

This document provides supporting information for the manuscript entitled:

How does rewetting propagate through restored peatlands? An integrated surface–subsurface modelling analysis of water–table dynamics

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Intended Use:

This supplementary data file provides detailed information supporting the manuscript, including model parameters, calibration settings, and spatial datasets. It is intended to ensure transparency of the modelling framework, support reproducibility, and facilitate further interpretation of the study results.

Table S1. Layer- and zone-specific model parameters describing subsurface flow, surface processes, and vegetation controls. Values were informed by literature and refined through calibration. Parameters marked as (manual/automated) underwent both first- and second-stage calibration, while those marked only as (automated) were adjusted in the second stage. Parameters labeled literature-constrained are hydrologically significant but fixed during calibration. All other parameters were default values, universal constants, or considered negligible, though they are available upon request.

<i>Parameter (Zone)</i>	<i>Process represented</i>	<i>Initial value</i>	<i>Lower bound</i>	<i>Upper bound</i>	<i>Calibrated value</i>	<i>Units</i>	<i>Calibration method</i>	<i>Guiding Source</i>
<i>Hz. Hydraulic Conductivity (Bottom peat; Disturbed)</i>	<i>Horizontal saturated groundwater flow (Darcy flow)</i>	3.00E-06	2.21E-07	7.74E-05	4.00E-06	(m/s)	<i>manual/ automated</i>	<i>(Menberu et al., 2021; Young et al., 2017)</i>
<i>Hz. Hydraulic Conductivity (Middle peat; Disturbed)</i>		9.00E-06	7.32E-08	3.90E-05	9.50E-06	(m/s)		
<i>Hz. Hydraulic Conductivity (Top peat; Disturbed)</i>		3.00E-05	9.48E-07	5.29E-04	3.50E-05	(m/s)		
<i>Hz. Hydraulic Conductivity (Bottom peat; Undisturbed)</i>		1.00E-06	1.30E-07	9.66E-05	7.50E-07	(m/s)		
<i>Hz. Hydraulic Conductivity (Middle peat; Undisturbed)</i>		1.20E-06	2.23E-07	4.02E-04	9.00E-07	(m/s)		
<i>Hz. Hydraulic Conductivity (Top peat; Undisturbed)</i>		8.50E-06	5.00E-07	6.99E-04	5.50E-06	(m/s)		
<i>Hz. Hydraulic Conductivity (Top till)</i>		2.00E-07	9.44E-08	2.36E-06	1.00E-07	(m/s)		<i>(Autio et al., 2023)</i>
<i>Hz. Hydraulic Conductivity (Middle till)</i>		1.00E-07	5.20E-08	2.36E-06	8.00E-08	(m/s)		
<i>Hz. Hydraulic Conductivity (Bottom till)</i>		1.00E-07	2.20E-08	2.36E-06	5.00E-08	(m/s)		
<i>Hz. Hydraulic Conductivity (Peat-Infilling)</i>	<i>Vertical saturated groundwater flow (Darcy flow)</i>	--	--	--	5.00E-06	(m/s)	<i>literature-constrained</i>	<i>(Addy & Wilkinson, 2019; Manners et al., 2007; Putra et al., 2022; Young et al., 2017)</i>
<i>Hz. Hydraulic Conductivity (Logs-Infilling)</i>		--	--	--	1.16E-03	(m/s)		
<i>Vl. Hydraulic Conductivity (Bottom peat; Disturbed)</i>		4.00E-07	2.21E-07	7.74E-05	3.00E-07	(m/s)	<i>automated</i>	<i>(Menberu et al., 2021; Young et al., 2017)</i>
<i>Vl. Hydraulic Conductivity (Middle peat; Disturbed)</i>		2.00E-06	7.32E-08	3.90E-05	1.00E-06	(m/s)		
<i>Vl. Hydraulic Conductivity (Top peat; Disturbed)</i>		9.00E-06	1.48E-07	5.29E-04	5.00E-06	(m/s)		
<i>Vl. Hydraulic Conductivity (Bottom peat; Undisturbed)</i>		2.00E-07	1.30E-07	9.66E-05	1.00E-07	(m/s)		

<i>VI. Hydraulic Conductivity (Middle peat; Undisturbed)</i>		<i>2.10E-07</i>	<i>1.23E-07</i>	<i>4.02E-04</i>	9.00E-08	<i>(m/s)</i>		
<i>VI. Hydraulic Conductivity (Top peat; Undisturbed)</i>		<i>1.50E-06</i>	<i>2.00E-07</i>	<i>6.99E-04</i>	8.00E-07	<i>(m/s)</i>		
<i>VI. Hydraulic Conductivity (Top till)</i>		<i>5.00E-08</i>	<i>2.36E-08</i>	<i>5.90E-07</i>	3.00E-08	<i>(m/s)</i>		
<i>VI. Hydraulic Conductivity (Middle till)</i>		<i>3.00E-08</i>	<i>1.30E-08</i>	<i>3.25E-06</i>	1.50E-08	<i>(m/s)</i>		
<i>VI. Hydraulic Conductivity (Bottom till)</i>		<i>3.00E-08</i>	<i>6.00E-09</i>	<i>3.25E-06</i>	9.00E-09	<i>(m/s)</i>		
<i>VI. Hydraulic Conductivity (Peat-Infilling)</i>		--	--	--	1.16E-04	<i>(m/s)</i>		
<i>VI. Hydraulic Conductivity (Logs-Infilling)</i>		--	--	--	5.00E-07	<i>(m/s)</i>	<i>literature-constrained</i>	<i>(Addy & Wilkinson, 2019; Manners et al., 2007; Putra et al., 2022; Young et al., 2017)</i>
<i>Manning roughness (forest)</i>		<i>4.50E-01</i>	<i>2.50E-01</i>	<i>7.00E-01</i>	4.04E-01	<i>(s/m^{1/3})</i>		
<i>Manning roughness (forested mire)</i>		<i>3.50E-01</i>	<i>2.50E-01</i>	<i>7.00E-01</i>	3.57E-01	<i>(s/m^{1/3})</i>		
<i>Manning roughness (open mire)</i>		<i>5.50E-01</i>	<i>2.50E-01</i>	<i>7.00E-01</i>	5.17E-01	<i>(s/m^{1/3})</i>		
<i>Manning roughness (drains/streams/riparian)</i>	<i>Overland flow (resistance and storage)</i>	--	--	--	1.00E-01	<i>(s/m^{1/3})</i>		
<i>Rill storage height (forest)</i>		<i>1.96E-03</i>	<i>1.00E-04</i>	<i>2.00E-01</i>	1.44E-03	<i>(m)</i>		
<i>Rill storage height (forested mire)</i>		<i>2.38E-03</i>	<i>1.00E-04</i>	<i>2.00E-01</i>	1.71E-03	--		
<i>Rill storage height (open mire)</i>		<i>6.33E-02</i>	<i>1.00E-04</i>	<i>2.00E-01</i>	6.46E-02	--		
<i>canopy storage parameter (Forest)</i>		<i>5.00E-05</i>	<i>1.00E-07</i>	<i>3.00E-03</i>	4.38E-05	<i>mm</i>	<i>automated</i>	
<i>canopy storage parameter (Peatlands)</i>		--	--	--	0.00E+00	<i>mm</i>		
<i>Transpiration limiting saturations (θ_{fc}/θ_s; Forests)</i>		<i>6.60E-01</i>	<i>3.00E-01</i>	<i>8.00E-01</i>	5.64E-01	--		
<i>Transpiration limiting saturations (θ_{fc}/θ_s; Peatlands)</i>	<i>Evapotranspiration and vegetation processes</i>	<i>6.60E-01</i>	<i>3.00E-01</i>	<i>8.00E-01</i>	7.04E-01	--		
<i>Leaf Area Index (LAI) (Forests)</i>		<i>2.50E+00</i>	<i>2.00E+00</i>	<i>1.00E+01</i>	7.83E+00	<i>m²m⁻²</i>		
<i>Leaf Area Index (LAI) (Peatlands)</i>		<i>1.50E+00</i>	<i>1.00E+00</i>	<i>6.00E+00</i>	3.05E+00	<i>m²m⁻²</i>		
<i>evaporation depth</i>		<i>1.00E-01</i>	<i>3.00E-02</i>	<i>3.00E-01</i>	1.03E-01	<i>m</i>		
<i>Leaf Area Index (LAI) (Cleared/Logged forest)</i>		--	--	--	2.50E+00	<i>m²m⁻²</i>	<i>literature-constrained</i>	
<i>Specific Storage (peat soils)</i>	<i>Aquifer elastic storage</i>	--	--	--	1.00E-02	<i>1/m</i>		
<i>Specific Storage (till soils)</i>		--	--	--	5.00E-04	<i>1/m</i>		<i>(Autio et al., 2023; Menberu et al., 2021)</i>

Table S2. van Genuchten soil hydraulic parameters used to represent unsaturated flow in peat and mineral soil units. The air-entry parameter α is expressed in cm^{-1} , and the parameter m is calculated as $m = 1 - 1/n$. All soil units are parameterized using the van Genuchten–Mualem formulation. Parameter values were guided by published literature (Menberu et al., 2021) and refined through an initial trial-and-error calibration stage.

Soil unit	θ_s (–)	θ_r (–)	α (L^{-1})	n (–)	m (–)
Peat Top (Disturbed)	9.10E-01	8.00E-02	3.00E-02	1.39E+00	2.81E-01
Peat Middle (Disturbed)	9.20E-01	2.00E-02	2.00E-02	1.42E+00	2.96E-01
Peat Bottom (Disturbed)	8.90E-01	5.00E-02	2.50E-02	1.40E+00	2.86E-01
Peat Top (Undisturbed)	9.30E-01	3.20E-01	2.00E-02	1.35E+00	2.59E-01
Peat Middle (Undisturbed)	9.30E-01	2.40E-01	3.00E-02	1.50E+00	3.33E-01
Peat Bottom (Undisturbed)	9.10E-01	3.30E-01	3.00E-02	1.53E+00	3.46E-01
Till Top	4.00E-01	1.00E-01	6.00E-02	2.50E+00	6.00E-01
Till Middle	4.00E-01	1.00E-01	5.50E-02	4.00E+00	7.50E-01
Till Bottom	3.40E-01	1.00E-01	4.50E-02	3.00E+00	6.67E-01

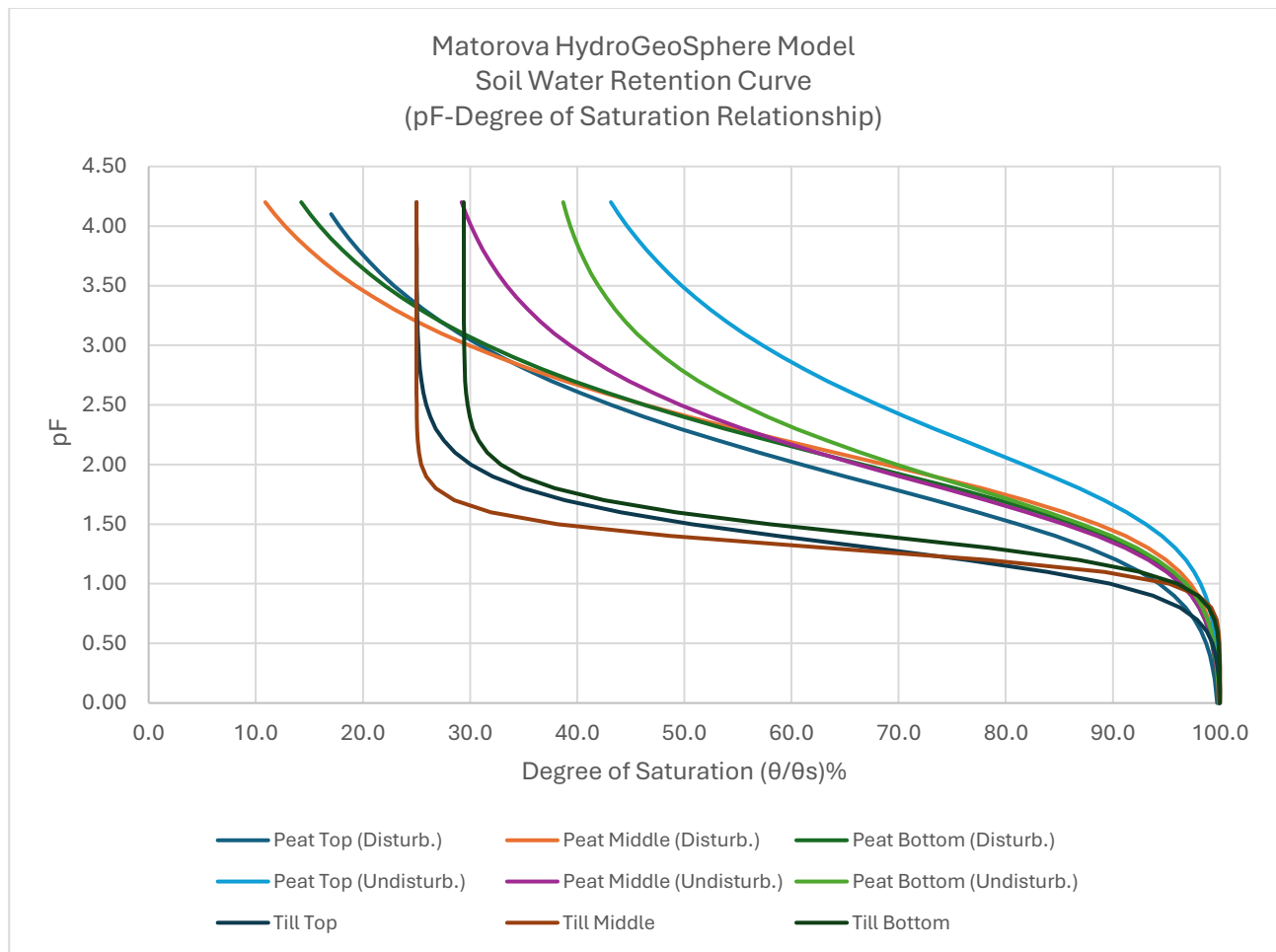


Figure S1. Soil water retention curves for the peat and mineral soil units used in this study, represented using the van Genuchten–Mualem formulation. Curves are based on the calibrated parameters listed in Table S1

Table S3. Weights assigned to observation groups for automatic calibration. The weights were designed to balance contributions across groups, targeting a total objective function value of $\phi = 10,000$. One-third of the total ϕ was allocated to the evapotranspiration (AET) observation group, while the remaining two-thirds were distributed equally among groundwater level (GWL) wells. The table lists the initial contribution (ϕ), desired contribution, and resulting weight (w_i) for each observation group. The actual initial total ϕ across all groups was 226.932.

Observation Group	Initial Contribution (ϕ)	Desired contribution	Weight (w_i)
Actual ET	4.81E-01	3.33E+03	8.33E+01
WT - PZ10	1.64E+01	8.33E+02	7.13E+00
WT - PZ11	1.63E+01	8.33E+02	7.15E+00
WT - PZ12	2.38E+01	8.33E+02	5.91E+00
WT - PZ13	5.77E+00	8.33E+02	1.20E+01
WT - PZ14	1.66E+01	8.33E+02	7.09E+00
WT - PZ19	4.25E+01	8.33E+02	4.43E+00
WT - PZ20	4.55E+01	8.33E+02	4.28E+00
WT - PZ27	5.95E+01	8.33E+02	3.74E+00

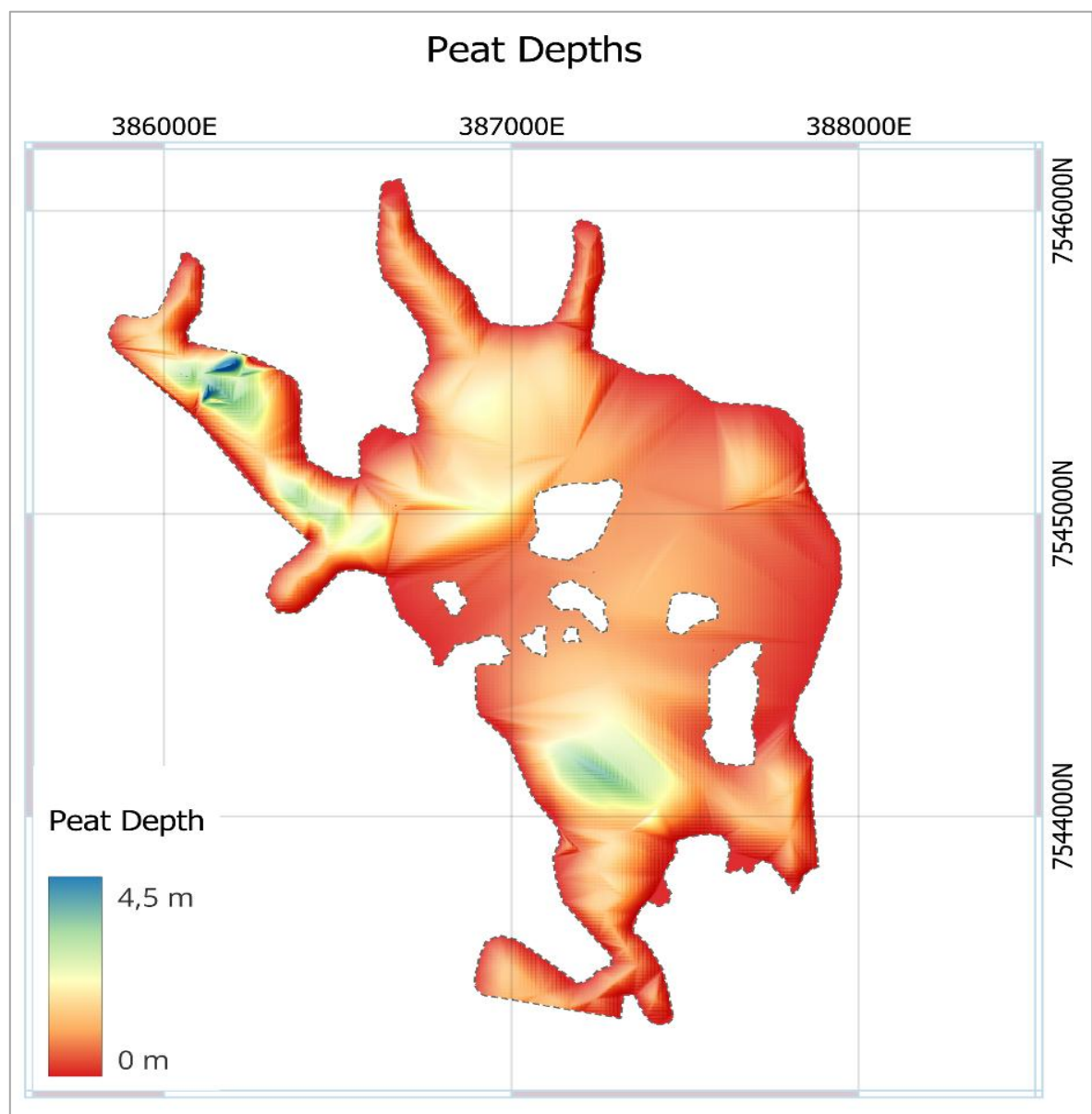


Figure S2. Spatial distribution of peat depth, interpolated from manual measurements

Supplementary Text S1. Linear parameter-uncertainty and identifiability analysis

S1.1 Method

After calibration, we quantified the degree to which the observation network (groundwater-level and actual-evapotranspiration records) constrains the estimated parameters using linear, first-order second-moment (FOSM) analysis applied to the calibration Jacobian. All analyses were performed with the pyEMU framework (White et al., 2016), which implements the PEST/PEST++ uncertainty theory of Doherty (2015). The analysis characterizes the parameters adjusted by automated calibration, organized into the process groups of Table S4 and Figure S3.

The prior parameter covariance C_θ is taken as diagonal, with each parameter assigned a standard deviation derived from its calibration bounds (Table S1; in $\log_{10}$ space for log-transformed parameters), as (Eq. S1).

$$\sigma_i = \frac{b_i^{\text{up}} - b_i^{\text{low}}}{s} \quad (\text{Eq. S1}),$$

where b_i^{up} and b_i^{low} are the upper and lower bounds and $s = 4$, so that the bounds span $\pm 2\sigma$. Given the Jacobian (sensitivity matrix) J evaluated at the calibrated parameters and the observation-noise covariance C_ϵ (diagonal, with entries equal to the inverse square of the calibration weights); the posterior parameter covariance follows from the Schur complement (Eq. S2),

$$C_{\theta|d} = C_\theta - C_\theta J^\top (J C_\theta J^\top + C_\epsilon)^{-1} J C_\theta \quad (\text{Eq. S2}).$$

This conditional covariance is the linear-Gaussian (FOSM) estimate of parameter uncertainty after calibration.

Uncertainty reduction (Figure S3; Table S4). For each process group g we report the fractional reduction in parameter variance (r_g) achieved by calibration (Eq. S3),

$$r_g = 1 - \frac{\text{tr}(C_{\theta|d,g})}{\text{tr}(C_{\theta,g})} \quad (\text{Eq. S3}),$$

where C_θ and $C_{\theta|d}$ are the prior and posterior covariance blocks for the parameters in group g , and $\text{tr}(\cdot)$ is the trace (i.e., the sum of their variances) over the parameters in that group. Figure S3 shows, for each group, the prior $\mathcal{N}(0,1)$ and posterior $\mathcal{N}(0, \sqrt{1-r_g})$ parameter densities, each parameter having been rescaled by its own prior standard deviation before plotting. This places every group on a common, dimensionless axis: the prior becomes the standard normal in every panel (hence the identical grey curves), and the posterior is shown as a fraction of that same prior width. The benefit is direct comparability; for instance, a hydraulic conductivity, a Manning roughness, and an evapotranspiration parameter have very different physical units and ranges, so their raw distributions cannot be placed side by side; once expressed in prior- σ units, the narrowing of each

posterior relative to its prior is read off the same scale. A posterior that fills the panel is essentially unconstrained by the data; one that collapses to a narrow spike near zero is tightly constrained, with the annotated percentage (Eq. S3) quantifying that narrowing.

In Table S4 each group is summarized qualitatively as strongly ($r_g \geq 90\%$), moderately ($70\% \leq r_g < 90\%$) or weakly/limited ($r_g < 70\%$) constrained; these are descriptive bands to aid interpretation, not formal thresholds. Both diagnostics are linear approximations taken about the calibrated parameter set and are conditional on the adopted model structure and the assumed prior; the reported values therefore express relative, group-level constraint rather than absolute predictive uncertainty.

Identifiability (Figure S4; Table S4). As a complementary diagnostic we computed parameter identifiability (Doherty and Hunt, 2009) from the singular value decomposition of the weighted Jacobian (Eq. S4),

$$Q^{1/2}J = USV^T \quad (\text{Eq. S4}),$$

where $Q = C_\epsilon^{-1}$ is the observation weight matrix, S holds the singular values, and the columns of V are the parameter-space (right) singular vectors. Retaining the first k vectors that span the calibration solution space (here the number capturing 95% of the spectral energy) the identifiability of parameter i is the squared length of its projection onto that space (Eq. S5),

$$d_i = \sum_{j=1}^k V_{ij}^2, \quad 0 \leq d_i \leq 1 \quad (\text{Eq. S5}),$$

with $d_i \rightarrow 1$ for a parameter lying within the solution space (well resolved) and $d_i \rightarrow 0$ for one confined to the null space (unresolved). Group identifiability, $\sum_{i \in g} d_i$, is the number of independent parameter directions the data resolve within group g ; summed over all groups it equals k . The effective dimensionality of the inverse problem, the number of singular values needed to capture 90, 95 and 99% of the spectral energy, provides a complementary, truncation-explicit measure of how many independent directions the observations resolve.

S1.2 Results and implications

The two diagnostics agree and are physically coherent. The saturated hydraulic conductivities dominate the resolved information; the disturbed-peat conductivities are the most strongly constrained ($r_g \approx 97\text{--}98\%$) and account for the largest share of resolved directions (summed identifiability $\approx 1.5\text{--}1.7$ each, together roughly half of the total), with the undisturbed peat close behind ($\approx 95\text{--}96\%$). Till and overland-flow parameters are moderately constrained ($\approx 77\text{--}84\%$), and evapotranspiration least (from $\approx 68\%$ (forest) to $\approx 10\%$ (mire), with correspondingly low identifiability). Across all groups, the observation network resolves approximately six independent parameter directions (effective dimensionality of four, six and twelve at the 90, 95 and 99% energy levels).

The practical implication is central for the reported results. The inversion concentrates its resolving power on the peat saturated conductivities; the parameters that govern lateral and vertical water movement and, through them, the magnitude of rewetting and the extent of hydrological influence around infilled ditches and dams. These are the best constrained parameter groups, exhibiting 95–98% uncertainty reduction and the highest identifiability (Table S4). In other words, the parameters the observations constrain most tightly are the same ones the predictions depend on most. Influence on the reported groundwater metrics declines in step with identifiability, so that the least-resolved parameters, principally evapotranspiration, contribute little to the headline results. The reported water-table changes and zones of influence thus rest on the best-determined parameters in the model, and the apparent dimensionality of the parameterization overstates the degrees of freedom actually informing the predictions.

Table S4. Process-group constraint summary from the linear (FOSM) parameter-uncertainty analysis.

<i>Parameter group</i>	<i>Process represented</i>	<i>Uncertainty reduction (%)</i>	<i>Identifiability (resolved directions)</i>	<i>Constraint</i>
<i>Kh (disturbed peat)</i>	<i>Horizontal saturated groundwater flow</i>	97	1.51	Strong
<i>Kh (undisturbed peat)</i>		96	0.55	Strong
<i>Kv (disturbed peat)</i>	<i>Vertical saturated groundwater flow</i>	98	1.70	Strong
<i>Kv (undisturbed peat)</i>		95	0.47	Strong
<i>Kh (till)</i>	<i>Horizontal saturated groundwater flow</i>	77	0.41	Moderate
<i>Kv (till)</i>	<i>Vertical saturated groundwater flow</i>	84	0.22	Moderate
<i>Overland (forest)</i>	<i>Overland flow (resistance and storage)</i>	79	0.45	Moderate
<i>Overland (mire)</i>		82	0.55	Moderate
<i>ET (forest)</i>	<i>Evapotranspiration and vegetation processes</i>	68	0.11	Limited
<i>ET (mire)</i>		10	0.03	Limited

Notes. Uncertainty reduction is the prior-to-posterior decrease in parameter variance (trace ratio) from first-order second-moment (FOSM) analysis of the calibration Jacobian, aggregated by process group. Identifiability is the summed Doherty and Hunt (2009) identifiability of a group's parameters at a 95%-information truncation, expressed as the number of independent parameter directions the observation network resolves for that group; the ranking is insensitive to the truncation level. Across all groups the data resolve approximately six independent directions, concentrated in the saturated conductivities that govern the simulated water-table response, indicating the inversion is far better-posed than the nominal parameter count implies.

Group definitions (Table S1). Peat and till conductivity groups comprise the horizontal (K_h) or vertical (K_v) saturated hydraulic conductivity of the disturbed-peat, undisturbed-peat, and till layers. Overland (forest/mire) comprises Manning roughness and rill storage height for the forest and mire zones. ET (forest/mire) comprises canopy storage, transpiration-limiting saturation, leaf-area index, and evaporation depth for the forest and mire zones.

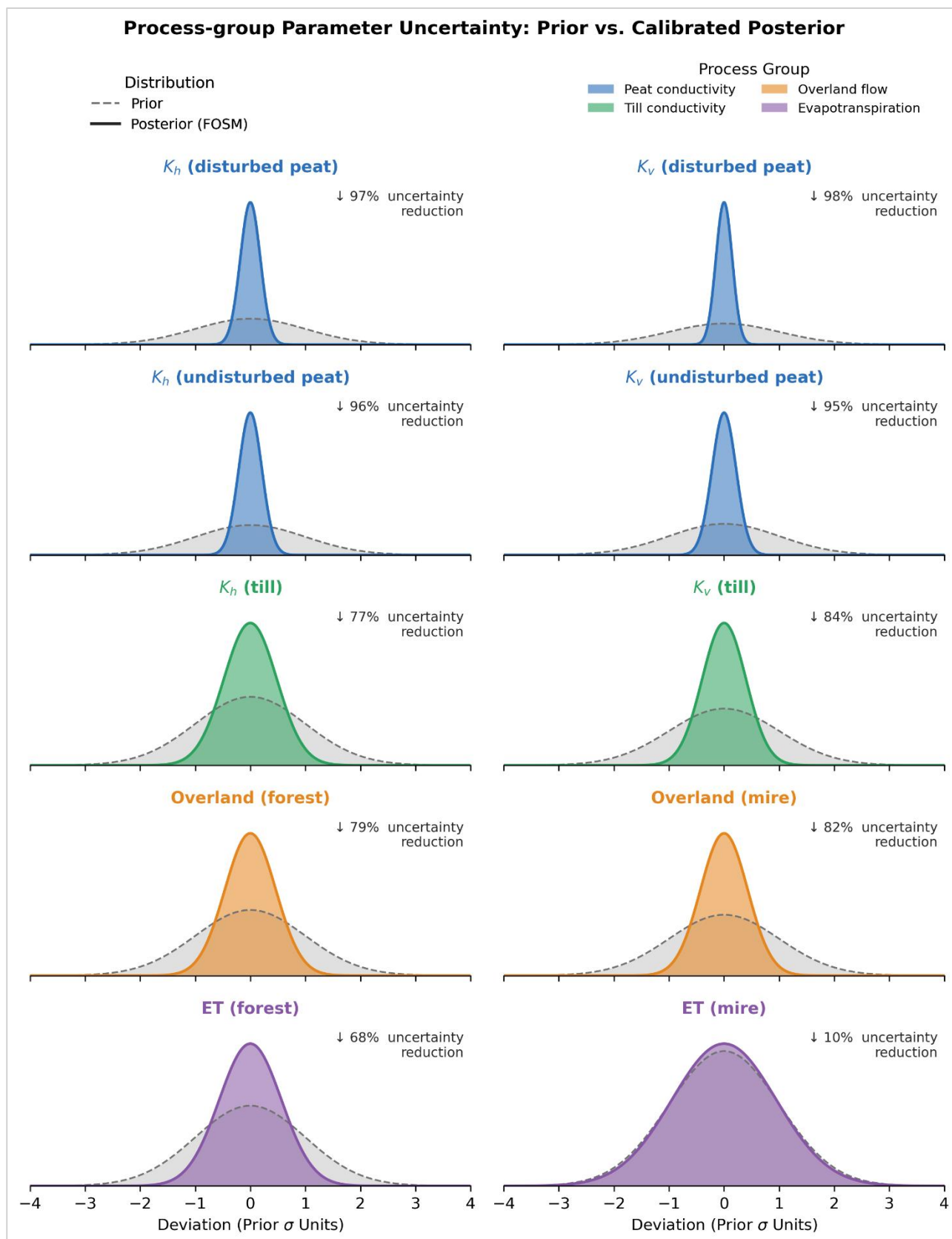


Figure S3. Prior-to-posterior reduction in parameter uncertainty by process group, from linear (FOSM) analysis of the calibration Jacobian (Eq. S2–S3). Each parameter is rescaled by its own prior standard deviation, so the prior is the standard normal in every panel (grey, dashed) and the posterior (filled) shows directly how far calibration narrowed it: a near-spike is tightly constrained, a curve close to the prior is not. The annotated percentage is this narrowing, expressed as the reduction in parameter variance.

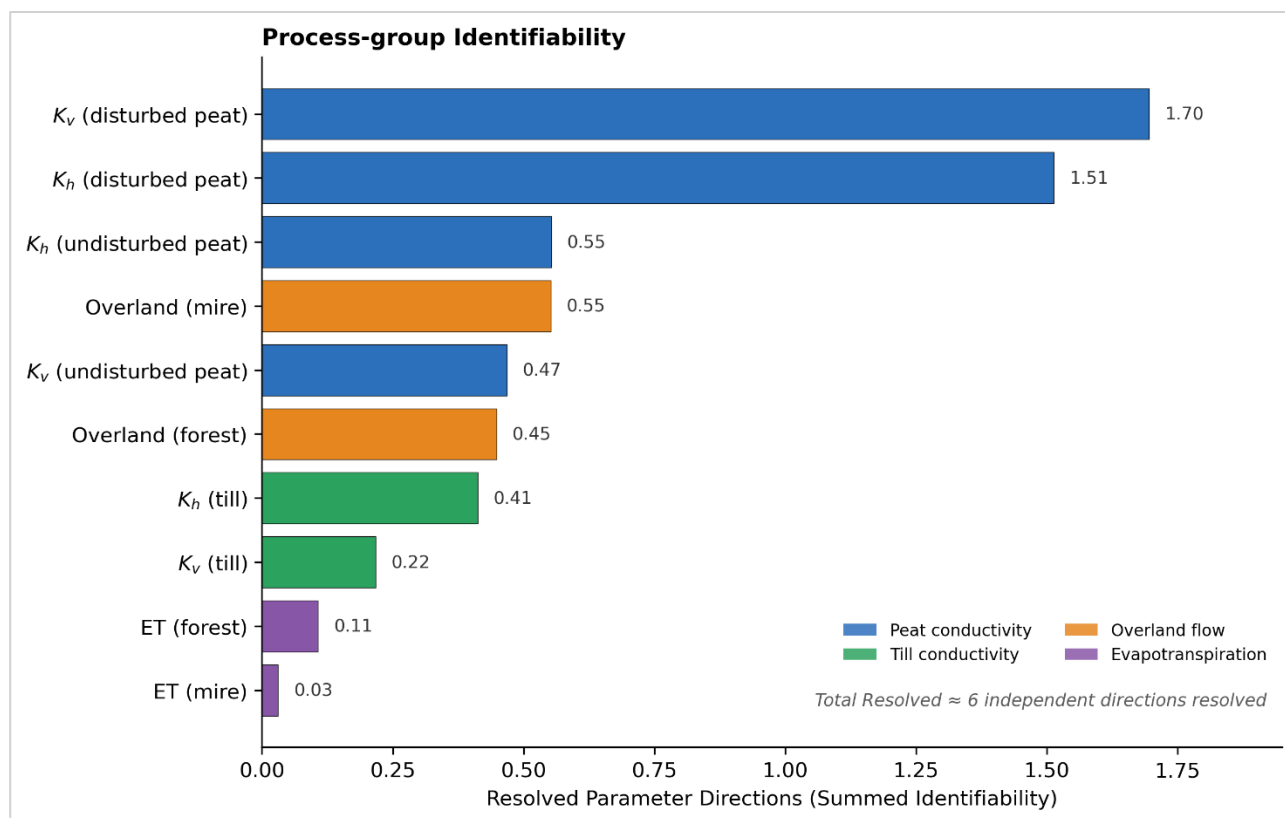


Figure S4. Process-group parameter identifiability from singular value decomposition of the weighted calibration Jacobian (Eq. S4), retaining the directions carrying 95% of the spectral energy. Bar length is the summed identifiability of a group's parameters (the number of independent directions in that 95%-information space attributable to the group), so longer bars mark process groups the observation network resolves most distinctly, not merely most precisely. Group values sum to the total number of independent directions the data resolve (≈ 6).

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