

# Unsaturated intercellular vapor pressure is relevant for leaf water heavy isotope enrichment

Charlotte Angove<sup>1\*</sup>, Marco M. Lehmann<sup>2</sup>, Matthias Saurer<sup>2</sup>, Yu Tang<sup>3</sup>, Petri Kilpeläinen<sup>1,4</sup>, Ansgar Kahmen<sup>5</sup>, Pauliina P. Schiestl-Aalto<sup>6</sup>, Olli-Pekka Tikkasalo<sup>7</sup>, Jaana K. Bäck<sup>6</sup> & Katja T. Rinne-Garmston<sup>1</sup>

<sup>1</sup>Stable Isotope Laboratory of Luke (SILL), Natural Resources Institute Finland (Luke), 00790 Helsinki, Finland.

<sup>2</sup>Forest Dynamics, Swiss Federal Institute for Forest, Snow and Landscape Research (WSL), 8903 Birmensdorf, Switzerland.

<sup>3</sup>College of Urban and Environmental Sciences, Peking University, Beijing 100871, China.

<sup>4</sup>Biorefinery and Bioproducts Group, Natural Resources Institute Finland (Luke), 00790 Helsinki, Finland.

<sup>5</sup>Department of Environmental Sciences–Botany, University of Basel, 4056 Basel, Switzerland.

<sup>6</sup>Faculty of Science, Institute for Atmospheric and Earth System Research (INAR)/Physics, University of Helsinki, 00014 Helsinki, Finland.

<sup>7</sup>Carbon Cycle Management Group, Natural Resources Institute Finland (Luke), 00790 Helsinki, Finland.

**\*Corresponding email:** charlotte.angove@luke.fi. Telephone: +358 295 322 575

**ORCID IDs:** Charlotte Angove: 0000-0003-2622-2667. Marco M. Lehmann: 0000-0003-2962-3351. Matthias Saurer: 0000-0002-3954-3534. Yu Tang: 0000-0002-2851-4762. Petri Kilpeläinen: 0000-0002-0982-0123. Ansgar Kahmen: 0000-0002-7823-5163. Pauliina P. Schiestl-Aalto: 0000-0003-1369-1923. Olli-Pekka Tikkasalo: 0000-0003-1729-6349. Jaana K. Bäck: 0000-0002-6107-667X. Katja T. Rinne-Garmston: 0000-0001-9793-2549

**Running head:** Vapor pressure effects to leaf water isotopes

## Manuscript content notes

Section	Content notes (excludes citations)
Abstract	249
Introduction	1774
Methods	2148
Results	1334
Discussion	1457
Figures	4
Tables (after text)	3
Supplemental Material	Table (1) & Figures (2)

## Abstract

Leaf intercellular vapor pressure ( $e_i$ ) can be unsaturated, but its effect on leaf water heavy isotope enrichment (LWE) has not yet been quantified. We evaluated the ecological relevance of unsaturated  $e_i$  for LWE, i.e., for leaf water oxygen-18 and deuterium enrichment, using data from a boreal forest stand and a large-scale dataset. Unsaturated  $e_i$  can firstly affect LWE by directly decreasing  $e_i$  in the Craig Gordon model (Mechanism 1), which leads to an increased influence of atmospheric vapor isotopic enrichment above source water ( $\Delta_v$ ), and a decreased influence of kinetic fractionation by diffusion through the stomata and boundary layer ( $\epsilon_k$ ). Unsaturated  $e_i$  can secondly affect LWE by changing  $\epsilon_k$  (Mechanism 2). To evaluate the effect of Mechanism 1 to LWE, we employed sensitivity tests on LWE model performance using varying measured intercellular relative humidity ( $RH_{\text{cellular}}$ ), or  $RH_{\text{cellular}}$  fitted to observed LWE. To explore the effects of Mechanism 2 to LWE, we modified the calculation of  $\epsilon_k$  and observed consequences to LWE predictions. Unsaturated  $e_i$  is relevant to LWE by Mechanism 1, since a lowered  $RH_{\text{cellular}}$  noticeably changed LWE predictions. It clearly improved deuterium predictions and conditionally improved oxygen-18 predictions. Isotope fractionation by Mechanism 2 is unlikely relevant to oxygen-18 and deuterium enrichment. Unsaturated  $e_i$  must now be recognized as a variable that introduces error to heavy isotope enrichment models and reconstructions from organic material, via Mechanism 1. We suggest a correction for unsaturated  $e_i$  for both oxygen-18 and deuterium enrichment using a variable  $RH_{\text{cellular}}$  calculated from atmospheric relative humidity.

## Introduction

### Background

Leaf intercellular spaces are specialized locations for gaseous exchange of CO<sub>2</sub> and water between leaves and the atmosphere. This exchange imprints on the stable isotope signal stored in leaf water, by leaf water heavy isotope enrichment (LWE; Table 1) (Dongmann *et al.*, 1974; Farquhar *et al.*, 1989; Flanagan and Ehleringer, 1991; Farquhar, Cernusak and Barnes, 2007). Such LWE is merged into the oxygen-18 ( $\delta^{18}\text{O}$ ) and deuterium ( $\delta^2\text{H}$ ) stable isotope values of long-term plant bioindicators (Gessler *et al.*, 2009; Cernusak and Kahmen, 2013; Cueni *et al.*, 2021). For instance, tree-ring  $\delta^{18}\text{O}$  is a widely applied tool to study environmental variables, such as temperature, precipitation, atmospheric relative humidity (RH<sub>atm</sub>), and weather phenomena, such as drought (Hartl-Meier *et al.*, 2014; Treydte *et al.*, 2014; Gessler *et al.*, 2018). On the other hand,  $\delta^2\text{H}$  of tree rings might be indicative for carbon metabolic changes (Lehmann *et al.*, 2021; Vitali *et al.*, 2022). Such differences in the behavior of  $\delta^{18}\text{O}$  and  $\delta^2\text{H}$  are owing to their different molecular masses, different biosynthetic fractionations, and the covariance between RH<sub>atm</sub> and water vapor  $\delta^{18}\text{O}$  that is not reciprocated by  $\delta^2\text{H}$  (Cernusak *et al.*, 2022; Holloway-Phillips *et al.*, 2022). Nevertheless, when  $\delta^2\text{H}$  and  $\delta^{18}\text{O}$  variabilities in tree rings are interpreted using a dual isotope approach, their changes in relative abundance can be used to reconstruct paleoclimatic RH<sub>atm</sub> (Voelker *et al.*, 2014; Hepp *et al.*, 2017). Leaf water  $\delta^2\text{H}$  is useful for another widely used climatic proxy, leaf *n*-alkanes, which can be used for ecohydrological reconstructions (Sachse *et al.*, 2012).

Despite the many climatic and physiological applications of LWE, recent studies challenge our view on the climate related processes regulating LWE, because LWE predictions assume that leaf intercellular vapor pressure ( $e_i$ ) is saturated, i.e., that RH inside those pores is 100%, while recent studies show that  $e_i$  can be unsaturated, i.e., that RH can drop to as low as 80% (Vesala

*et al.*, 2017; Cernusak *et al.*, 2018; Wong *et al.*, 2022). The effect of unsaturated  $e_i$  to LWE is not yet known. If not accounted for, such unsaturated  $e_i$  could be a significant source of error to LWE predictions and reconstructions of past climate and plant response to climate change, via interpretation of tree rings and  $n$ -alkanes.

Currently, LWE is predicted using an adaptation of a model originally used to predict ocean water heavy isotope enrichment, known as the Craig-Gordon model (Craig, 1965; Dongmann *et al.*, 1974; Farquhar *et al.*, 1989; Flanagan and Ehleringer, 1991). An approximate calculation for LWE is:

$$\Delta_e \approx \varepsilon^+ + \varepsilon_k + (\Delta_v - \varepsilon_k) \frac{e_a}{e_i}, \quad (\text{Equation 1})$$

where  $\Delta_e$  is the enrichment of the heavy isotope in leaf water above source water, which is  $\Delta^{18}\text{O}_{\text{lw}}$  for oxygen-18 and  $\Delta^2\text{H}_{\text{lw}}$  for deuterium. Source water is often represented by measured or modelled xylem water isotopic value. Then,  $\varepsilon^+$  is the equilibrium fractionation factor between liquid water and vapor, and  $\varepsilon_k$  is the combined kinetic fractionation factor for diffusion of water vapor through the stomata and leaf boundary layer. Next,  $\Delta_v$  is the isotopic enrichment of atmospheric water vapor compared to source water,  $e_a$  is the atmospheric water vapor pressure and  $e_i$  is the water vapor pressure in leaf intercellular spaces. Calculations for all variables are demonstrated in supporting information by Cernusak *et al.* (2022). We will hereafter refer to a more accurately assembled version of Equation 1 (Farquhar, Cernusak and Barnes, 2007):

$$\Delta_e = (1 + \varepsilon^+) \times \left[ (1 + \varepsilon_k) \left( 1 - \frac{e_a}{e_i} \right) + \frac{e_a}{e_i} (1 + \Delta_v) \right] - 1, \quad (\text{Equation 2})$$

The Craig Gordon model tends to overestimate LWE (Allison, Gat and Leaney, 1985; Leaney *et al.*, 1985; Bariac *et al.*, 1989; Walker *et al.*, 1989). There are three commonly known model corrections to improve LWE model prediction accuracy by considering isotopic inhomogeneities within leaves, and non-steady state conditions. Firstly, the two-pool correction was introduced to reduce LWE overestimation by accounting for the morphological observation that not all leaf water is equally exposed to evaporative enrichment, since most evaporation from leaves occurs at specialized evaporative sites (Leaney *et al.*, 1985; Song *et al.*, 2015). Then, the Péclet correction was introduced to correct for back-diffusion of heavier stable isotopologues from evaporative sites (Farquhar and Lloyd, 1993). Finally, non-steady state modelling was introduced for circumstances when transpiration rate is low enough that a relatively slow leaf water turnover rate leads to cumulative LWE (Farquhar, Cernusak and Barnes, 2007). But model corrections do not ubiquitously improve LWE predictions across studies, for example, the Péclet correction is unreliable at improving model accuracy for reasons that are not fully understood, related to the effective path-length ( $L$ ), which is more like a “fitting parameter” than a measurable dimension (Cernusak and Kahmen, 2013). Other factors known to affect LWE that have not been accounted for in models include xylem water deuterium inaccuracies by cryogenic water extraction artefacts, and xylem sampling effects (Chen *et al.*, 2020; Barbeta *et al.*, 2022; Diao *et al.*, 2022; Nehemy *et al.*, 2022).

## **Theory for unsaturated $e_i$ effects on LWE**

### *Mechanism 1*

Water vapor pressure is saturated when water vapor is in thermodynamic equilibrium with its condensed state. Originally, there were conflicting views about whether leaf intercellular vapor pressure ( $e_i$ ) is saturated or unsaturated (Jarvis and Slatyer, 1970; Farquhar and Raschke, 1978; Sharkey *et al.*, 1982; Canny and Huang, 2006). It was only recently, when the first direct

experimental evidence of unsaturated  $e_i$  was released (Cernusak *et al.*, 2018; Wong *et al.*, 2022). Unsaturated  $e_i$  is particularly relevant to LWE because LWE is caused by the isotopic exchange between leaf water and intercellular vapor. Predictions of LWE rely on an  $e_i$  estimate (Equation 2). When  $e_i$  is lowered in Equation 2, it increases the influence of  $\Delta_v$ , and decreases the influence of  $\varepsilon_k$ , to LWE by increasing  $\frac{e_a}{e_i}$  (Mechanism 1, Equation 2). Since very high  $RH_{atm}$  (93%) can affect the influence of atmospheric water vapor isotopologues to LWE (Lehmann *et al.*, 2018), an increased influence of  $\Delta_v$  by decreased intercellular RH ( $RH_{cellular}$ ) is likely relevant to LWE. Similarly, since  $\varepsilon_k$  is renowned to be important for LWE (Farquhar *et al.*, 1989), a reduced influence of  $\varepsilon_k$  will likely have a noticeable impact to LWE. Therefore, the effect of unsaturated  $e_i$  to LWE by Mechanism 1 is likely impactful to LWE.

If  $e_i$  is saturated, it is possible to calculate  $e_i$  using only leaf temperature ( $T_{leaf}$ ; Nobel (2005)). But, since  $e_i$  can be unsaturated, there are more factors that contribute to  $e_i$  than  $T_{leaf}$  (Vesala *et al.*, 2017; Buckley and Sack, 2019). For instance, changes in leaf-atmosphere water fluxes could interact with  $e_i$ . Indeed, unsaturated  $e_i$  could lead to reduced gross foliar water loss (GFWL), if the equation for transpiration, below, can be used to infer effects of unsaturated  $e_i$ :

$$E = \frac{g_s(e_i - e_a)}{p}, \quad \text{(Equation 3)}$$

where  $E$  is transpiration rate,  $g_s$  is stomatal conductance, and  $p$  is air pressure (Farquhar *et al.*, 1980). But the effects of unsaturated  $e_i$  can unlikely be evaluated using Equation 3, because unsaturated  $e_i$  may increase  $g_s$  (Buckley and Sack, 2019). Indeed, the water potential ( $\psi$ ) of intercellular spaces is lowered by unsaturated  $e_i$ , which arises many questions about our understanding of leaf water transport biology (Buckley and Sack, 2019). Leaf intercellular spaces might withstand lower  $\psi$  by unsaturated  $e_i$ , via humidity gradients inside of leaf air spaces that reduce  $\psi$  differences between leaf cell walls and intercellular spaces, and by concavely curved water-air interfaces in intercellular spaces (Vesala *et al.*, 2017; Cernusak *et*

*al.*, 2018; Wong *et al.*, 2022). Another consequence of unsaturated  $e_i$  is that more water vapor molecules could be up taken from the atmosphere into leaf intercellular spaces, otherwise known as increased gross foliar water uptake (GFWU) which would also depend on  $RH_{atm}$  and stomatal conductance (Vesala *et al.*, 2017). Overall, there is no empirical evidence showing that unsaturated  $e_i$  would lead to reduced GFWL (Equation 3) or increased GFWU. Nevertheless, the outcome of both, either reduced GFWL or increased GFWU, contribute to a reduced GFWL:GFWU ratio. The reduced GFWL:GFWU ratio could partly explain the response observed in Equation 2 when  $e_i$  is lowered from saturated vapor pressure, which is currently used by literature, to unsaturated vapor pressure.

## Mechanism 2

When  $e_i$  is unsaturated, it can influence LWE, not only by directly changing  $e_i$  in Equation 2 (Mechanism 1), but also by changing the kinetic fractionation factor for diffusion through the stomata and boundary layer ( $\varepsilon_k$ ) used in Equation 2 (Mechanism 2). Unsaturated  $e_i$  can change  $\varepsilon_k$  in two ways. Firstly, it can increase  $g_s$  (Buckley & Sack 2019), which affects the calculation of  $\varepsilon_k$ :

$$\varepsilon_k(H_2^{18}O) = \frac{28r+19r_b}{r+r_b}, \quad \text{and} \quad \text{(Equation 4)}$$

$$\varepsilon_k(HDO) = \frac{25r+17r_b}{r+r_b}, \quad \text{(Equation 5)}$$

where  $r$  is stomatal resistance and  $r_b$  is boundary layer resistance (Farquhar *et al.*, 1989). A similar calculation for  $\varepsilon_k$  has been suggested by Flanagan *et al.* (1991) (Horita, Rozanski and Cohen, 2008). Since  $r$  is the inverse of  $g_s$  ( $r = \frac{1}{g_s}$ ) (Horita, Rozanski and Cohen, 2008), an increase in  $g_s$  decreases  $r$ . Such a decrease in  $r$  by increased  $g_s$  changes  $\varepsilon_k$ , and could thus affect LWE.

The second way that unsaturated  $e_i$  can affect  $\varepsilon_k$ , is based on the understanding that  $\varepsilon_k$  represents the nonequilibrium component of leaf water evaporation, where isotope fractionation is controlled by molecular diffusion (Farquhar *et al.*, 1989; Flanagan *et al.*, 1991; Horita, Rozanski and Cohen, 2008). Such nonequilibrium isotope fractionation has recently been adapted to the specialized marine conditions for evaporation from seawater, for example investigating a turbulent component in response to wind speed (Zannoni *et al.*, 2022). Given that  $\varepsilon_k$  can be adapted for specialized evaporative conditions,  $\varepsilon_k$  has not yet been adapted for unsaturated  $e_i$ . Indeed, if  $e_i$  is unsaturated, there would not be  $\psi$  equilibrium between apoplastic water and vapor in intercellular spaces, owing to vapor diffusion away from evaporative sites by a small water vapor concentration gradient (Buckley & Sack 2019). Diffusion along a concentration gradient is a source of isotopic fractionation (Merlivat 1978), therefore such diffusion along a concentration gradient within leaf intercellular spaces is a source of isotopic fractionation that could have implications to LWE. Given that Equations 4 & 5 describe kinetic fractionation by stomatal resistance ( $r$ ) and boundary layer resistance ( $r_b$ ), we suggest incorporating intercellular resistance ( $r_i$ ) to account for isotope fractionation by diffusion along a vapor concentration gradient within the leaf intercellular space. We suggest that  $r_i$  occurs in Equations 4 & 5 as:

$$\varepsilon_k(H_2^{18}O) = \frac{28(r + r_i) + 19r_b}{r + r_i + r_b}, \quad (\text{Equation 6})$$

and

$$\varepsilon_k(HDO) = \frac{25(r + r_i) + 17r_b}{r + r_i + r_b}, \quad (\text{Equation 7})$$

respectively. Here,  $r_i$  is exposed to the same isotope fractionation (28 & 25) as  $r$ , because they are both characterized by diffusive water vapor molecule movement, and they both contribute to a diffusion layer between an equilibrium layer at the air-water interface, and the boundary



layer which is characterized by laminar flow. Since Buckley & Sack (2019) calculated that the water vapor concentration gradient in intercellular spaces would be small, it is unlikely that  $r_i$  is as influential driving factor to LWE compared to, for example,  $r$ . Nevertheless, since it has not been tested before, it is essential to explore whether an introduction of  $r_i$  by unsaturated  $e_i$  is relevant to LWE.

Overall, if  $e_i$  is unsaturated, it can have two effects to LWE. Firstly, it increases the influence of  $\Delta_v$  while decreasing the influence of  $\varepsilon_k$  (via higher  $\frac{e_a}{e_i}$  in Equation 2, Mechanism 1). Secondly, it can affect  $\varepsilon_k$  by decreasing  $r$  and introducing  $r_i$  (Equation 6, 7, Mechanism 2). Therefore, the main aim of the study was to quantify the effects of unsaturated  $e_i$  to LWE model predictions through testing two hypotheses:

- Hypothesis 1: Unsaturated  $e_i$  increases the influence of  $\Delta_v$  and decreases the influence of  $\varepsilon_k$  to an extent that is relevant for LWE, shown by a change in LWE predictions in response to a lower RH<sub>cellular</sub> (Mechanism 1).
- Hypothesis 2: The effect of unsaturated  $e_i$  to LWE by changing  $\varepsilon_k$ , from decreased  $r$  and introduced  $r_i$  (Mechanism 2), is not influential to LWE compared to other drivers, such as Mechanism 1.

There are assets to using *in situ* measurements for evaluating the ecological relevance of violated model assumptions, because there are large quantities of data available, and *in situ* measurements provide an ecological perspective to the relative importance of violated model assumptions compared to other sources of error. We firstly tested hypotheses using survey data on Scots pine (*Pinus sylvestris* L.) in a boreal forest. Since LWE changes between species, seasons, and sites, we also applied our analyses to a large-scale dataset from Cernusak *et al.* (2022) (Snyder *et al.*, 2010; Bögelein, Thomas and Kahmen, 2017; Munksgaard *et al.*, 2017).

## Materials and Methods

### Field site and sampling

Sampling was conducted at Hyytiälä Forest, which is a managed forest approximately 55 years old, in the southern boreal vegetation zone, southern Finland (61°51'N, 24°17'E, Kolari *et al.* 2022). It is dominated by Scots pine (*Pinus sylvestris* L.), amongst other species, such as Norway spruce (*Picea abies* (L.) H. Karst), birch (*Betula pendula* Roth, *B. pubescens* Ehrh) and European aspen (*Populus tremula* L.) (Kolari *et al.*, 2022). In 2018, the dominant tree height was 23.5m and mean tree height was 19.9m, while tree density was 1304 trees ha<sup>-1</sup> (Kolari *et al.*, 2022). The soil type is Haplic podzol on glacial till, and in most places soil depth is less than 1m, except for moist depressions, which have a thicker layer of soil with a thin layer of peat above them (Kolari *et al.*, 2022). Precipitation is distributed somewhat evenly throughout the year and mean annual precipitation between 1981 and 2010 was 711mm (Pirinen *et al.*, 2012). Hyytiälä belongs to the Integrated Carbon Observation System (ICOS) network, and a variety of meteorological and leaf gas-exchange parameters are continuously monitored at the site. It is beneficial that there are additional, related tree-physiological investigations from the same site, which can provide deeper insights during data interpretation from this study (Soudant *et al.*, 2016; Leppä *et al.*, 2022; Tang *et al.*, 2022).

Samples were collected between 13:00 and 16:00 during six sampling days with no rain, distributed across the 2019 summer growth season (17 May, 07 June, 28 June, 26 July, 27 August, 23 September). One-year old needles and 2 – 4mm diameter twigs (twig bark was removed) at 18m height were sampled from sun-exposed branches from five Scots pine trees and stored in 12 ml gas-tight glass vials (Exetainer, Labco, UK). All samples were immediately transferred to a cool box. Atmospheric water vapor was collected within the canopy at the same height as needle and twig sampling (18m), on each sampling day, for three hours between 13:00

and 16:00. A dry ice-ethanol cold trap was used, wherein air was pumped into 6mm tubes leading to a U-shaped cold trap ( $< -70^{\circ}\text{C}$ ) at  $0.7 - 1\text{ lmin}^{-1}$ . The U-tube was then immediately capped tightly, removed, then stored in a cool box. Immediately after fieldwork, the collected moisture was transferred into 2ml IRMS vials using a glass Pasteur pipette and stored in a freezer ( $-20^{\circ}\text{C}$ ) together with the collected needle and twig samples.

Atmospheric temperature ( $T_{\text{atm}}$ ) and RH ( $\text{RH}_{\text{atm}}$ ) were downloaded from the Smart SMEAR AVAA portal (<https://smear.avaa.csc.fi/>). They were measured onsite, at the ICOS ecosystem station profile, by a Rotronic MP102H RH/T sensor at 16.8m. Leaf transpiration rate was measured using two automated, box-shaped shoot chamber systems made of acrylic plastic ( $2.1\text{ dm}^3$ ), surrounding debudded shoots in the uppermost canopy (20m, Aalto et al. (2014)). One cuvette monitored one-year old shoots and a second cuvette measured two-year old shoots, and averages from both cuvettes were used. Cuvettes were ventilated and equipped with a fan. Transpiration rate was calculated by applying a non-linear equation to chamber  $\text{H}_2\text{O}$  vapor concentrations during the first 5 – 35s of intermittent chamber closures (Kolari *et al.*, 2012; Leppä *et al.*, 2022).

## **Laboratory analysis**

Water was cryogenically extracted from needles and twigs at the Swiss Federal Institute for Forest, Snow and Landscape Research (WSL) (West, Patrickson and Ehleringer, 2006). Stable isotope analyses were conducted at The University of Basel Stable Isotope Ecology Laboratory, Switzerland, by Thermal Conversion / Elemental Analyzer (TC/EA) coupled to a Delta V Plus isotope ratio mass spectrometer (IRMS) through a ConFlo IV interface (Thermo Fisher Scientific, Bremen, Germany) (Newberry, Nelson and Kahmen, 2017). Samples were injected at least six times, and a minimum of three of the measurements were used to calculate a mean value, since starting measurements were omitted to compensate for memory effects from the previous sample. Measurements were normalized to Vienna Standard Mean

Ocean Water (VSMOW) using calibrated in-house standards with a  $\delta^2\text{H}$  value of -76.4‰, and a  $\delta^{18}\text{O}$  value of -10.7‰. Isotope values were defined as:

$$\delta = (\text{R}_{\text{sample}} - \text{R}_{\text{standard}}) / \text{R}_{\text{standard}}, \quad (\text{Equation 8})$$

relative to VSMOW, where R is the D/H or  $^{18}\text{O}/^{16}\text{O}$  ratio for  $\delta^2\text{H}$  and  $\delta^{18}\text{O}$ , respectively.

The standard deviations of quality controls during the time of analyses were 0.3‰ (n = 49) for  $\delta^2\text{H}$  and 0.12‰ (n = 49) for  $\delta^{18}\text{O}$ .

### Large-scale dataset sourcing

The large-scale dataset and its LWE predictions were first sourced from the review published by Cernusak *et al.* (2022). This large-scale dataset comprises of 546 datapoints for paired  $\Delta^2\text{H}_{\text{lw}}$  and  $\Delta^{18}\text{O}_{\text{lw}}$ . The geographical range extends across more than 100° of latitude and there is an elevation range larger than 3000m. Most of the data is from temperate forests or woodlands, followed by tropical forests or woodlands. The data from Hyytiälä was added to the large-scale dataset and, after a grassland in Greenland, it contributed the highest-latitude data and the only boreal forest measurements. The large-scale dataset was filtered to select sampling sites with at least five different sampling times, to meet statistical analysis criteria. Data from Kahmen *et al.* (2011) were clustered into five main sampling sites, and three sites from Munksgaard *et al.* (2017) were clustered into one site (Herberton, Wild River & Mount Garnet), so that data met the filter criterion and thus could be included. The resultant dataset constituted of 534 datapoints from Cernusak *et al.* (2022) and 29 datapoints from this Hyytiälä ( $\Sigma = 563$ ).

### Leaf water heavy isotope enrichment modelling

All modelling and statistical analyses were performed in R (R Core Team, 2022). Observed leaf water and water vapor enrichments were calculated as:

$$(\delta_e - \delta_{\text{source}}) / (1 + \delta_{\text{source}}/1000), \quad (\text{Equation 9})$$

where  $\delta_e$  is the isotope value of the parameter whose enrichment above source water is being estimated, i.e., leaf water or water vapor (Cernusak *et al.*, 2016). Firstly, LWE was modelled using Equation 2, using the calculations provided in the supporting materials by Cernusak *et al.* (2022), for both Hyytiälä and the large-scale dataset. At Hyytiälä,  $T_{\text{leaf}}$  was first assumed to be the same as  $T_{\text{atm}}$ , which is a reasonable assumption because the Scots pine needles are small and well-coupled to the atmosphere (Launiainen *et al.*, 2016; Kim *et al.*, 2018; Leppä *et al.*, 2022). Nevertheless, given that there are uncertainties relating to the assumption that  $T_{\text{leaf}}$  is equal to  $T_{\text{atm}}$ , and that recent evidence shows that the relationship between  $T_{\text{leaf}}$  and  $T_{\text{atm}}$  can change on a diurnal basis (Still *et al.*, 2022), we expanded analyses to include sensitivity of results to a  $T_{\text{leaf}}$  change of  $\pm 2^\circ\text{C}$  from  $T_{\text{atm}}$ , to guide inferences on the relative influence of unsaturated  $e_i$  to LWE compared to a  $\pm 2^\circ\text{C}$  change in  $T_{\text{leaf}}$ .

Main results were inferred from the foundational CG model (Equation 2). A two-pool correction and a Péclet correction were additionally applied, as an initial demonstration of how such corrections can interact with unsaturated  $e_i$ . The two-pool correction was calculated as:

$$\Delta_L = (1 - \varphi)\Delta_e, \quad (\text{Equation 10})$$

where  $\Delta_L$  is the final calculated leaf water heavy isotope enrichment (LWE),  $\Delta_e$  is the modelled LWE by the Craig-Gordon model, and  $\varphi$  is the proportion of unenriched xylem water in leaf water (Leaney *et al.*, 1985; Song *et al.*, 2015). The estimate for  $\varphi$  was 0.316, based on Scots pine leaf anatomical measurements by Roden *et al.* (2015). For the Péclet correction, the Péclet number was calculated as:

$$\wp = \frac{LE}{CD}, \quad (\text{Equation 11})$$

where  $L$  is effective path length,  $E$  is transpiration rate ( $\text{mol m}^{-2} \text{s}^{-1}$ ),  $C$  is the molar concentration of water ( $5.5 \times 10^{-4} \text{ mol m}^{-3}$ ) and  $D$  is the diffusivity of the water isotopologue responsible for enrichment. Their calculation is described in further detail by Cernusak *et al.*

(2016), and in this study,  $L$  was calculated for each sampling date based on transpiration rate.

The Péclet correction is applied as  $P$ :

$$P = \left( \frac{1 - e^{\phi}}{\phi} \right), \quad (\text{Equation 12})$$

where:

$$\Delta_L = \Delta_e \times P. \quad (\text{Equation 13})$$

There was limited transpiration rate and  $\phi$  data availability for the large-scale dataset, so this additional model correction demonstration was only performed for Hyytiälä data.

To explore the effects of unsaturated  $e_i$  to LWE by increasing influence of  $\Delta_v$  and decreasing influence of  $\epsilon_k$  (Hypothesis 1), Equation 2 was applied with different assumptions for  $RH_{\text{cellular}}$  when calculating  $e_i$ . For example, in Equation 2, atmospheric vapor pressure ( $e_a$ ) can be expressed as:

$$e_a = \text{psat} \times (RH_{\text{atm}}/100), \quad (\text{Equation 14})$$

where psat is saturated vapor pressure. Since  $e_i$  was assumed to be saturated during LWE modelling, it has been estimated as  $e_i = \text{psat}$ . In this study, we calculated  $e_i$  in the same way that  $e_a$  has been expressed, in Equation 14, by replacing  $RH_{\text{atm}}$  with  $RH_{\text{cellular}}$ :

$$e_i = \text{psat} \times (RH_{\text{cellular}}/100), \quad (\text{Equation 15})$$

using the following assumptions for  $RH_{\text{cellular}}$ :

1.  $RH_{\text{cellular}} = 100\%$ . Saturated  $e_i$ .
2.  $RH_{\text{cellular}} = 90\%$ . Within the observed range reported by literature (Cernusak et al., 2018; Wong et al., 2022).
3.  $RH_{\text{cellular}} = 80\%$ . The lowest approximate  $RH_{\text{cellular}}$  reported by literature (Cernusak et al., 2018; Wong et al., 2022).

Finally, since  $RH_{atm}$  potentially affects  $RH_{cellular}$  (Vesala *et al.*, 2017; Cernusak *et al.*, 2018), we modelled  $RH_{cellular}$  as a response to  $RH_{atm}$ . This was a model-optimization, which used measured LWE to find a fitted  $e_i$  along an  $RH_{atm}$  gradient for both  $\Delta^2H_{lw}$  and  $\Delta^{18}O_{lw}$ . We used:

$$e_i = 0.65 + \frac{0.35}{(1+A \times e^{-B \times RH_{atm}})^{\frac{1}{C}}} . \quad (\text{Equation 16})$$

Calculants A, B and C were solved simultaneously for both  $\Delta^2H_{lw}$  and  $\Delta^{18}O_{lw}$ , to find one fitted  $RH_{cellular}$  for both elements using the optim function in the ‘stats’ package. The optim function was run with default configuration using the Nelder-Mead algorithm. Fitted  $RH_{cellular}$  was also solved for each of  $\Delta^2H_{lw}$  and  $\Delta^{18}O_{lw}$  separately.

When calculating  $psat$  for  $e_a$ ,  $T_{atm}$  is used, meanwhile, when calculating  $psat$  for  $e_i$ ,  $T_{leaf}$  is used (Cernusak *et al.*, 2016). In Equation 2,  $e_i$  occurs twice, and main results are given for adjustment of both  $e_i$  occurrences. An additional post-hoc analysis was performed on data from Hyytiälä, where each occurrence of  $e_i$  was adjusted to different  $RH_{cellular}$  assumptions, separately.

To test the effect of unsaturated  $e_i$  to isotope fractionation associated with  $r_i$ , we calculated  $\epsilon_k$  using Equations 6 & 7 and implemented the altered  $\epsilon_k$  to Equation 2, to look for observable changes in predicted LWE compared to modelled LWE using  $\epsilon_k$  that had been calculated using Equations 4 & 5. For this, we used data from Hyytiälä when  $RH_{cellular}$  was 90% or 80%, and we applied leaf anatomical measurements of Scots Pine needles by Roden *et al.* (2015). Intercellular resistance ( $r_i$ ) was estimated using three calculation steps. First, the rate of water vapor diffusion along a concentration gradient within an intercellular space ( $J$ ,  $\text{mol m}^{-2} \text{s}^{-1}$ ) was estimated using Fick’s law of diffusion:

$$J = \frac{DA[c_1 - c_2]}{T}, \quad (\text{Equation 17})$$

where  $D$  is the diffusion constant, at  $2.44 \times 10^{-5} \text{ m}^2 \text{ s}^{-1}$  (Merlivat 1978),  $A$  is the cross-sectional area of diffusion, which we approximated by using cross-sectional leaf area exposed to evaporation per square meter using Scots Pine measurements by Roden *et al.* (2015) ( $A = 1 - \phi = 0.684$ ). Then,  $c_1$  was the concentration of water vapor in the equilibrium layer at the air-water interface in the leaf intercellular space ( $\text{mol m}^{-3}$ ), calculated as saturated vapor concentration at leaf temperature, and  $c_2$  was the unsaturated concentration of water vapor in the unsaturated portion of the leaf intercellular space ( $c_2 = c_1 \times (\text{RH}_{\text{cellular}}/100)$ ). Such definitions of  $c_1$  and  $c_2$  were based on the principle that there is an equilibrium layer at the air-water interface during evaporation, and because there are humidity gradients inside of leaf intercellular spaces (Wong *et al.* 2022), but they can be improved if more knowledge arises about leaf intercellular space humidity conditions. Finally,  $T$  was the length of the diffusion pathway, which has not yet been quantified, we approximated  $T$  by using measured mean mesophyll thickness for Scots Pine by Roden *et al.* (2015) ( $1.71 \times 10^{-4} \text{ m}$ ).

Intercellular conductance ( $g_i$ ,  $\text{mol m}^{-2} \text{ s}^{-1}$ ) was then calculated using an adaptation of the following calculation:

$$g_s = \frac{E \times p}{(e_i - e_a)} \quad (\text{Equation 18})$$

where  $g_s$  is stomatal conductance ( $\text{mol m}^{-2} \text{ s}^{-1}$ ),  $E$  is transpiration rate ( $\text{mol m}^{-2} \text{ s}^{-1}$ ),  $p$  is air pressure (kPa),  $e_a$  is atmospheric water vapor pressure (kPa) and  $e_i$  is water vapor pressure in the leaf intercellular space (kPa). We adapted the equation to:

$$g_i = \frac{J \times p}{(e_e - e_i)} \quad (\text{Equation 19})$$

where  $e_e$  is water vapor pressure at the equilibrium layer of the air-water interface in the leaf intercellular space (kPa), calculated as saturated vapor pressure at leaf temperature. Then,  $e_i$



(kPa) was adjusted to the tested level of unsaturation within the leaf intercellular space ( $e_i = e_e \times (\text{RH}_{\text{cellular}}/100)$ ). We then calculated intercellular resistance ( $\text{mol m}^{-2} \text{s}^{-1}$ ) as:

$$r_i = \frac{1}{g_i} . \quad (\text{Equation 20})$$

During the calculations, we assumed that the length of the diffusion pathway was equal to mean mesophyll thickness, and that the cross-sectional area of diffusion was equal to the cross-sectional area of a leaf exposed to evaporation, therefore  $r_i$  estimates were approximate. However, given that the  $r_i$  response to unsaturated  $e_i$  varies along a much smaller magnitude than the variability of  $r$ , the consequences of the described assumptions are unlikely consequential to this study, where  $r_i$  has been added to  $r$  when calculating  $\varepsilon_k$  (Equation 6, 7).

## Statistical analyses

At Hyytiälä and in the large-scale dataset, linear mixed models (LMMs) with random intercepts were used to compare modelled to observed LWE. At Hyytiälä, the random intercept was sampling date, while in the larger dataset the random intercept was site ID with rank sampling time nested inside of site ID. Unadjusted Intraclass Correlations (ICC) were used to quantify unexplained variability between random factors which remained after modelled LWE was compared to observed LWE (Nakagawa, Johnson and Schielzeth, 2017). One outlier leaf water  $\delta^{18}\text{O}$  measurement was removed from Hyytiälä data. Each LMM analysis was accompanied with a calculation of Root Mean Square Error (RMSE), which is an estimate of overall proximity of predicted LWE to observed LWE.

## Results

### Data Overview

Data used as input to the Craig-Gordon model to predict LWE at Hyytiälä were within the (Still *et al.*, 2022) range of the large-scale dataset (Fig. **1a-d**). Their means were lower at Hyytiälä compared to the large-scale dataset, most noticeably so for  $^2\text{H}$  enrichment of water vapor above source water, which was 11.4‰ lower at Hyytiälä than in the large-scale dataset ( $\Delta^2\text{H}_{\text{wv}}$ , Fig. **1c**). Congruently, observed LWE at Hyytiälä was within the range of observed LWE in the large-scale dataset (Fig. **1e-f**). Nevertheless, mean observed  $\Delta^2\text{H}_{\text{lw}}$  was approximately the same at Hyytiälä and in the large-scale dataset, while mean observed  $\Delta^{18}\text{O}_{\text{lw}}$  was 2.4‰ higher at Hyytiälä than in the large-scale dataset (Fig. **1e-f**). The seasonal variability of leaf water isotope enrichment at Hyytiälä covered a substantial proportion of the data range in the large-scale dataset, at 34% for each of  $\Delta^2\text{H}_{\text{lw}}$  and  $\Delta^{18}\text{O}_{\text{lw}}$ .

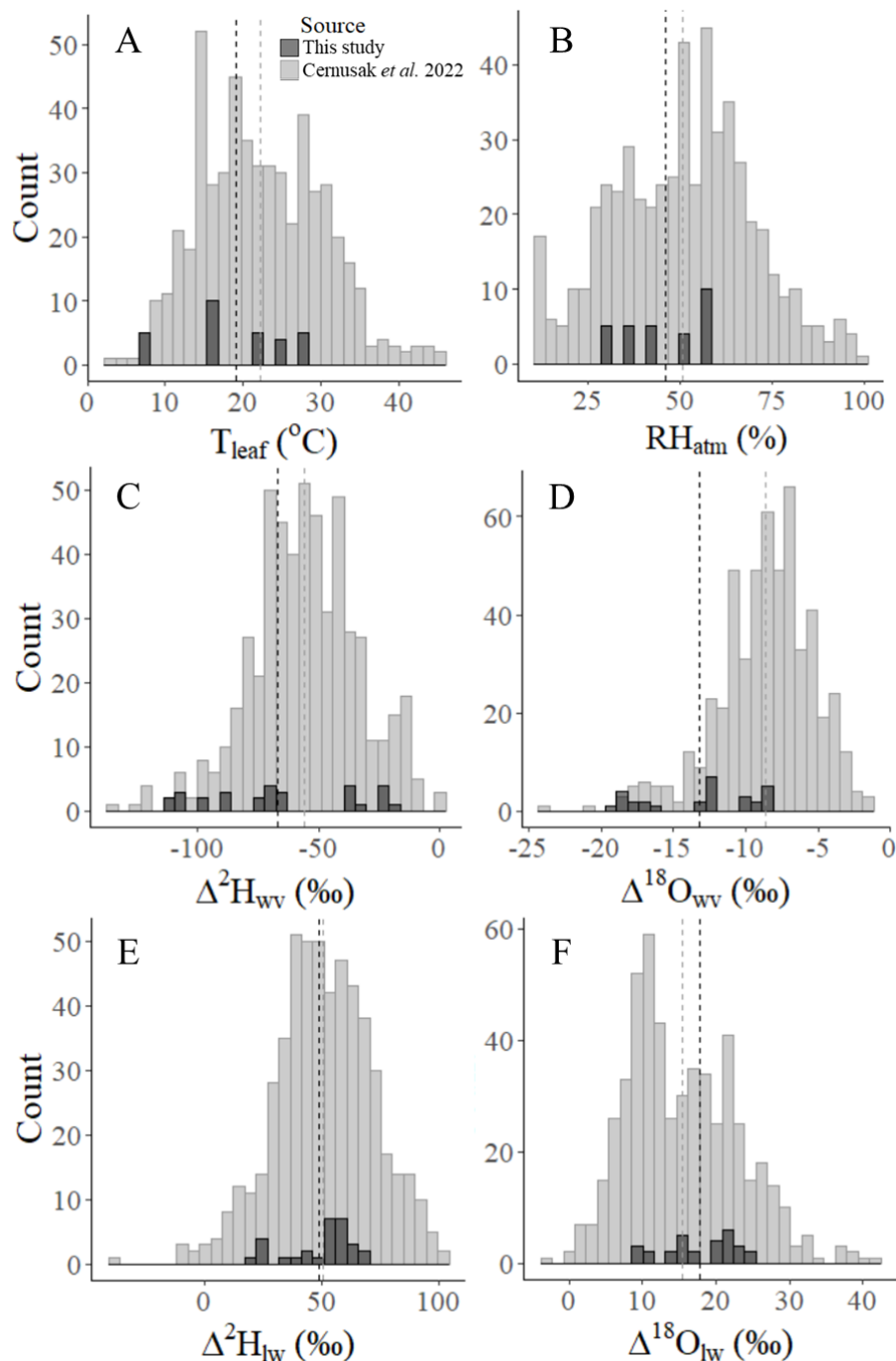


Figure 1. Frequency distributions of leaf temperature ( $T_{\text{leaf}}$  (°C), A), atmospheric relative humidity ( $RH_{\text{atm}}$  (%), B), water vapor deuterium ( $\Delta^2H_{\text{wv}}$  (‰), C) and oxygen-18 ( $\Delta^{18}O_{\text{wv}}$  (‰), D) enrichment above source water, and observed leaf water deuterium ( $\Delta^2H_{\text{lw}}$  (‰), E) and oxygen-18 ( $\Delta^{18}O_{\text{lw}}$  (‰), F) enrichment above source water,  $n = 563$ . Data from this study (dark grey) shows seasonal variability for *P. sylvestris* during the 2019 growing season at Hyytiälä, Finland, and it overlays a selection of review data collected by Cernusak et al. (2022, lighter grey). Dashed lines show the mean of each parameter, for Hyytiälä and the review data.

**Hypothesis 1: Increased influence of  $\Delta_v$  and decreased influence of  $\epsilon_k$ , by unsaturated  $e_i$ , is relevant to LWE**

**Hyytiälä**

*Foundational Craig-Gordon model*

When assumed  $RH_{\text{cellular}}$  was lowered from 100% to 90% and 80%, predicted  $\Delta^2H_{\text{lw}}$  and  $\Delta^{18}O_{\text{lw}}$  became noticeably lower (red series in Fig. **2a-c**; Table **2**). This improved  $\Delta^2H_{\text{lw}}$  predictions by reducing the offset between observed and modelled values, because the predictions based on 100%  $RH_{\text{cellular}}$  largely overestimated  $\Delta^2H_{\text{lw}}$  (red series in Fig. **2a**; Table **2**). However, for  $\Delta^{18}O_{\text{lw}}$ , 100%  $RH_{\text{cellular}}$  already provided a good agreement between the measured and modelled  $\Delta^{18}O_{\text{lw}}$ , with only a modest average model overestimation of 1‰ (red series in Fig. **2e**). Hence, the lowering of  $RH_{\text{cellular}}$  to 90% or 80% led to increased error of  $\Delta^{18}O_{\text{lw}}$  predictions, by underestimation (red series in Fig. **2f-g**; Table **2**). The accuracy of LWE predictions was affected by  $\pm 2^\circ\text{C}$  variability in  $T_{\text{leaf}}$  more for  $\Delta^{18}O_{\text{lw}}$  than for  $\Delta^2H_{\text{lw}}$ , and the impact was larger on lower enrichments, for predictions by models with 100%, 90% and 80%  $RH_{\text{cellular}}$  (horizontal lines in Fig. **2a-c, e-g**).

When  $RH_{\text{cellular}}$  was reduced to 90% or 80%, the lower predicted enrichments were lowered to a larger extent than higher predicted enrichments, as indicated by the increase in intercepts and the decline in slopes, for both elements (Fig. **2a-c, e-g**; Table **2**). This attribute meant that, while reductions in  $RH_{\text{cellular}}$  could reduce model prediction offsets from observed values if a model otherwise overestimated LWE ( $\Delta^2H_{\text{lw}}$ ), they had a biased influence on model prediction accuracy. Such a prediction accuracy bias was completely remediated for  $\Delta^{18}O_{\text{lw}}$ , by the model optimization that found a fitted  $RH_{\text{cellular}}$  that varied along a  $RH_{\text{atm}}$  gradient, albeit with an offset between observed and measured values (Fig. **2 h**; Table **2**). Meanwhile, for  $\Delta^2H_{\text{lw}}$  predictions, the prediction accuracy bias was only partly remediated by fitted  $RH_{\text{cellular}}$ , because it improved the prediction accuracy bias compared to 80%  $RH_{\text{cellular}}$ , but it worsened the prediction accuracy bias compared to 90%  $RH_{\text{cellular}}$  (Table **2**).

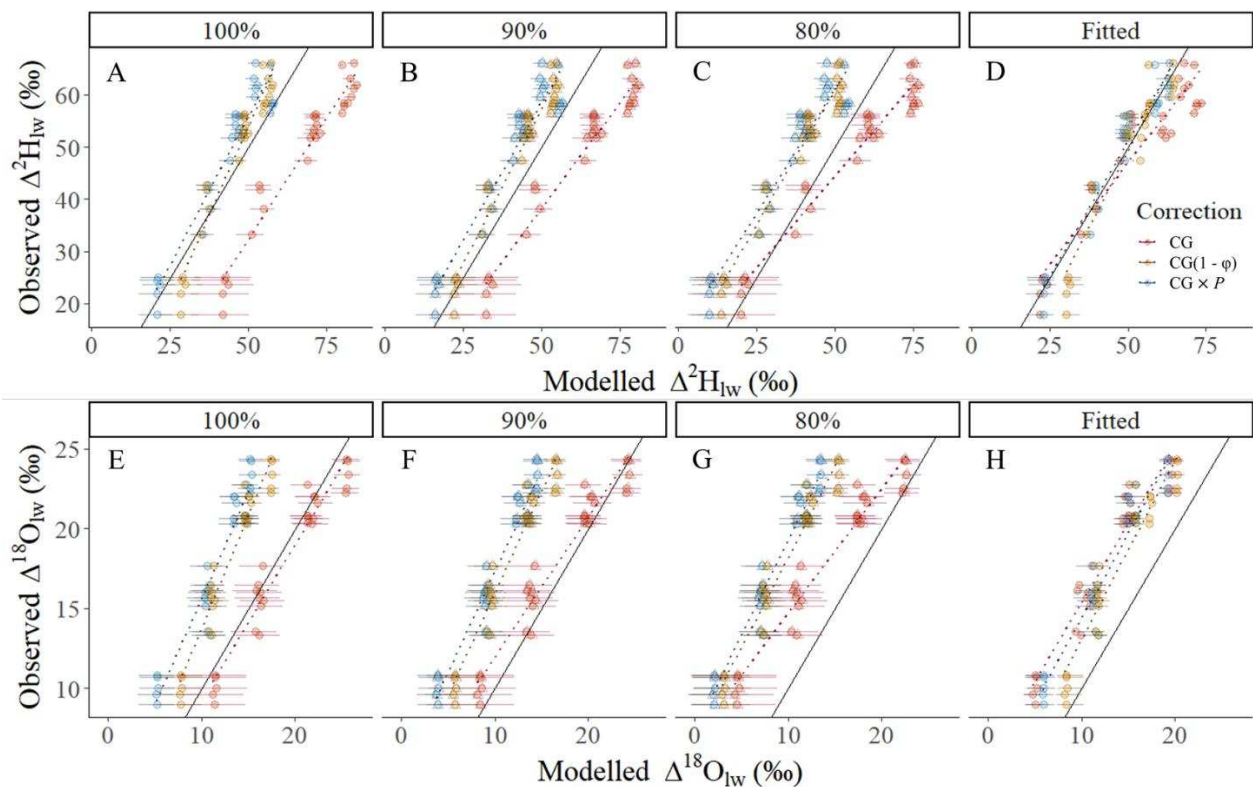


Figure 2. Relationships between modelled and measured Hyytiälä leaf water deuterium ( $\Delta^2\text{H}_{\text{lw}}$ ) and oxygen-18 ( $\Delta^{18}\text{O}_{\text{lw}}$ ) enrichment, when leaf intercellular space relative humidity ( $\text{RH}_{\text{cellular}}$ ) was changed in the models (100%, 90%, 80%, fitted  $\text{RH}_{\text{cellular}}$ ,  $n = 29$ ), to test unsaturated  $e_i$  effects to  $\Delta^2\text{H}_{\text{lw}}$  and  $\Delta^{18}\text{O}_{\text{lw}}$  via increased influence of  $\Delta_v$  and decreased influence of  $\epsilon_k$  to LWE. Dashed lines show linear mixed model fits, solid black lines demonstrate a 1:1 relationship, and horizontal lines show model variability in response to  $\pm 2^\circ\text{C}$  leaf temperature. Triangles in graphs with 90% and 80%  $\text{RH}_{\text{cellular}}$  show model results once intercellular resistance ( $r_i$ ) has been included in the calculation of  $\epsilon_k$ . CG: Craig-Gordon model;  $\text{CG}(1 - \phi)$ : Craig-Gordon model with two-pool correction;  $\text{CG} \times P$ : Craig-Gordon model with Péclet correction.

The fitted- $\text{RH}_{\text{cellular}}$  for  $\Delta^{18}\text{O}_{\text{lw}}$  consistently underestimated observed  $\Delta^{18}\text{O}_{\text{lw}}$ , for the foundational CG model (Fig. 2 h, Table 2). Indeed, the Craig Gordon model assuming 100%  $\text{RH}_{\text{cellular}}$  remained the best predictor of  $\Delta^{18}\text{O}_{\text{lw}}$  (Fig. 2 e, Table 2). In contrast, for  $\Delta^2\text{H}_{\text{lw}}$ , the fitted  $\text{RH}_{\text{cellular}}$  exhibited reduced offsets between modelled and measured values, producing better  $\Delta^2\text{H}_{\text{lw}}$  predictions compared to non-fitted  $\text{RH}_{\text{cellular}}$ , observed by a lowered Root Mean Square Error (RMSE) (Fig. 2 d; Table 2).

Performance of LWE models deteriorated extremely when only one of the two  $e_i$  occurrences in Equation 2 was adjusted for unsaturated  $e_i$  (Supplemental Table 1), showing that the

relationships between  $e_i$  and both  $\Delta_v$  and  $\varepsilon_k$ , are important to the response of LWE to unsaturated  $e_i$ .

# *Péclet and two-pool corrections*

Main results from this study can be derived from the foundational CG model, and results of additional Péclet and two-pool corrections are described to demonstrate how such corrections might interact with a decrease in  $e_i$  in Equation 2 tested for Hypothesis 1. Therefore, we used one calculation of effective path length for the Péclet correction, and a literature-derived constant  $\varphi$  for the two-pool correction.

The two-pool and Péclet correction almost always lowered  $\Delta^2\text{H}_{\text{lw}}$  and  $\Delta^{18}\text{O}_{\text{lw}}$  predictions compared to the CG model and they had larger effects at higher enrichments, except for when  $\text{RH}_{\text{cellular}}$  was fitted (orange series in Fig. 2; Table 2). Resultantly, they mostly underestimated  $\Delta^2\text{H}_{\text{lw}}$  and  $\Delta^{18}\text{O}_{\text{lw}}$ , but they still improved  $\Delta^2\text{H}_{\text{lw}}$  predictions when  $\text{RH}_{\text{cellular}}$  was 100%, 90%, or fitted (RMSE in Table 2). The Péclet correction had less of an effect bias to higher enrichments compared to the two-pool correction (blue series in Fig. 2; Table 2). Since the two-pool correction, the Péclet correction and the lowered  $\text{RH}_{\text{cellular}}$  all typically lowered predicted  $\Delta^2\text{H}_{\text{lw}}$  and  $\Delta^{18}\text{O}_{\text{lw}}$ , when the two-pool or Péclet correction were combined with lowered  $\text{RH}_{\text{cellular}}$ , they led to even lower predicted  $\Delta^2\text{H}_{\text{lw}}$  and  $\Delta^{18}\text{O}_{\text{lw}}$  than if applied individually, except for when  $\text{RH}_{\text{cellular}}$  was fitted (Fig. 2; Table 2). Indeed,  $\Delta^2\text{H}_{\text{lw}}$  was almost perfectly predicted, when  $\text{RH}_{\text{cellular}}$  was fitted after a Péclet correction had been applied (Fig. 2 d; Table 2). However, unrealistically high fitted  $\text{RH}_{\text{cellular}}$  were needed for the model optimization (103 – 146% and 105 – 210%, respectively; Supplemental Fig. 1), showing that the versions of two-pool and Péclet corrections used in this study were thus fundamentally incompatible with reductions in  $\text{RH}_{\text{cellular}}$  at Hyytiälä. Nevertheless, the larger effect to higher enrichments by the two-pool and Péclet corrections balanced the larger effect to lower enrichments by  $\text{RH}_{\text{cellular}}$  at 90% or 80%,

thus reducing resultant model prediction accuracy bias at different LWE, despite frequent underestimations.

### *Large-scale dataset*

Results from the large-scale dataset were mostly parallel to results from Hyytiälä. Like at Hyytiälä, a reduction in  $RH_{\text{cellular}}$  from 100%, to 90% and 80%, led to less enriched  $\Delta^2H_{\text{lw}}$  and  $\Delta^{18}O_{\text{lw}}$  predictions (Fig. 3; Table 3). Such reductions in predicted  $\Delta^2H_{\text{lw}}$  and  $\Delta^{18}O_{\text{lw}}$  clearly benefited  $\Delta^2H_{\text{lw}}$  prediction accuracy by reducing overestimates, most evidently shown by a large decrease in RMSE of model predictions (Table 3). These outcomes are the same as results observed for Hyytiälä (Table 2). However,  $\Delta^{18}O_{\text{lw}}$  prediction accuracy improved when  $RH_{\text{cellular}}$  was lower than 100%, as shown by a decrease in RMSE (Table 3), whereas  $\Delta^{18}O_{\text{lw}}$  prediction accuracy decreased when  $RH_{\text{cellular}}$  was lower than 100% at Hyytiälä (Table 2). The larger decrease in predicted LWE at lower predicted enrichments when  $RH_{\text{cellular}}$  was lowered from 100% to 90% or 80%, persisted beyond the Hyytiälä dataset to the large-scale dataset, for both elements (Fig. 3; Table 3). Like for Hyytiälä, this bias was mostly remediated for  $\Delta^{18}O_{\text{lw}}$  by using a fitted  $RH_{\text{cellular}}$  based on observed LWE and  $RH_{\text{atm}}$  (Fig. 3; Table 3). However, the fitted  $RH_{\text{cellular}}$  also largely remediated the bias for  $\Delta^2H_{\text{lw}}$ , unlike at Hyytiälä (Fig. 3; Table 3). In congruence with findings from Hyytiälä, the best-fitting model for  $\Delta^2H_{\text{lw}}$  was the model with a fitted  $RH_{\text{cellular}}$ , while unlike at Hyytiälä,  $\Delta^{18}O_{\text{lw}}$  was best explained by a model assuming 90%  $RH_{\text{cellular}}$  rather than 100%  $RH_{\text{cellular}}$ . Overall, results from the large-scale dataset reinforce the observed relevance of reduced  $RH_{\text{cellular}}$  to LWE observed at Hyytiälä, because they demonstrate that predictions of both  $\Delta^2H_{\text{lw}}$  and  $\Delta^{18}O_{\text{lw}}$  noticeably change, and even improve, in response to unsaturated  $e_i$ .



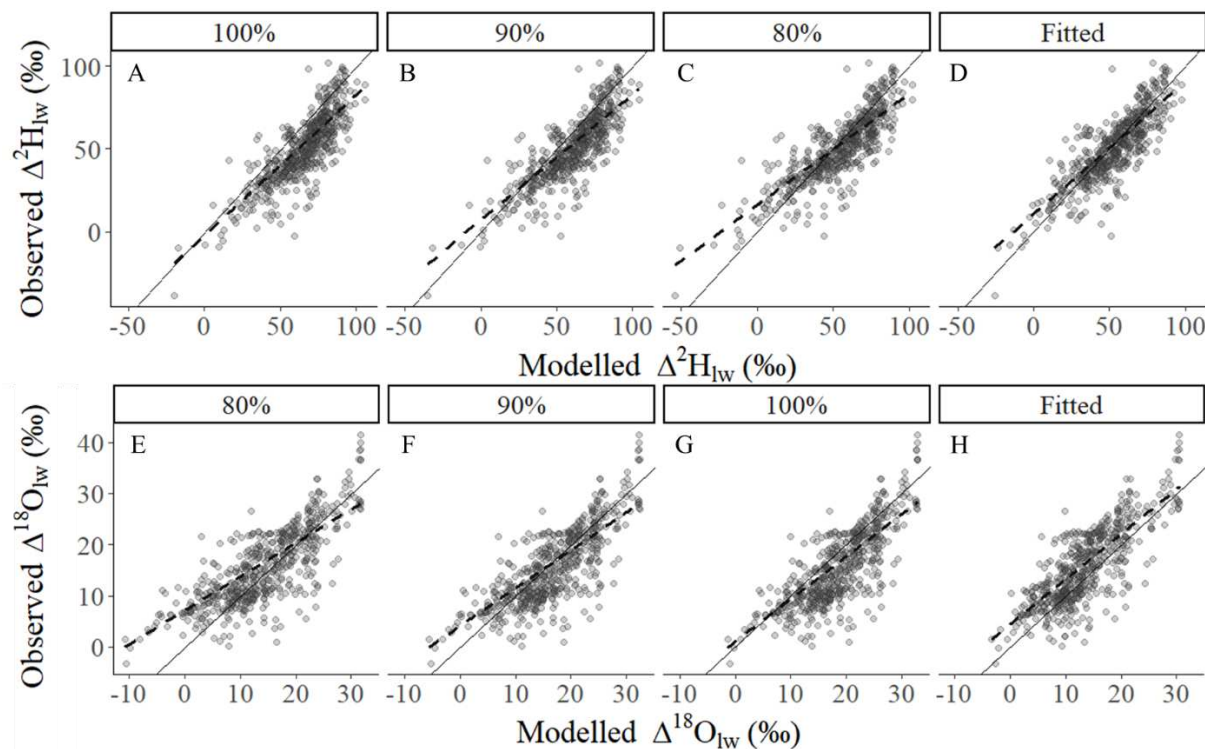


Figure 3. Relationships between Craig-Gordon model predictions and measured leaf water deuterium ( $\Delta^2H_{lw}$ ) and oxygen-18 ( $\Delta^{18}O_{lw}$ ) enrichment with different assumptions of leaf intercellular space relative humidity (100%, 90%, 80%, fitted), in the studied large-scale dataset. The dataset includes data from this study combined with review data from Cernusak *et al.* (2022) (Mechanism 1,  $n = 563$ ). Dashed lines show linear mixed model fits and solid lines demonstrate the 1:1 relationship.

### Fitted $RH_{cellular}$ predictions

The fitted  $RH_{cellular}$  increased as  $RH_{atm}$  increased (Fig. 4). The fitted  $RH_{cellular}$  for *P. sylvestris* at Hyytiälä was highly complementary to the fitted  $RH_{cellular}$  for the larger dataset, as indicated by the almost overlapping fitted  $RH_{cellular}$  along the common  $RH_{atm}$  gradient. Sensitivity tests for  $\pm 2^\circ\text{C}$  change in  $T_{leaf}$  showed that fitted  $RH_{cellular}$  is influenced by  $\pm 2^\circ\text{C}$  changes in  $T_{leaf}$ , at both Hyytiälä and in the larger dataset (shaded regions in Fig. 4).



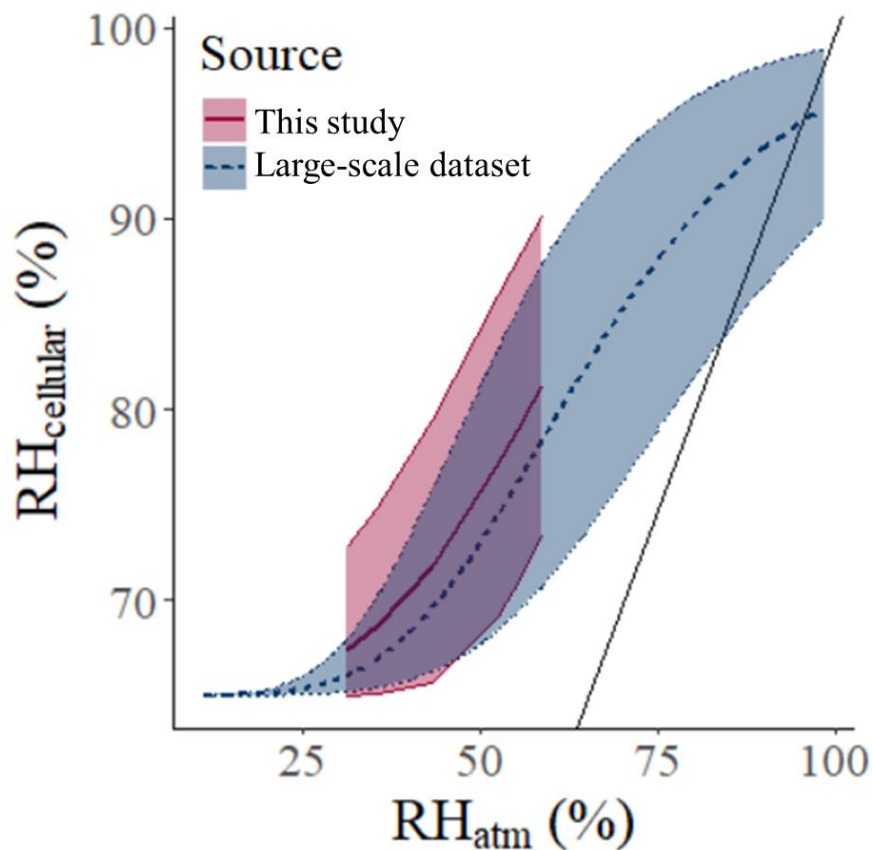


Figure 4. Fitted intercellular relative humidity ( $RH_{cellular}$ ) in response to atmospheric RH ( $RH_{atm}$ ) for *Pinus sylvestris* at Hyytiälä, Finland ( $n = 29$ , “This study”), and for the large-scale dataset which combines data from this study with review data from Cernusak *et al.* (2022) ( $n = 563$ , “Large-scale dataset”). The solid line demonstrates the 1:1 relationship, and shaded areas show fitted  $RH_{cellular}$  sensitivity to  $\pm 2^\circ\text{C}$  leaf temperature.

## Hypothesis 2: Intercellular resistance fractionation irrelevant to LWE

At Hyytiälä, the isotope fractionation by decreased  $r$  and introduced intercellular resistance ( $r_i$ ) from unsaturated  $e_i$  had a negligible influence on predicted  $\Delta^2H_{lw}$  and  $\Delta^{18}O_{lw}$ , at  $RH_{cellular}$  90% and 80% (triangles strongly overlapped by circles in Figure 3 B, C, F & G). It changed  $\epsilon_k$  estimates by less than 0.26 and 0.29 for  $\Delta^2H_{lw}$  and  $\Delta^{18}O_{lw}$ , respectively, for 90% and 80%  $RH_{cellular}$ . Resultantly, it changed LWE by only 0 – 0.17‰ at 90% and 80%  $RH_{cellular}$  for both  $\Delta^2H_{lw}$  and  $\Delta^{18}O_{lw}$ .

## Discussion

This study is the first to quantitatively evaluate the ecological relevance of unsaturated  $e_i$  to LWE. Overall, results showed that unsaturated  $e_i$  effects is likely relevant to LWE by changing LWE predictions, via both increased influence of  $\Delta_v$  and decreased influence of  $\epsilon_k$  (Fig. 2, 3; Table 2, 3, Supplemental Table 1). This means that it is necessary to consider unsaturated  $e_i$  as an important source of error to LWE predictions and reconstructions from organic material, albeit one which can be corrected. In this study, such corrections to  $e_i$  clearly benefited  $\Delta^2\text{H}_{\text{lw}}$  predictions, and conditionally benefited  $\Delta^{18}\text{O}_{\text{lw}}$  predictions (Fig. 2, 3; Table 2, 3). Results suggested that additional fractionation by concentration-driven diffusion in leaf intercellular spaces (Equation 6, 7) is unlikely relevant to LWE.

### **Correction for unsaturated $e_i$ in studies that use leaf water isotopes**

Overall, when  $\text{RH}_{\text{cellular}}$  and thus  $e_i$  was lowered in the foundational CG model, both  $\Delta^2\text{H}_{\text{lw}}$  and  $\Delta^{18}\text{O}_{\text{lw}}$  predictions changed (Fig. 2, 3; Table 2, 3). Such changes improved  $\Delta^2\text{H}_{\text{lw}}$  predictions produced by the CG model because the offset between observed and measured  $\Delta^2\text{H}_{\text{lw}}$  decreased, at both Hyytiälä and in the large-scale dataset (RMSE in Table 2, 3). Meanwhile, the benefits of lowered  $\text{RH}_{\text{cellular}}$  were not clear for  $\Delta^{18}\text{O}_{\text{lw}}$  because all reductions in  $\text{RH}_{\text{cellular}}$  in the CG model had effects too large for  $\Delta^{18}\text{O}_{\text{lw}}$  predictions at Hyytiälä, while all reductions in  $\text{RH}_{\text{cellular}}$  in the CG model improved  $\Delta^{18}\text{O}_{\text{lw}}$  predictions in the large-scale dataset compared to the CG model assuming saturated  $e_i$  (RMSE in Table 2, 3). The more evident benefit to  $\Delta^2\text{H}_{\text{lw}}$  could have been because  $\Delta^2\text{H}_{\text{lw}}$  can be strongly related to the isotopic disequilibrium between water vapor and source water, which was changed by the reductions in  $\text{RH}_{\text{cellular}}$  tested in this study, while  $\Delta^{18}\text{O}_{\text{lw}}$  is more strongly related to  $\text{RH}_{\text{atm}}$  (Munksgaard *et al.*, 2017; Cernusak *et al.*, 2022). These results show how it is potentially valuable to account for unsaturated  $e_i$  during  $\Delta^2\text{H}_{\text{lw}}$  predictions and  $\Delta^2\text{H}_{\text{lw}}$  reconstructions from plant compounds, such as tree rings or *n*-alkanes, because unsaturated  $e_i$  directly affects the factors known to be most strongly related to  $\Delta^2\text{H}_{\text{lw}}$ .

When using a constant lowered  $RH_{\text{cellular}}$  (90% or 80%), model bias increased, because the reduced  $RH_{\text{cellular}}$  affected lower predicted LWE more than higher predicted LWE for both  $\Delta^2H_{\text{lw}}$  and  $\Delta^{18}O_{\text{lw}}$  (Fig. 2, 3; Table 2, 3). It is noteworthy to recognize that this means that when 100%  $RH_{\text{cellular}}$  is being used when intercellular spaces are unsaturated, then it thus brings a model prediction accuracy bias of its own. This shows that it is valuable to start using a variable  $RH_{\text{cellular}}$  along a range of LWE values when calculating  $e_i$ , which is supported by evidence that  $RH_{\text{cellular}}$  changes (Cernusak *et al.*, 2018; Wong *et al.*, 2022). When results from this study are combined with measurements of  $RH_{\text{cellular}}$  responses to VPD from Cernusak *et al.* (2018), a viable solution for estimating  $RH_{\text{cellular}}$  is calculating  $RH_{\text{cellular}}$  from  $RH_{\text{atm}}$  or atmospheric VPD, which are negatively correlated to one another. More studies like Cernusak *et al.* (2018) are required to gather species-specific  $RH_{\text{cellular}}$  responses to changing  $RH_{\text{atm}}$  or VPD, their study can be used to tentatively estimate  $e_i$  of two species: *Juniperus monosperma* and *Pinus edulis*, in response to changing VPD. Otherwise, we suggest using the following equation to estimate  $e_i$ :

$$e_i = 0.65 + \frac{0.35}{(1 + A \times e^{-B \times RH_{\text{atm}}})^{\frac{1}{C}}}$$

wherein generalized suggested parameters are:  $A = 2.03$ ,  $B = 5.179$ , and  $C = 0.096$ , based on fitted  $RH_{\text{cellular}}$  from the large-scale dataset. More details can be found in the methods section (Equation 14). The large-scale dataset is a collection of different plant functional groups, and such diversity in the dataset could affect fitted  $RH_{\text{cellular}}$ , perhaps more so at the upper and lower  $RH_{\text{cellular}}$  limits. For example, variability in stomatal conductance could be responsible for extremely low fitted  $RH_{\text{cellular}}$  at low  $RH_{\text{atm}}$ , therefore it is likely important to incorporate non-steady state modelling in future studies when  $RH_{\text{atm}}$  is low. The correction can be refined to specific ecological contexts using site-specific and species-specific information, for example, by calculating a fitted  $RH_{\text{cellular}}$  based on an existing study of the same species in a similar

location, like this study evaluated Scots pine at Hyytiälä. Or, ideally, A and B are refined based on experimental data on species-specific  $RH_{\text{cellular}}$  responses to  $RH_{\text{atm}}$  or VPD. Indeed, these are suggested starting points for correcting  $e_i$  for its unsaturation when predicting or reconstructing LWE.

The model optimization estimated that fitted  $RH_{\text{cellular}}$  for optimal LWE predictions would reach much lower  $RH_{\text{cellular}}$  than what has been empirically measured by Cernusak *et al.* (2018) and Wong *et al.* (2022), especially at low  $RH_{\text{atm}}$  (Fig. 4). When the optimization was adjusted to limit fitted  $RH_{\text{cellular}}$  to measured values, the fitted  $RH_{\text{cellular}}$  for Hyytiälä was bounded to 80% across all measured  $RH_{\text{atm}}$  at Hyytiälä, which predicted  $\Delta^{18}O_{\text{lw}}$  poorly (Fig. 2G; Table 2). At low  $RH_{\text{atm}}$ , the extremely low fitted  $RH_{\text{cellular}}$  could have been affected by increased stomatal closure, because stomatal closure disrupts the hypothesized relationship between  $RH_{\text{atm}}$  and  $RH_{\text{cellular}}$ . Also, if  $\Delta^{18}O_{\text{lw}}$  was fitted separately to  $\Delta^2H_{\text{lw}}$  then the fitted  $RH_{\text{cellular}}$  of  $\Delta^{18}O_{\text{lw}}$  is closer to empirical measurements of  $RH_{\text{cellular}}$  by Cernusak *et al.* (2018) and Wong *et al.* (2022), especially at Hyytiälä (Supplemental Fig. 2). A potential reason for such low fitted  $RH_{\text{cellular}}$  for  $\Delta^2H_{\text{lw}}$ , is that the CG model did not predict  $\Delta^2H_{\text{lw}}$  as accurately as  $\Delta^{18}O_{\text{lw}}$  in this study (Fig. 2, 3; Table 2, 3). Therefore, a lower fitted  $RH_{\text{cellular}}$  for  $\Delta^2H_{\text{lw}}$  might have been necessary to remediate other sources of error in the CG model for  $\Delta^2H_{\text{lw}}$ . An alternative fitted  $RH_{\text{cellular}}$  to correct for unsaturated  $e_i$  for  $\Delta^{18}O_{\text{lw}}$  only, is based on separate fitting of  $RH_{\text{cellular}}$  for  $\Delta^{18}O_{\text{lw}}$  in the large-scale dataset ( $A = 1088.18$ ,  $B = 9.81$  and  $C = 3.06$ , Supplemental Fig. 2).

Results suggested that  $T_{\text{leaf}}$  is important to consider alongside accounting for unsaturated  $e_i$  in future studies, because fitted  $RH_{\text{cellular}}$  is sensitive to  $\pm 2^\circ\text{C}$  variability in  $T_{\text{leaf}}$  (Fig. 4). Cryogenic water extraction artefacts, and xylem sampling effects, may also affect LWE values (Chen *et al.*, 2020; Barbeta *et al.*, 2022; Diao *et al.*, 2022; Nehemy *et al.*, 2022).

When applying the Péclet correction,  $L$  is dependent on assumptions in the CG model (Table 1; Loucos et al. (2014)). In this study, we tested assumptions that could affect the calculation of  $L$ . Also, the Péclet and two-pool corrections can affect the accuracy of  $\Delta^2\text{H}_{\text{lw}}$  and  $\Delta^{18}\text{O}_{\text{lw}}$  predictions differently (Bögelein, Thomas and Kahmen, 2017). Therefore, it is understandable that in this study, the selected Péclet and two-pool corrections were favorable to only a minority of scenarios (Fig. 2; Table 2). Importantly, we have shown that it is necessary to develop co-implementation of the two-pool and Péclet with unsaturated  $e_i$  further, because the versions used in this study were incompatible with unsaturated  $e_i$  effects to  $\frac{e_a}{e_i}$  of the CG model (Equation 2; Fig. 2; Table 2). After all, when  $\text{RH}_{\text{cellular}}$  was fitted after the two-pool and Péclet corrections, the fitted  $\text{RH}_{\text{cellular}}$  became unrealistically high (103 – 146% and 105 – 210%, respectively, Supplemental Fig. 1). It is worthwhile to further explore the co-implementation of two-pool and Péclet corrections alongside adjustments for unsaturated  $e_i$ , because Péclet and two-pool corrections have potential to remediate model prediction accuracy bias introduced by unsaturated  $e_i$  via  $\frac{e_a}{e_i}$  of the CG model (Fig. 2; Table 2).

### **Unsaturated $e_i$ effects to fractionation within $\varepsilon_k$**

Results from this study showed that it is not necessary to further explore the effect of unsaturated  $e_i$  to fractionation within  $\varepsilon_k$ , by decreased  $r$  and introduced  $r_i$ , for 80 – 100%  $\text{RH}_{\text{cellular}}$ , because it had a negligible effect to predicted  $\Delta^2\text{H}_{\text{lw}}$  and  $\Delta^{18}\text{O}_{\text{lw}}$  ( $< 0.17\text{‰}$ , Fig. 2 B, C, F, G). A contributing factor to this finding, is that the influence of  $\varepsilon_k$  to LWE decreases in response to unsaturated  $e_i$ , as observed for Hypothesis 1. Therefore, intercellular resistance ( $r_i$ ) does not need to be incorporated into the calculation of  $\varepsilon_k$  in response to unsaturated  $e_i$ , unless the calculation of  $\varepsilon_k$  receives major revision in the future. There is opportunity for future investigations to explore how different calculation techniques for  $g_s$  might be affected by unsaturated  $e_i$  (see Damour *et al.*, 2010).

## Conclusion

Our results show that accounting for unsaturated  $e_i$  changes spatiotemporal LWE predictions and can even improve them. We therefore conclude that unsaturated  $e_i$  should be considered as a key modification factor of leaf water stable isotopes in future studies. Particularly, to account for higher influence of  $\Delta_p$  and lower influence of  $\varepsilon_k$  by decreasing  $e_i$  in  $\frac{e_a}{e_i}$  of the CG model (Equation 2). Corrections which use a constant value of  $RH_{\text{cellular}}$  when calculating  $\frac{e_a}{e_i}$  are not effective, likewise it is ineffective to continue to use a constant  $RH_{\text{cellular}}$  of 100%, when  $e_i$  is assumed to be saturated. We propose a model correction for both  $\Delta^2H_{lw}$  and  $\Delta^{18}O_{lw}$  based on  $RH_{\text{atm}}$ , and we suggest that such an approach can alternatively be applied with VPD. This model correction is a starting point for more accurately predicting LWE or reconstructing LWE from plant-derived organic proxies such as tree rings and  $n$ -alkanes. This may particularly benefit  $^2H$  interpretations, due to the noticeable improvement on  $\Delta^2H_{lw}$  predictions by lowered  $RH_{\text{cellular}}$  during LWE modelling, but it may not benefit  $^{18}O$  interpretations.

## Acknowledgements

Many thanks to Elina Sahlstedt, Giles Young, Kersti Leppä, Eloise Angove, Magdalena Drys, Aleksi Lehtonen, Yann Salmon, Daniel Zannoni and three anonymous reviewers for constructive comments, to Juha Heikkinen for statistical consultation, to Pasi Kolari for providing leaf cuvette gas exchange data, to Aino Seppänen for water extractions and to Daniel Nelson for performing stable isotope measurements.

## Funding

This work was supported by the Academy of Finland (#295319, #341984, #343059), the Academy of Finland Flagship Program (#337549), the Kone Foundation (#202006108), the Swiss National Science Foundation (#179978) and the European Research Council (#755865).

## Author contributions

YT, PS-A, KTR-G, PK & JB planned, facilitated and/or conducted field work at Hyytiälä. The subsequent manuscript idea was realized by CA, KTR-G, ML & MS. Data processing, isotope modelling, and analyses were conducted by CA and O-PT. CA was responsible for writing the manuscript, with major contributions from KTR-G, ML, MS, YT, AK, O-PT and all authors contributed to the writing of the manuscript.

## Data availability

Review data used in this study is freely available online thanks to Cernusak *et al.* (2022). The data from Hyytiälä which support findings from this study will be made freely available.

## Competing interests

None declared.

## Supplemental Materials

**Supplemental Table 1** Linear mixed model fits between modelled and observed leaf water deuterium ( $\Delta^2\text{H}_{\text{lw}}$ ) and oxygen-18 ( $\Delta^{18}\text{O}_{\text{lw}}$ ) when intercellular relative humidity ( $\text{RH}_{\text{cellular}}$ ) has been adjusted in association with, either, enrichment of atmospheric vapor relative to source water ( $\Delta^2\text{H}_{\text{wv}}$  or  $\Delta^{18}\text{O}_{\text{wv}}$ ), or, the kinetic fractionation during diffusion through the stomata and boundary layer ( $\epsilon_k$ ) in the Craig Gordon model.



**Supplemental Fig. 1** Fitted leaf intercellular space relative humidity, in response to atmospheric relative humidity, with different corrections for leaf water heavy isotope enrichment modelling.

**Supplemental Fig. 2** Fitted leaf intercellular relative humidity, in response to atmospheric relative humidity, separately fitted for each of  $\Delta^{18}\text{O}_{\text{lw}}$  and  $\Delta^2\text{H}_{\text{lw}}$ .

## References

- Aalto, J. *et al.* (2014) ‘New foliage growth is a significant, unaccounted source for volatiles in boreal evergreen forests’, *Biogeosciences*, 11(5). Available at: <https://doi.org/10.5194/bg-11-1331-2014>.
- Allison, G.B., Gat, J.R. and Leaney, F.W.J. (1985) ‘The relationship between deuterium and oxygen-18 delta values in leaf water’, *Chemical Geology: Isotope Geoscience Section*, 58(1–2). Available at: [https://doi.org/10.1016/0168-9622\(85\)90035-1](https://doi.org/10.1016/0168-9622(85)90035-1).
- Barbeta, A. *et al.* (2022) ‘Evidence for distinct isotopic compositions of sap and tissue water in tree stems: consequences for plant water source identification’, *New Phytologist*, 233(3). Available at: <https://doi.org/10.1111/nph.17857>.
- Bariac, T. *et al.* (1989) ‘Evaluating water fluxes of field-grown alfalfa from diurnal observations of natural isotope concentrations, energy budget and ecophysiological parameters’, *Agricultural and Forest Meteorology*, 48(3–4). Available at: [https://doi.org/10.1016/0168-1923\(89\)90073-7](https://doi.org/10.1016/0168-1923(89)90073-7).
- Bögelein, R., Thomas, F.M. and Kahmen, A. (2017) ‘Leaf water  $^{18}\text{O}$  and  $^2\text{H}$  enrichment along vertical canopy profiles in a broadleaved and a conifer forest tree’, *Plant Cell and Environment*, 40(7). Available at: <https://doi.org/10.1111/pce.12895>.
- Buckley, T.N. and Sack, L. (2019) ‘The humidity inside leaves and why you should care: implications of unsaturation of leaf intercellular airspaces’, *American Journal of Botany*, 106(5). Available at: <https://doi.org/10.1002/ajb2.1282>.
- Canny, M.J. and Huang, C.X. (2006) ‘Leaf water content and palisade cell size’, *New Phytologist*, 170(1). Available at: <https://doi.org/10.1111/j.1469-8137.2005.01633.x>.
- Cernusak, L.A. *et al.* (2016) ‘Stable isotopes in leaf water of terrestrial plants’, *Plant Cell and Environment*. Available at: <https://doi.org/10.1111/pce.12703>.
- Cernusak, L.A. *et al.* (2018) ‘Unsaturation of vapour pressure inside leaves of two conifer species’, *Scientific Reports*, 8(1). Available at: <https://doi.org/10.1038/s41598-018-25838-2>.



684 Cernusak, L.A. *et al.* (2022) ‘Do 2H and 18O in leaf water reflect environmental drivers  
685 differently?’, *New Phytologist*, 235(1). Available at: <https://doi.org/10.1111/nph.18113>.

686 Cernusak, L.A. and Kahmen, A. (2013) ‘The multifaceted relationship between leaf water  
687 18O enrichment and transpiration rate’, *Plant, Cell and Environment*, 36(7). Available at:  
688 <https://doi.org/10.1111/pce.12081>.

689 Chen, Y. *et al.* (2020) ‘Stem water cryogenic extraction biases estimation in deuterium  
690 isotope composition of plant source water’, *Proceedings of the National Academy of Sciences*  
691 *of the United States of America*, 117(52). Available at:  
692 <https://doi.org/10.1073/PNAS.2014422117>.

693 Craig, H. and G.L.I. (1965) ‘Isotope oceanography: Deuterium and oxygen 18 variations in  
694 the ocean and the marine atmosphere’, in *Symposium on Marine Geochemistry*.

695 Cueni, F. *et al.* (2021) ‘Using plant physiological stable oxygen isotope models to counter  
696 food fraud’, *Scientific Reports*, 11(1). Available at: [https://doi.org/10.1038/s41598-021-96722-](https://doi.org/10.1038/s41598-021-96722-9)  
697 9.

698 Damour, G., Simonneau, T., Cochard, H., & Urban, L. (2010). An overview of models of  
699 stomatal conductance at the leaf level. In *Plant, Cell and Environment* (Vol. 33, Issue 9).  
700 <https://doi.org/10.1111/j.1365-3040.2010.02181.x>

701 Diao, H. *et al.* (2022) ‘Technical note: On uncertainties in plant water isotopic composition  
702 following extraction by cryogenic vacuum distillation’, *Hydrology and Earth System*  
703 *Sciences*, 26(22). Available at: <https://doi.org/10.5194/hess-26-5835-2022>.

704 Dongmann, G. *et al.* (1974) ‘On the enrichment of H218O in the leaves of transpiring plants’,  
705 *Radiation and Environmental Biophysics*, 11(1). Available at:  
706 <https://doi.org/10.1007/BF01323099>.

707 Farquhar, G. D., Firth, P. M., Wetselaar, R., & Weir, B. (1980). On the Gaseous Exchange of  
708 Ammonia between Leaves and the Environment: Determination of the Ammonia  
709 Compensation Point. *Plant Physiology*, 66(4). <https://doi.org/10.1104/pp.66.4.710>

710 Farquhar, G.D. *et al.* (1989) ‘Carbon Isotope Fractionation and Plant Water-Use Efficiency’,  
711 in. Available at: [https://doi.org/10.1007/978-1-4612-3498-2\\_2](https://doi.org/10.1007/978-1-4612-3498-2_2).

712 Farquhar, G.D., Cernusak, L.A. and Barnes, B. (2007) ‘Heavy water fractionation during  
713 transpiration’, *Plant Physiology*. Available at: <https://doi.org/10.1104/pp.106.093278>.

714 Farquhar, G.D. and Lloyd, J. (1993) ‘Carbon and Oxygen Isotope Effects in the Exchange of  
715 Carbon Dioxide between Terrestrial Plants and the Atmosphere’, in *Stable Isotopes and Plant*  
716 *Carbon-water Relations*. Available at: <https://doi.org/10.1016/b978-0-08-091801-3.50011-8>.

717 Farquhar, G.D. and Raschke, K. (1978) ‘On the Resistance to Transpiration of the Sites of  
718 Evaporation within the Leaf’, *Plant Physiology*, 61(6). Available at:  
719 <https://doi.org/10.1104/pp.61.6.1000>.

720 Flanagan, L.B. and Ehleringer, J.R. (1991) 'Stable Isotope Composition of Stem and Leaf  
721 Water: Applications to the Study of Plant Water Use', *Functional Ecology*, 5(2). Available at:  
722 <https://doi.org/10.2307/2389264>.

723 Gessler, A. *et al.* (2009) 'Tracing carbon and oxygen isotope signals from newly assimilated  
724 sugars in the leaves to the tree-ring archive', *Plant, Cell and Environment*, 32(7). Available  
725 at: <https://doi.org/10.1111/j.1365-3040.2009.01957.x>.

726 Gessler, A. *et al.* (2018) 'Drought induced tree mortality – a tree-ring isotope based  
727 conceptual model to assess mechanisms and predispositions', *New Phytologist*. Available at:  
728 <https://doi.org/10.1111/nph.15154>.

729 Hartl-Meier, C. *et al.* (2014) 'Uniform climate sensitivity in tree-ring stable isotopes across  
730 species and sites in a mid-latitude temperate forest', *Tree Physiology*, 35(1). Available at:  
731 <https://doi.org/10.1093/treephys/tpu096>.

732 Hepp, J. *et al.* (2017) 'Late Quaternary relative humidity changes from Mt. Kilimanjaro,  
733 based on a coupled 2H-18O biomarker paleohygrometer approach', *Quaternary*  
734 *International*, 438. Available at: <https://doi.org/10.1016/j.quaint.2017.03.059>.

735 Holloway-Phillips, M. *et al.* (2022) 'Species variation in the hydrogen isotope composition of  
736 leaf cellulose is mostly driven by isotopic variation in leaf sucrose', *Plant Cell and*  
737 *Environment*, 45(9). Available at: <https://doi.org/10.1111/pce.14362>.

738 Horita, J., Rozanski, K. and Cohen, S. (2008) 'Isotope effects in the evaporation of water: A  
739 status report of the Craig-Gordon model', in *Isotopes in Environmental and Health Studies*.  
740 Available at: <https://doi.org/10.1080/10256010801887174>.

741 Jarvis, P.G. and Slatyer, R.O. (1970) 'The role of the mesophyll cell wall in leaf  
742 transpiration', *Planta*, 90(4). Available at: <https://doi.org/10.1007/BF00386383>.

743 Kahmen, A. *et al.* (2011) 'Cellulose  $\delta^{18}\text{O}$  is an index of leaf-to-air vapor pressure difference  
744 (VPD) in tropical plants', *Proceedings of the National Academy of Sciences of the United*  
745 *States of America*, 108(5). Available at: <https://doi.org/10.1073/pnas.1018906108>.

746 Kim, Y. *et al.* (2018) 'Thermal infrared imaging of conifer leaf temperatures: Comparison to  
747 thermocouple measurements and assessment of environmental influences', *Agricultural and*  
748 *Forest Meteorology*, 248. Available at: <https://doi.org/10.1016/j.agrformet.2017.10.010>.

749 Kolari, P. *et al.* (2012) 'Evaluation of accuracy in measurements of VOC emissions with  
750 dynamic chamber system', *Atmospheric Environment*, 62. Available at:  
751 <https://doi.org/10.1016/j.atmosenv.2012.08.054>.

752 Kolari, P. *et al.* (2022) *Hyytiälä SMEAR II site characteristics, [Data set]*. Available at:  
753 <https://dspace.uef.fi/handle/123456789/26786> (Accessed: 16 February 2023).

754 Launiainen, S. *et al.* (2016) ‘Do the energy fluxes and surface conductance of boreal  
755 coniferous forests in Europe scale with leaf area?’, *Global Change Biology*, 22(12). Available  
756 at: <https://doi.org/10.1111/gcb.13497>.

757 Leaney, F.W. *et al.* (1985) ‘Hydrogen-isotope composition of leaf water in C3 and C4 plants:  
758 its relationship to the hydrogen-isotope composition of dry matter’, *Planta*, 164(2). Available  
759 at: <https://doi.org/10.1007/BF00396084>.

760 Lehmann, M.M. *et al.* (2018) ‘The effect of 18O-labelled water vapour on the oxygen isotope  
761 ratio of water and assimilates in plants at high humidity’, *New Phytologist*, 217(1). Available  
762 at: <https://doi.org/10.1111/nph.14788>.

763 Lehmann, M.M. *et al.* (2021) ‘More than climate: Hydrogen isotope ratios in tree rings as  
764 novel plant physiological indicator for stress conditions’, *Dendrochronologia*, 65. Available  
765 at: <https://doi.org/10.1016/j.dendro.2020.125788>.

766 Leppä, K. *et al.* (2022) ‘Explicitly accounting for needle sugar pool size crucial for predicting  
767 intra-seasonal dynamics of needle carbohydrates  $\delta^{18}\text{O}$  and  $\delta^{13}\text{C}$ .’, *New Phytologist*, 236(6),  
768 pp. 2044–2060.

769 Loucos, K.E. *et al.* (2014) ‘Observed relationships between leaf H<sub>2</sub><sup>18</sup>O Péclet effective  
770 length and leaf hydraulic conductance reflect assumptions in Craig-Gordon model  
771 calculations’, *Tree Physiology*, 35(1). Available at: <https://doi.org/10.1093/treephys/tpu110>.

772 Merlivat, L. (1978). Molecular diffusivities of H<sub>2</sub><sup>16</sup>O, HD<sup>16</sup>O, and H<sub>2</sub><sup>18</sup>O in gases. The  
773 Journal of Chemical Physics, 69(6). <https://doi.org/10.1063/1.436884>

774 Munksgaard, N.C. *et al.* (2017) ‘Identifying drivers of leaf water and cellulose stable isotope  
775 enrichment in Eucalyptus in northern Australia’, *Oecologia*, 183(1). Available at:  
776 <https://doi.org/10.1007/s00442-016-3761-8>.

777 Nakagawa, S., Johnson, P.C.D. and Schielzeth, H. (2017) ‘The coefficient of determination  
778 R<sup>2</sup> and intra-class correlation coefficient from generalized linear mixed-effects models  
779 revisited and expanded’, *Journal of the Royal Society Interface*, 14(134). Available at:  
780 <https://doi.org/10.1098/rsif.2017.0213>.

781 Nehemy, M.F. *et al.* (2022) ‘Phloem water isotopically different to xylem water: Potential  
782 causes and implications for ecohydrological tracing’, *Ecohydrology*, 15(3). Available at:  
783 <https://doi.org/10.1002/eco.2417>.

784 Newberry, S.L., Nelson, D.B. and Kahmen, A. (2017) ‘Cryogenic vacuum artifacts do not  
785 affect plant water-uptake studies using stable isotope analysis’, *Ecohydrology*, 10(8).  
786 Available at: <https://doi.org/10.1002/eco.1892>.

787 Nobel, P.S. (2005) *Physicochemical and Environmental Plant Physiology, Third Edition*,  
788 *Physicochemical and Environmental Plant Physiology, Third Edition*. Available at:  
789 <https://doi.org/10.1016/B978-0-12-520026-4.X5000-8>.

790 Pirinen, P. *et al.* (2012) *Climatological statistics of Finland 1981-2010, Reports*.

791 R Core Team (2022) 'R: A language and environment for statistical computing'. Vienna,  
792 Austria: R Foundation for Statistical Computing. Available at: <https://www.R-project.org/>  
793 (Accessed: 19 January 2023).

794 Roden, J. *et al.* (2015) 'The enigma of effective path length for  $^{18}\text{O}$  enrichment in leaf water  
795 of conifers', *Plant Cell and Environment*, 38(12). Available at:  
796 <https://doi.org/10.1111/pce.12568>.

797 Sachse, D. *et al.* (2012) 'Molecular paleohydrology: Interpreting the hydrogen-isotopic  
798 composition of lipid biomarkers from photosynthesizing organisms', *Annual Review of Earth  
799 and Planetary Sciences*, 40. Available at: <https://doi.org/10.1146/annurev-earth-042711-105535>.

801 Sharkey, T.D. *et al.* (1982) 'A Direct Confirmation of the Standard Method of Estimating  
802 Intercellular Partial Pressure of  $\text{CO}_2$ ', *Plant Physiology*, 69(3). Available at:  
803 <https://doi.org/10.1104/pp.69.3.657>.

804 Snyder, K.A. *et al.* (2010) 'Diurnal variations of needle water isotopic ratios in two pine  
805 species', *Trees - Structure and Function*, 24(3). Available at: <https://doi.org/10.1007/s00468-010-0429-6>.

807 Song, X. *et al.* (2015) 'Measurements of transpiration isotopologues and leaf water to assess  
808 enrichment models in cotton', *New Phytologist*, 206(2). Available at:  
809 <https://doi.org/10.1111/nph.13296>.

810 Soudant, A. *et al.* (2016) 'Intra-annual variability of wood formation and  $\delta^{13}\text{C}$  in tree-rings  
811 at Hyytiälä, Finland', *Agricultural and Forest Meteorology*, 224. Available at:  
812 <https://doi.org/10.1016/j.agrformet.2016.04.015>.

813 Still, C.J. *et al.* (2022) 'No evidence of canopy-scale leaf thermoregulation to cool leaves  
814 below air temperature across a range of forest ecosystems', *Proceedings of the National  
815 Academy of Sciences of the United States of America*, 119(38). Available at:  
816 <https://doi.org/10.1073/pnas.2205682119>.

817 Tang, Y. *et al.* (2022) 'Tree organ growth and carbon allocation dynamics impact the  
818 magnitude and  $\delta^{13}\text{C}$  signal of stem and soil  $\text{CO}_2$  fluxes', *Tree Physiology*, 42(12). Available  
819 at: <https://doi.org/10.1093/treephys/tpac079>.

820 Treydte, K. *et al.* (2014) 'Seasonal transfer of oxygen isotopes from precipitation and soil to  
821 the tree ring: Source water versus needle water enrichment', *New Phytologist*, 202(3).  
822 Available at: <https://doi.org/10.1111/nph.12741>.

823 Vesala, T. *et al.* (2017) 'Effect of leaf water potential on internal humidity and  $\text{CO}_2$   
824 dissolution: Reverse transpiration and improved water use efficiency under negative  
825 pressure', *Frontiers in Plant Science*, 8(FEBRUARY). Available at:  
826 <https://doi.org/10.3389/fpls.2017.00054>.

827 Vitali, V. *et al.* (2022) ‘The unknown third – Hydrogen isotopes in tree-ring cellulose across  
828 Europe’, *Science of the Total Environment*, 813. Available at:  
829 <https://doi.org/10.1016/j.scitotenv.2021.152281>.

830 Voelker, S.L. *et al.* (2014) ‘Reconstructing relative humidity from plant  $\delta^{18}\text{O}$  and  $\delta\text{D}$  as  
831 deuterium deviations from the global meteoric water line’, *Ecological Applications*, 24(5).  
832 Available at: <https://doi.org/10.1890/13-0988.1>.

833 Walker, C.D. *et al.* (1989) ‘The influence of transpiration on the equilibration of leaf water  
834 with atmospheric water vapour’, *Plant, Cell & Environment*, 12(3). Available at:  
835 <https://doi.org/10.1111/j.1365-3040.1989.tb01937.x>.

836 West, A.G., Patrickson, S.J. and Ehleringer, J.R. (2006) ‘Water extraction times for plant and  
837 soil materials used in stable isotope analysis’, *Rapid Communications in Mass Spectrometry*,  
838 20(8). Available at: <https://doi.org/10.1002/rcm.2456>.

839 Wong, S.C. *et al.* (2022) ‘Humidity gradients in the air spaces of leaves’, *Nature Plants*, 8(8).  
840 Available at: <https://doi.org/10.1038/s41477-022-01202-1>.

841 Zannoni, D. *et al.* (2022) ‘Non-Equilibrium Fractionation Factors for D/H and  $^{18}\text{O}/^{16}\text{O}$   
842 During Oceanic Evaporation in the North-West Atlantic Region’, *Journal of Geophysical*  
843 *Research: Atmospheres*, 127(21). Available at: <https://doi.org/10.1029/2022JD037076>.

844

845

846

847

848

849

850

851

## Tables

Table 1. Abbreviations and symbols.

Abbreviation	Description	
LWE	Leaf water heavy isotope enrichment	
$\delta^2\text{H}$	Isotope ratio of $^2\text{H}$ compared to $^1\text{H}$ , relative to VSMOW (‰, Equation 4)	
$\delta^{18}\text{O}$	Isotope ratio of $^{18}\text{O}$ compared to $^{16}\text{O}$ , relative to VSMOW (‰, Equation 4)	855
$\text{RH}_{\text{atm}}$	Atmospheric relative humidity (%)	
$\text{RH}_{\text{cellular}}$	Relative humidity within leaf intercellular spaces (%)	
$\Delta^{18}\text{O}_{\text{lw}}$	Leaf water $^{18}\text{O}$ enrichment above source (xylem/twig) water (‰, Equation 5)	856
$\Delta^2\text{H}_{\text{lw}}$	Leaf water $^2\text{H}$ enrichment above source (xylem/twig) water (‰, Equation 5)	
$e_i$	Leaf intercellular water vapor pressure (kPa)	
$\varepsilon_k$	Combined kinetic fractionation factor for diffusion of water vapor through the stomata and leaf boundary layer. This study explores additional fractionation by $\varepsilon_k$ within $\varepsilon_k$ .	857
$\Delta_v$	Isotopic enrichment of atmospheric water vapor from source water (Equation 5)	
$L$	Effective path length for the Péclet effect	858
$T_{\text{leaf}}$	Leaf temperature (°C)	
$T_{\text{atm}}$	Atmospheric temperature (°C)	
$g_s$	Stomatal conductance ( $\text{mol m}^{-2}\text{s}^{-1}$ )	859
GFWL	Gross foliar water loss; all foliar water loss	
GFWU	Gross foliar water uptake; all foliar water uptake	
$\Psi$	Water potential (mPa)	860
$r$	Stomatal resistance ( $\text{mol m}^{-2}\text{s}^{-1}$ )	
$r_b$	Boundary layer resistance ( $\text{mol m}^{-2}\text{s}^{-1}$ )	
$r_i$	Intercellular resistance ( $\text{mol m}^{-2}\text{s}^{-1}$ ) (Supplemental Methods 2)	861
$\phi$	Proportion of unenriched xylem water in leaf water for the two-pool correction	
VPD	Vapor pressure deficit (kPa)	
RMSE	Root Mean Square Error. An estimate for overall proximity of predictions to observations.	862
CG	Craig Gordon leaf water heavy isotope enrichment model (Equation 2)	
$\text{CG}(1 - \phi)$	Craig-Gordon derived leaf water heavy isotope enrichment model with two-pool correction applied (Methods S1)	863
$\text{CG} \times P$	Craig-Gordon derived leaf water heavy isotope enrichment model with Péclet correction applied (Methods S1)	
$R^2(\text{M})$	Marginal $R^2$ . A pseudo- $R^2$ estimate for the models being tested	864
$R^2(\text{C})$	Conditional $R^2$ . A pseudo- $R^2$ estimate for the models being tested combined with model random effects, such as sampling date, time, and site	865
ICC	Intraclass Correlation. The probability that two values from the same sampling date and time, and/or site, correlate, on a scale of 0-1.	



Table 2. Linear mixed model fits between modelled and observed leaf water deuterium ( $\Delta^2\text{H}_{\text{lw}}$ ) and oxygen-18 ( $\Delta^{18}\text{O}_{\text{lw}}$ ) enrichment at Hyytiälä ( $n = 29$ ), with models using different intercellular relative humidity ( $\text{RH}_{\text{cellular}}$ , %, Mechanism 1. CG: Craig-Gordon model; CG(1 -  $\varphi$ ): Craig-Gordon model with two-pool correction; CG  $\times$  P: Craig-Gordon model with Péclet correction;  $\text{R}^2(\text{M})$ : Marginal  $\text{R}^2$ ;  $\text{R}^2(\text{C})$ : Conditional  $\text{R}^2$ ; ICC: Intraclass correlation between sampling dates).

	Model correction	$\text{RH}_{\text{cellular}}$ (%)	Intercept	Slope <sup>a</sup>	ICC	$\text{R}^2(\text{M})$	$\text{R}^2(\text{C})$	RMSE
$\Delta^2\text{H}_{\text{lw}}$	CG	100	$-14.26 \pm 3.88$	<b><math>0.93 \pm 0.06</math></b>	0.01	0.95	0.96	19.27
	CG(1 - $\varphi$ )		$-14.26 \pm 3.88$	<b><math>1.36 \pm 0.08</math></b>	0.01	0.95	0.96	5.44
	CG $\times$ P		$-1.29 \pm 4.55$	<b><math>1.14 \pm 0.1</math></b>	0.03	0.93	0.96	6.37
	CG	90	$-2.26 \pm 2.67$	<b><math>0.81 \pm 0.04</math></b>	0.01	0.95	0.96	14.52
	CG(1 - $\varphi$ )		$-2.26 \pm 2.67$	<b><math>1.19 \pm 0.06</math></b>	0.01	0.95	0.96	7
	CG $\times$ P		$5.91 \pm 4$	<b><math>1.05 \pm 0.09</math></b>	0.03	0.92	0.96	8.87
	CG	80	$9.29 \pm 2.01$	<b><math>0.7 \pm 0.03</math></b>	< 0.005	0.95	0.96	9.94
	CG(1 - $\varphi$ )		$9.29 \pm 2.01$	<b><math>1.03 \pm 0.05</math></b>	< 0.005	0.95	0.96	10.7
	CG $\times$ P		$13.48 \pm 3.44$	<b><math>0.95 \pm 0.09</math></b>	0.04	0.92	0.96	12.51
	CG	Fitted	$8.46 \pm 4.67$	<b><math>0.77 \pm 0.09</math></b>	0.06	0.9	0.96	7.24
	CG(1 - $\varphi$ )		$-9.79 \pm 6.06$	<b><math>1.18 \pm 0.12</math></b>	0.05	0.91	0.96	4.79
	CG $\times$ P		$-0.45 \pm 3.08$	<b><math>1.03 \pm 0.06</math></b>	0.01	0.95	0.96	3.48
$\Delta^{18}\text{O}_{\text{lw}}$	CG	100	$-0.58 \pm 1.12$	<b><math>0.98 \pm 0.06</math></b>	0.01	0.95	0.96	1.51
	CG(1 - $\varphi$ )		$-0.58 \pm 1.12$	<b><math>1.43 \pm 0.08</math></b>	0.01	0.95	0.96	5.26
	CG $\times$ P		$2.32 \pm 1.4$	<b><math>1.33 \pm 0.12</math></b>	0.03	0.93	0.96	6.4
	CG	90	$3.18 \pm 0.86$	<b><math>0.88 \pm 0.05</math></b>	0.01	0.95	0.96	1.68
	CG(1 - $\varphi$ )		$3.18 \pm 0.86$	<b><math>1.28 \pm 0.07</math></b>	0.01	0.95	0.96	6.57
	CG $\times$ P		$4.61 \pm 0.94$	<b><math>1.27 \pm 0.09</math></b>	0.02	0.94	0.96	7.59
	CG	80	$6.91 \pm 0.63$	<b><math>0.78 \pm 0.04</math></b>	0.01	0.95	0.96	4.12
	CG(1 - $\varphi$ )		$6.91 \pm 0.63$	<b><math>1.13 \pm 0.06</math></b>	0.01	0.95	0.96	8.3
	CG $\times$ P		$7.28 \pm 0.57$	<b><math>1.2 \pm 0.06</math></b>	< 0.005	0.95	0.96	9.12
	CG	Fitted	$5.46 \pm 1.02$	<b><math>0.99 \pm 0.08</math></b>	0.02	0.93	0.96	5.44
	CG(1 - $\varphi$ )		$1.74 \pm 1.56$	<b><math>1.13 \pm 0.11</math></b>	0.04	0.92	0.96	3.9
	CG $\times$ P		$3.68 \pm 1.24$	<b><math>1.07 \pm 0.09</math></b>	0.03	0.93	0.96	4.88

<sup>a</sup>Significant relationship when slope is **bold** ( $p < .001$ ).

Table 3. Linear mixed model fits between modelled and observed leaf water deuterium ( $\Delta^2\text{H}_{\text{lw}}$ ) and oxygen-18 ( $\Delta^{18}\text{O}_{\text{lw}}$ ) enrichment in the studied large-scale dataset, with models using different intercellular relative humidity ( $\text{RH}_{\text{cellular}}$  (%), Mechanism 1,  $n = 563$ ).

			Intercept	Slope <sup>a</sup>	ICC	R <sup>2</sup> (M)	R <sup>2</sup> (C)	RMSE
881	$\Delta^2\text{H}_{\text{lw}}$	100	$-2.54 \pm 2.43$	<b><math>0.85 \pm 0.03</math></b>	0.3	0.61	0.91	18.83
		90	$6.8 \pm 2.18$	<b><math>0.76 \pm 0.02</math></b>	0.29	0.62	0.91	15.58
		80	$16.08 \pm 1.95$	<b><math>0.67 \pm 0.02</math></b>	0.28	0.63	0.91	13.68
882	$\Delta^{18}\text{O}_{\text{lw}}$	Fitted	$10.52 \pm 1.87$	<b><math>0.8 \pm 0.03</math></b>	0.24	0.67	0.9	11.82
		100	$1.02 \pm 0.77$	<b><math>0.83 \pm 0.03</math></b>	0.24	0.61	0.84	5.58
		90	$4.08 \pm 0.69$	<b><math>0.74 \pm 0.03</math></b>	0.24	0.61	0.84	4.92
883		80	$7.12 \pm 0.62$	<b><math>0.66 \pm 0.02</math></b>	0.24	0.61	0.84	5.32
		Fitted	$4.46 \pm 0.64$	<b><math>0.88 \pm 0.03</math></b>	0.21	0.66	0.86	5.06

<sup>a</sup>Significant relationship when slope is **bold** ( $p < .001$ ).