimates, and consequently that skipping  
16 model selection entirely has no negative impact on many phylogenetic applications. Focussing on  
17 this claim, I here revisit and re-analyse some of the data put forward by Abadi et al. I argue that  
18 while the presented analyses are sound, the results are misrepresented and in fact - in line with  
19 previous work - demonstrate that model selection consistently leads to different phylogenetic  
20 estimates compared with using fixed models.

## 21 **MAIN TEXT**

22 To assess the impact of different model selection criteria on phylogenetic accuracy, Abadi et al.  
23 acquired 7,200 nucleotide alignments from various databases (empirical dataset), from which three  
24 equal-sized datasets with increasing complexity were simulated under common nucleotide  
25 substitution models (datasets  $c_0$ – $c_2$ ). A smaller dataset was simulated under a codon substitution  
26 model ( $c_3$ ). For all alignments across datasets, maximum likelihood estimations were performed  
27 using the “best” models determined by six different selection criteria, and the fixed models  
28 GTR+I+G4 and JC. Differences in topologies were recorded using Robinson-Foulds distances or by  
29 simply counting non-identical trees. Abadi et al.’s claim that model selection is redundant stems  
30 mainly from three observations: 1) Trees inferred under different model selection criteria are often  
31 identical; 2) The proportion of correctly inferred topologies is highly similar between all model

32 selection criteria and fixed models; 3) Topological distances between trees inferred under any  
33 strategy are also very similar. However, as I will detail below, these observations are based on  
34 misleading or incomplete reporting of data.

35 Firstly, the authors compared pairwise topological differences between the trees inferred under six  
36 different model selection criteria and reported 0–26% incongruently inferred topologies, depending  
37 on the criteria assessed and the dataset employed (their Fig. 1). While it is debatable if this level of  
38 incongruence constitutes a “marginal impact on the resulting tree topology”<sup>1</sup>, the most striking trend  
39 from these comparisons was not addressed: Across all datasets, differences in topologies between  
40 any two best models are considerably lower than distances between a fixed model (GTR+I+G4 or  
41 JC) and a best model (Fig 1.). Consistently, all model selection criteria result in very similar trees,  
42 which however are fairly dissimilar to trees reconstructed without prior model selection. While  
43 these comparisons do not take “accuracy” into account, they are compatible with previous studies  
44 finding that any form of model selection results in more accurate topologies compared with using a  
45 fixed model<sup>2,3</sup>.

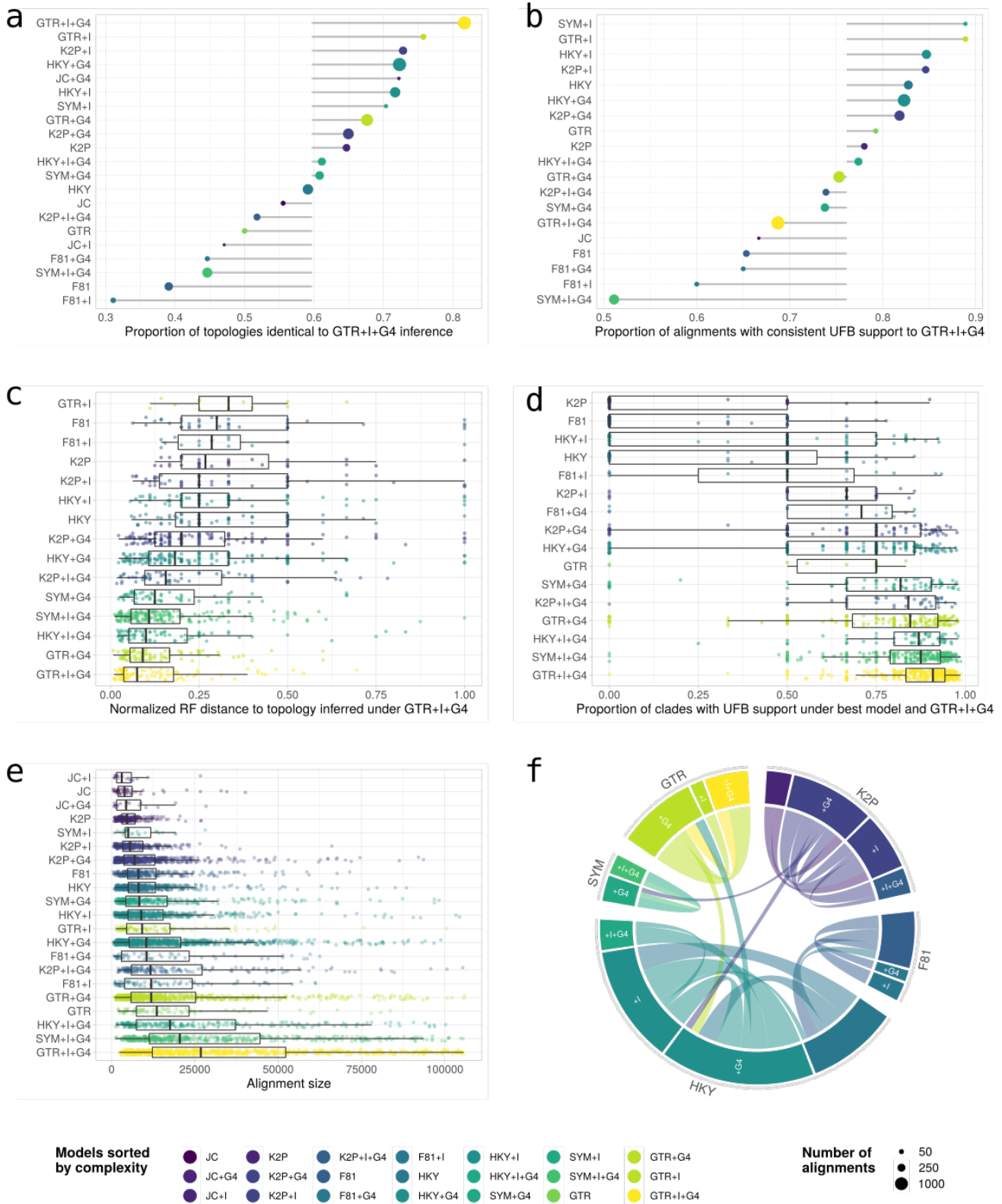


**Fig. 1** Pairwise comparisons between topologies inferred after model selection or a fixed model. The percentage of differently inferred topologies is plotted, grouped by comparisons between best models inferred by a model selection criterion and comparisons between a best model and a fixed model. Each plotted point represents one comparison, and the panels correspond to the different datasets. All data taken from Fig. 1 in Abadi et al.<sup>1</sup>.

46 Secondly, the authors counted the number of trees inferred with best, fixed, and true models that are  
47 identical to the “true tree”, and found that on average ~50% of trees are correctly inferred by any  
48 model or criterion (their Table 2). This representation is problematic, as it does not account for  
49 differences in incorrectly inferred trees, and more importantly, averages over all true models. While  
50 on average the proportion of correctly inferred trees may be similar, it is unclear if the similarities  
51 are consistent across all 7,200 alignments, or if certain selection criteria perform better or worse  
52 under certain alignment properties. To address this issue, I have re-analysed the empirical dataset.  
53 Maximum likelihood tree reconstructions were performed for all alignments under GTR+I+G4 and  
54 under a best model determined using BIC. Both approaches resulted in identical topologies for  
55 ~60% of the alignments, which is in agreement with what Abadi et al. found for the empirical  
56 dataset (their Fig. 1b). However, the proportion of identically inferred topologies strongly depended  
57 on the substitution model that best describes the data, and showed a large variation (~30% – >80%,  
58 Fig. 2a). Trees from alignments that were best described by simpler models (such as JC and F81)  
59 were generally less well recovered by GTR+I+G4 (the most complex of the 24 models  
60 investigated), although this trend was not very pronounced (Fig. 2A). This suggests that the  
61 characteristics of an alignment are important in determining to what extent GTR+I+G4 can recover  
62 the same topology as a best model. Notably, the same can be observed when ignoring differences in  
63 nodes that are not statistically supported (Fig. 2b). Although this analysis is based on an empirical  
64 dataset, and the true tree is therefore not known, it demonstrates that tree inferences may differ  
65 substantially under GTR+I+G4 and an optimal model selected by BIC. This finding agrees with  
66 previous studies on empirical and simulated datasets<sup>2,4</sup>.

67 Thirdly, topological distances between trees obtained under various criteria were reported by the  
68 authors to be very similar between all model selection criteria. However, these were either averaged  
69 across models and ranked (their Table 3) or binned into 9 categories and averaged (their Fig. 4).  
70 Moreover, including distances equal to zero (~50% of all distances) may have obscured patterns in  
71 these representations. In my re-analysis, I have therefore investigated topological distances between  
72 non-identical trees obtained under GTR+I+G4 and under the best model determined by BIC. Again,  
73 distances were inconsistent between alignments, and GTR+I+G4 topologies were most similar to  
74 topologies obtained under more complex best models (Fig. 2c). This pattern can also be observed  
75 when considering only statistically supported nodes (Fig. 2d).

76 In summary, the authors’ own data and the here presented re-analysis comparing the best model  
77 under BIC with GTR+I+G4 provide compelling evidence that model selection does affect  
78 phylogenetic inference. While using GTR+I+G4 produces identical or very similar topologies to



**Fig. 2** Re-analysis of the empirical dataset. Maximum likelihood trees were reconstructed for all 7200 alignments under a fixed, parameter rich model (GTR+I+G4) and a best model as inferred by BIC. **a** Proportion of identically inferred topologies for each best model compared with GTR+I+G4. **b** Proportion of identically inferred topologies for each best model compared with GTR+I+G4, only considering statistically supported nodes (UFB  $\geq 95$ ). **c** Robinson Foulds distances for non-identical topologies for each best model compared with GTR+I+G4. **d** For non-identical trees, proportion of statistically supported nodes found in trees inferred by a best model and under GTR+I+G4. **e** Alignment size (number of taxa  $\times$  number of aligned positions) for best models inferred by BIC. **f** Uncertainty in model selection by BIC. Connections in chord diagram represent instances in which multiple models were within the 95% CI set of the BIC. The size of a connection is relative to how often the two models were within the same CI set, and the size of sectors is relative to how often each model occurred in any CI set. To improve visualisation, only connections with at least 100 occurrences in CI sets are displayed. The total number of displayed connections is 6919.

79 any best model identified by a model selection criterion in most cases, the degree of similarity  
80 strongly depends on the properties of the underlying alignment: for those alignments that are best  
81 described by simple, parameter-poor evolutionary models, GTR+I+G4 often produces very  
82 different, but statistically supported phylogenetic estimates (Fig 2a–d). For the empirical dataset,  
83 the complexity of the best model chosen by BIC seemed to positively correlate with the size of the  
84 dataset (Fig 2e). This suggests that consistently using a fixed parameter-rich model is especially  
85 inappropriate for smaller alignments (few taxa and/or few aligned positions).

86 Overall, the findings discussed here are in agreement with what seems to be a consensus of the  
87 literature: There are nuanced differences between model selection criteria<sup>5–7</sup>, but model selection is  
88 generally beneficial for phylogenetic accuracy<sup>8–10</sup>.

89 In addition to inappropriate averaging over alignments with divergent properties, other factors  
90 might explain why Abadi et al. did not find differences between the investigated model selection  
91 criteria. For example, although a single best model is selected by each of the criteria, other models  
92 often cannot be rejected with confidence. In the empirical dataset, the 95% confidence set of BIC  
93 supported more than one model for ~79% (5695/7200) of the alignments (Fig. 1f). Taking into  
94 account overlapping confidence intervals of different model selection criteria might reduce spurious  
95 differences in model choice between the criteria potentially observed by Abadi et al.. Another factor  
96 that should be accounted for in future investigations is tree shape. Ripplinger and Sullivan<sup>11</sup> found  
97 that model fitting is more important when tree stemminess is low. In line with this, for the empirical  
98 dataset, topological distances between GTR+I+G4 and the best model inferred by BIC correlated  
99 with the proportion of small internal nodes (here defined as internal nodes shorter than 0.1% of the  
100 tree length,  $R^2=0.6$ ,  $p < 2.2e-16$ ).

101 In conclusion, while GTR+I+G4 very often results in accurate phylogenetic estimates even when it  
102 is not the best fitting model, its performance is inconsistent across empirically determined  
103 alignment properties. There is a large body of literature illustrating the benefits of model selection  
104 to phylogenetic inference (reviewed in reference 10). The data presented by Abadi et al. do not  
105 provide a convincing justification for skipping model selection. Since convenient and accurate  
106 approaches to model selection for maximum likelihood phylogenetics exist<sup>12,13</sup>, the current practice  
107 of model selection is not computationally prohibitive. Importantly, only a very limited number of  
108 nucleotide substitution models was discussed here. As the field of phylogenetics moves towards  
109 larger datasets and increasingly realistic models<sup>14,15</sup>, model selection and fitting will likely become  
110 more relevant in the future.

## 111 **Methods**

112 The empirical alignments were obtained from <https://doi.org/10.17605/OSF.IO/T3PF2>. All  
113 maximum likelihood analyses were done with IQ-TREE version 1.4.2.<sup>16</sup>, and support estimated with  
114 1,000 ultrafast bootstrap replicates<sup>17</sup>. Best models were determined by BIC under full tree searches  
115 for all models and alignments with ModelFinder<sup>13</sup> implemented in IQ-TREE.

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### 158 **Author contributions**

159 MG conceived the work, analysed and interpreted data, and wrote the manuscript.

### 160 **Competing interests**

161 The author declares no competing interests.