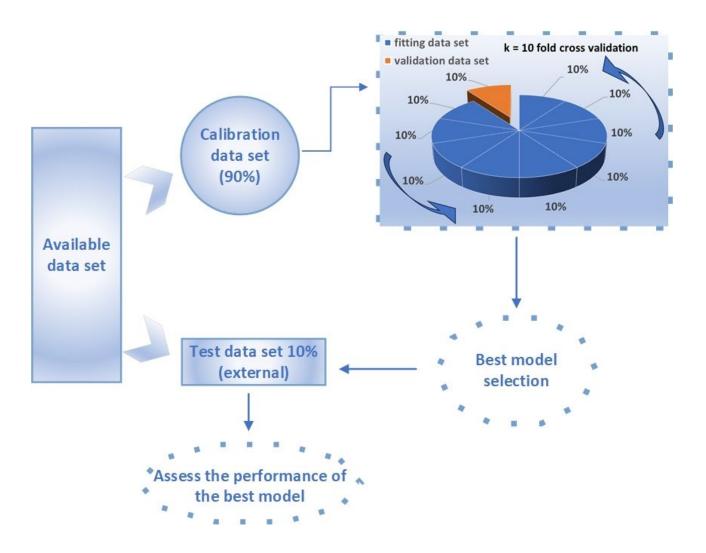
Diamantopoulou M, Cömez A, Ozçelik R, Güner ST (2024). Exploring machine learning modeling approaches for biomass and carbon dioxide weight estimation in Lebanon cedar trees iForest – Biogeosciences and Forestry – doi: 10.3832/ifor4328-016

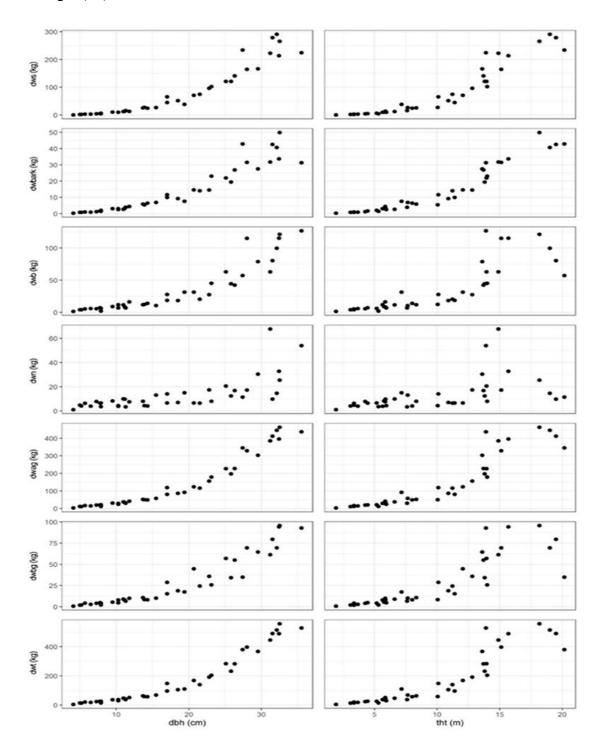
Supplementary Material

Fig. S1 – Data division. Three-way data splits method.



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Fig. S2 – Relationship between dry a) stem wood (dws), b) stem-bark (dwbark), c) branches (live + dead) (dwb), d) needle (dwn), e) total above-ground biomass (dwag), f) below-ground biomass (dwbg) and g) total biomass (dwt) of the sampled trees and the tree diameter at breast height (dbh) and total height (tht).



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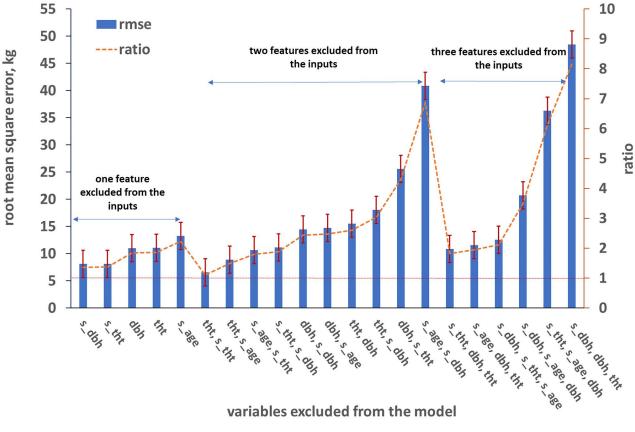


Fig. S3 – Sensitivity analysis for the variable (dwb).

variables excluded from the model

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Fig. S4 - (a) Sum of the component biomass estimations (dwn, dwb, dws, dwbark, dwbg, dwag) derived by LMANN and SVR modeling approaches, versus the observed total biomass (dwt), along with the (b) LMANN histogram and (c) SVR histogram, of their respective residuals.

