**An architectural understanding of natural sway frequencies in trees – supplementary materials**

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| **Field data** | | | | |
|  | **Study** | **N** | **Heights** | **Species** |
| Te | Wytham Woods, UK (Jackson et al., 2019) | 17 | 12-25 m | *Fraxinus excelsiori (8), Betula spp.i (4), Quercus roburi (1), Acer pseudoplatanusi (4)* |
| Te | CT, USA (Bunce et al., 2019) | 39 | 8-32 m | *Acer rubrum (7), Acer saccharum (7), Betula lentai (3), Carya glabra (4), Carya ovata (5), Liriodendron tulipifera (3), Nyssa sylvatica (4), Quercus rubrai (6)* |
| Tr | Danum Valley, Malaysia (Jackson, 2018) | 21 | 17-56 m | *Hydnocarpus anomalus (1), Orophea myriantha (2), Canarium pilosumi (1), Lophopetalum javanicum (1), Terminalia citrinai (1), Parashorea malaanonani (3), Shorea parvifoliai (2), Shorea pauciflorai (1), Diospyros tuberculata (1), Caryodaphnopsis tonkinensis (1), Eusideroxylon zwageri (1), Syzygium panzer (1), Aporusa benthamiana (1), Pometia pinnata (1)* |
| Tr | Manaus, Brazil (Van Emmerik et al., 2017) | 20 | 18-38 m | *Dipterix odorata (2), Eschweilera coriacea (4), Goupia glabra (3), Lecythis prance (3), Maquira sclerophylla (3), Pouteria anomala (2), Scleronema micranthum (2)* |
| O | Nottingham campus (Baker, 1997) | 26 | 5-20 m | *Titlia europai (26)* |
| O | MA, USA (Kane et al., 2014) | 15 | 15-30 m | *Acer saccharum (8), Quercus rubrai (7)* |
| O | Victoria, Australia (K R James et al., 2006) | 5 | 14-25 m | *Eucalyptus tereticornis (2), Agathis australis (1), Corymbia maculate (1), Allocasuarina fraseriana (1)* |
| O | Singapore, Daniel Burcham, personal communication | 20 | 21-32 m | *Khaya senegalensis (11), Samanea saman (9)* |
| C | UK and North America, (Moore and Maguire, 2004) | 603 | 6-20 m | *Pinus nigra (57), Pseudotsuga menziesii (17), Pinus contorta (40), Picea abies (8), Pinus radiata (284), Pinus sylvestris (16), Picea sitchensis (175), Picea glauca (6)* |
| **TLS-derived QSMs** | | | | |
|  | **Study** | **N** | **Heights** | **Scanning conditions** |
| Te | Wytham Woods, UK (Calders et al., 2018) | 559 | 5-30 m | *Riegl VZ-400, 0.04° angular sampling, 20x20 m grid, leaf off.* |
| Te | Rushworth, Australia (Calders et al., 2015) | 65 | 8-24 m | *Riegl VZ-400, 0.06° angular sampling, 5 scans per 40 m radius plot* |
| Tr | Caxiuanã, Brazil (Disney et al., 2018) | 151 | 20-56 m | *Riegl VZ-400, 0.04° angular sampling, 10x10 m grid* |
| Tr | Nouragues,  French Guiana (Disney et al., 2018) | 155 | 16-51 m | *Riegl VZ-400, 0.04° angular sampling, 10x10 m grid* |
| Tr | Lopé, Gabon (Disney et al., 2018) | 107 | 15-43 m | *Riegl VZ-400, 0.04° angular sampling, 10x10 m grid* |
| Tr | Danum Valley, Malaysia | 13 | 20-56 m | *Riegl VZ-400, 0.04° angular sampling, 10x10 m grid* |
| Tr | Wineperu, Guyana (Gonzalez de Tanago Menaca et al., 2017) | 10 | 29-36 m | *Riegl VZ-400, 0.06° angular sampling, 13 scans in a 30x40 m area surrounding each focal tree* |
| Tr | Terantang Hilir, Indonesia (Gonzalez de Tanago Menaca et al., 2017) | 15 | 18-40 m | *Riegl VZ-400, 0.06° angular sampling, 13 scans in a 30x40 m area surrounding each focal tree* |
| O | Russell Square,  London, UK (Wilkes et al., 2018) | 32 | 5-35 m | *Riegl VZ-400, 0.04° angular sampling, 11 scan positions* |
| O | Malet street, London (Wilkes et al., 2018) | 30 | 6-25 m | *Riegl VZ-400, 0.04° angular sampling, 24 scan positions* |

**Table S1 – Overview of data sources**. This table summarizes the field data we collated on the fundamental frequencies of trees as well as the previous studies from which QSMs were sourced. The subset of trees for which material properties information was available is denoted by i superscripts in the species column. The left hand column denotes the subset of trees – whether from a temperate forest (Te), tropical forest (Tr), open-grown (O) or from a conifer plantation (C).

**Material properties**

We collated data on green wood material properties for those trees for which we have field data. We found that reliable data on green wood elasticity was sparse and different sources used different measurement techniques. This led to our decision to use values from a single publication only (Niklas and Spatz, 2010). This publication contained information on 11 of the 59 broadleaf species for which we have field data, representing 40 out of 163 trees. We tested whether the material properties data improved the model for the subset of 40 trees and found no significant change.

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| **Linear models** | **N** | **R2** |
| All broadleaves | 163 | 0.25 |
| Subset | 40 | 0.33 |
| Subset | 40 | 0.31 |

**Table S2 – Variation in f0 explained by material properties**. Linear model summaries for the broadleaf trees with, and without, material properties data.

**Finite element parameters and sensitivity analysis**

The finite element simulations represented each tree as a series of beams, a quantitative structure model (QSM), with a uniform density and elasticity, 800 kgm-*3* and 9.5 GPa respectively. The root-soil boundary is modelled by a dashpot-spring system. We extracted all the undamped sway modes using a subspace method. This analysis can be done in the free student version of Abaqus as long as the tree model consists of less than 1000 nodes. The parameters used in the simulation and the sensitivity of fundamental frequency on these parameters are given in table S3.

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| **Parameter** | **Values** | **Δ*f0 (%)*** |
| Radius limit | 2cm 🡪 4cm | 17 |
| Averaging iterations | 2 🡪 1 | 18 |
| Beam type | B31 🡪 B33H | 1 |
| Green wood density, ρ | 800 *kgm-3* | -15 |
| Elasticity, E | 9.5*GPa* | 12 |
| Root elasticity | 50*MPa* | 0.3 |

**Table S3 – Finite element parameters and sensitivity.** Parameters used in finite element analysis and sensitivity of fundamental frequency extraction on these parameters. The sensitivity is measured by increasing each parameter value by 20% and re-calculating f0. Non-continuous variables were changed as indicated.

**Choice of linear model for the effect of architecture on** *f0*

**The main conclusion of this paper is that architectural information helps explain variation in simulated *f0*. Detailed conclusions about which architectural indices are most important depend on the selection of an appropriate linear model. We do not discuss all possible models in the main text since there are seven architectural indices in addition to and a number of models give similar results. We added architectural indices to the linear model one-by-one, each time choosing the index which explained the most residual variation in *f0*. The result is shown in figure S1.**



**Figure S1 – Summary of linear models for *f0.*** Top panel – Coefficient of determination (R2) for each linear model. Lower panel – Akaike’s information criterion (AIC) for each linear model. The x-axis for both panels represents the architectural indices added cumulatively to the linear model (i.e. the model at denoted ‘Path Fraction’ contains all architectural indices up to and including Path Fraction).

**Multiplicative models consistently outperformed additive models, both in terms of R2 and AIC. We find that three architectural indices (as presented in the main text) account for most of the variation in *f0* and that further architectural indices are unnecessary. The coefficients of the predictor variables in the best three-parameter model for each subset of trees are presented in figure S2.**



**Figure S2 – Effect sizes in selected multiplicative models for simulated *f0*.** The central vertical line represents the mean value and the horizontal lines represent the standard error.

**Choice of linear model for the effect of architecture on *D0***

**With no theory to build from, we used  as the basic term in linear model predictions, since these variables are readily available for many trees and also describe most of the variation in tree size. We then followed a similar approach to our prediction of *f0*, adding architectural indices in order of variation explained. We did not use multiplicative models for since they performed poorly. The result is summarized in figure S3.**



**Figure S3 – Summary of linear models for *D0.*** The x-axis for both panels represents the architectural indices added cumulatively to the linear model (i.e. the model at denoted ‘Path Fraction’ contains all architectural indices up to and including Path Fraction). Top panel – coefficient of determination (R2) each linear model. Lower panel – Akaike’s information criterion (AIC) for each linear model. Architectural indices were added in the order in which they increase the R2 by the largest amount. Note the difference in scale between this figure and the corresponding figure for *f0*.

***D0* proved less predictable than *f0*, and the various linear model forms tested for *f0* made little difference to the accuracy of the prediction of *D0*. We found little support for including interaction terms in linear models of *D0* and so present the architectural indices as purely additive in the main text.**



**Figure S4 – Summary of architectural models for *D0***. Predicting *D0* from architectural indices for TLS derived QSMs. The central vertical line represents the mean value and the horizontal lines represent the standard error.

**Correlation of architectural indices**

In this paper we used architectural indices as explanatory variables to predict the dynamic properties of trees. Figure 4 in the main text presents a principal component analysis for these architectural indices and, unsurprisingly, many of them are correlated. Since it is not the main purpose of this study, we do not quantify these correlations in the main text. Figure S5 presents a covariance matrix for these architectural indices as well as and .



**Figure S5 – Covariance matrix**. Pearson’s correlation coefficients for each pair of architectural variables as well as and . Note the uneven limits of the colour range.

**Sensitivity of architectural indices to QSM simplification**



**Figure S6 – Architecture sensitivity**. This demonstrates the sensitivity of the architectural indices to the number of averaging iterations used to simplify the QSMs. At each averaging iteration the pairs of neighbouring cylinders were combined, with the resultant cylinder having the mean properties of the pair. In the main text we used two averaging iterations.



**Figure S7 – Architecture sensitivity**. This demonstrates the sensitivity of the architectural indices to the minimum diameter, below which small cylinders were deleted to simplify the QSMs. In the main text we used a minimum diameter of 2 cm.