

Corrigendum to Predicting leaf traits across functional groups using reflectance spectroscopy

New Phytologist 238 (2023), 549-566, doi: 10.1111/nph.18713.

Since its publication, the authors of Kothari *et al.* (2023b) have identified an error in the Supporting Information published alongside their article. In the Supporting Information Methods S1 section, it is stated that both the fresh and the rehydrated mass of all leaf samples were measured. Leaf dry matter content (LDMC, mg g⁻¹) and equivalent water thickness (EWT, mm) were reported to have been calculated based on the fresh mass under field conditions. The latter statement is incorrect; both traits were calculated based on the rehydrated mass.

The authors note that, for LDMC, this decision was deliberate and in accordance with best practices for taking standardized measurements, as described in Pérez-Harguindeguy *et al.* (2013) and in the published protocol (Laliberté, 2018).

For EWT, by contrast, users are usually interested in knowing about the fresh leaf under field conditions rather than after rehydration. In the published protocol, Laliberté (2018) states that EWT is calculated based on fresh mass and not rehydrated mass. The authors note that using models trained on rehydrated EWT to predict fresh-leaf EWT would likely result in overestimation. In addition, leaf optical properties should be more related to water content at measurement time than to water content after rehydration. Given these considerations, the authors trained new models to predict EWT based on the fresh mass rather than the rehydrated mass.

Fresh-leaf and rehydrated EWT values were very strongly correlated ($R^2 = 0.971$) because the authors' protocol focused on sampling healthy mature green leaves without visible signs of stress, including water stress (Laliberté, 2018). Nevertheless, fresh EWT was generally lower because most leaves were not fully hydrated under field conditions (median ratio: 87.7%, 2.5–97.5th percentile: 68.3–97.6%).

The authors used the internal validation procedure described in Kothari *et al.* (2023b) to train prediction models for freshleaf EWT based on reflectance, transmittance, and absorptance spectra. The retrained models showed similar but (as predicted) slightly better performance compared with the original models for rehydrated EWT. The authors also applied the retrained reflectance-based models to the three external validation datasets. The retrained models showed somewhat better performance on Dessain and LOPEX, in large part due to reductions in bias, but somewhat worse performance on ANGERS. The measured EWT values in these datasets are rehydrated for Dessain, fresh for LOPEX, and not clearly specified in ANGERS.

Here, the authors present corrected versions of Table 2 and Figs 3 and 5 from Kothari *et al.* (2023b) to display results from analyses based on fresh-leaf EWT models. The authors have corrected Methods S1 and S2 to correctly describe the calculation of LDMC in the article and the change in the calculation of EWT described here. The authors have also corrected Fig. S4 and Table S2. The retrained models are available at Kothari *et al.* (2023a), and the corrected code at Kothari (2023).

We apologize to our readers for any confusion caused by these errors.

Author for correspondence: Shan Kothari Email: shan.kothari@umontreal.ca

References

- Kothari S. 2023. ShanKothari/CABO-trait-models: CABO Trait Modeling code (v.1.0.2). Zenodo. doi: 10.5281/zenodo.7308792.
- Kothari S, Beauchamp-Rioux R, Blanchard F, Crofts AL, Girard A, Guilbeault-Mayers X, Hacker PW, Pardo J, Schweiger AK, Demers-Thibeault S *et al.* 2023a. CABO 2018–2019 leaf-level spectra v.2 [Data set]. *EcoSIS*. doi: 10. 21232/58kApoRy.
- Kothari S, Beauchamp-Rioux R, Blanchard F, Crofts AL, Girard A, Guilbeault-Mayers X, Hacker PW, Pardo J, Schweiger AK, Demers-Thibeault S *et al.* 2023b. Predicting leaf traits across functional groups using reflectance spectroscopy. *New Phytologist* 238: 549–566.
- Kothari S, Beauchamp-Rioux R, Blanchard F, Crofts AL, Girard A, GuilbeaultMayers X, Hacker PW, Pardo J, Schweiger AK, Demers-Thibeault S et al. 2022. Models for Predicting leaf traits across functional groups using reflectance spectroscopy [Data set]. Borealis. doi: 10.5683/SP3/NYABAG.
- Laliberté E. 2018. Measuring specific leaf area and water content. doi: 10.17504/ protocols.io.p3tdqnn.
- Pérez-Harguindeguy N, Díaz S, Garnier E, Lavorel S, Poorter H, Jaureguiberry P, Bret-Harte MS, Cornwell WK, Craine JM, Gurvich DE *et al.* 2013. New handbook for standardised measurement of plant functional traits worldwide. *Australian Journal of Botany* 61: 167–234.

4

Corrected Table 2 and Figs 3 & 5:

latasets.	 Internal					Dessair	1		LOPEX			ANGERS		
	No.	No.	₂	DAASE	% DMSE		DAACE	% DAASE		DAACE	% DMSE		DAASE	% DAASE
$\Lambda\Lambda\Lambda$ (leg m ⁻²)	1042	22	^ 	0.0175	8 04	0.502	0.0955	122	0.657	0.111	112	0.510	0.127	117
$DMC (mg g^{-1})$	1943	23 20	0.892	0.0175 32.9	8.04 9.78	0.593	0.0855 40.6	123	0.657	0.111 46.4	112	0.519	0.137	117
EWT (mm)	1929	18	0.912	0.0232	7.34	0.652	0.0327	20.0	0.895	0.0576	22.5	0.777	0.0751	39.3
N (%)	1963	19	0.709	0.403	13.7	0.417	0.664	21.6	0.537	0.854	20.2			
C(%)	1963	20	0.747	1.38	13.2	0.410	2.23	31.6	0.148	2.81	25.5			
Solubles (%)	1919	23	0.733	6.59	15.1	0.284	10.9	26.7						
Hemicellulose	1915	20	0.695	4.35	16.1	0.324	5.28	19.7						
(%) Cellulose (%)	1946	25	0.826	2 74	12 7	0 327	6 68	43 5	0 355	5 47	23.1			
_ignin (%)	1946	20	0.558	2.82	19.1	0.152	4.68	29.9	0.167	4.79	26.8			
Chla (mg g ^{-1})	1941	13	0.689	2.07	13.8	0.312	2.88	26.7	0.411	2.72	28.1	0.505	2.80	21.9
$\cosh b (mg g^{-1})$	1941	14	0.679	0.716	15.0	0.318	1.05	31.6	0.443	0.927	23.4	0.412	1.32	28.7
Carotenoids $(mg g^{-1})$	1941	12	0.644	0.434	14.7	0.195	0.585	27.0	0.290	0.694	24.8	0.421	1.09	29.9
ヽ゚゚゚゚ヹぢ <i>゚</i> \ (mg g ⁻¹)	677	6	0 304	0 0203	24 6	0.006	0 0813	33.5						
" \'''ຽຽ / ໂa (mg σ ^{−1})	678	17	0.504	4 03	2 1 .0 20.4	0.000	10.4	32.2 32.8						
ນາຍອ່າ ໂມ (mg g ⁻¹)	675	5	0.295	0.00311	25.9	0.004	0 0147	34.0						
$e (mgg^{-1})$	677	4	0.286	0.0295	23.0	0.045	0.053	26.6						
(mg g ⁻¹)	678	10	0.550	2.32	15.7	0.443	9.13	28.9						
$\Lambda g (mg g^{-1})$	678	18	0.394	0.714	22.8	0.149	2.3	53.6						
$\Lambda n (mg g^{-1})$	678	10	0.254	0.164	22.8	0.005	0.504	54.6						
$la (mg g^{-1})$	678	6	0.519	0.451	16.7	0.085	0.881	22.6						
$P(mgg^{-1})$	678	15	0.313	0.607	20.5	0.051	2.06	51.2						
$(mg g^{-1})$	677	17	0.487	0.0486	24.2	0.045	0.118	34.9						



Fig. 3 Plots of observations against reflectance-based partial least-squares regression predictions among internal validation data for various leaf structural and chemical traits. The black dashed line in each panel is the 1 : 1 line. Colored lines represent best-fit lines from ordinary least squares (OLS) regression for each functional group. Error bars around each point represent 95% confidence intervals based on the ensemble of models produced in the 100× jackknife analysis. EWT, equivalent water thickness; LDMC, leaf dry matter content; LMA, leaf mass per area.

New Phytologist



Fig. 5 Plots of observations against reflectance-based partial least-squares regression predictions among external validation data for various leaf structural and chemical traits. The black dashed line is the 1 : 1 line. Colored lines represent best-fit lines from ordinary least squares (OLS) regression for each dataset. Error bars around each point represent 95% confidence intervals based on the ensemble of models produced in the 100× jackknife analysis. EWT, equivalent water thickness; LDMC, leaf dry matter content; LMA, leaf mass per area.