

Supplementary Materials for

Human activities shape global patterns of decomposition rates in rivers

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Materials and Methods

Cellulose decomposition

We used a global dataset of cellulose-decomposition rates generated by a coordinated field experiment (Cellulose Decomposition Experiment [CELLDEX]) (19). Cotton strips were incubated in 514 flowing waters spanning 135 degrees of latitude by a consortium of over 150 peer-sourced researchers. Cotton strips are composed of cellulose, the primary constituent of most terrestrially derived leaf litter and the most abundant organic polymer on Earth; as such, cellulose is a plant polymer that is highly relevant for global biogeochemical cycles. The cotton-strip assay is an integrative measure of the activity of heterotrophic microbes and is highly sensitive to an array of environmental factors including nutrient concentrations, temperature, and pollutants (24). As used in our study the assay is not believed to be directly influenced by the feeding activity of macroinvertebrates. Cotton strips were deployed in 2015-2016 during periods of peak organic-matter inputs to flowing waters (e.g., autumn in temperate zones, dry season in tropical deciduous forests) at sites relatively free of major anthropogenic impacts. We typically chose stream orders 1-3 (45) and had sites located in each of Earth's major terrestrial biomes (19), and the cellulose-decomposition rate at each river was summarized as the exponential decay rate (K_d) of tensile-strength loss:

$K_d = -\ln(T_f/T_i)/t$

where T_f is the final tensile strength of each cotton strip after incubation in the field, T_i is an average tensile-strength value of control strips not incubated in the field to establish initial tensile strength, and *t* the field incubation time in days (usually 21-30 days). The loss of tensile strength corresponds to the decomposition of the cotton fabric and is driven predominantly by the activity of microbes. Field and laboratory methods are detailed in (19, 24).

Environmental data sources

For data on environmental variables other than *in-situ* water temperature, we relied on publicly available datasets with global coverage: 1) (46) for estimates of river yields of dissolved reactive phosphorus (kg DRP-P ha⁻¹ yr⁻¹) and nitrate+nitrite (kg NO_X-N ha⁻¹ yr⁻¹); 2) (47) for estimates of nitrogen (N) deposition; 3) (48) and (49) for estimates of phosphorus (P) deposition that we then interpolated; and 4) (38) for data on 96 variables summarized at the 12-digit hydrological scale or for the area upstream (HydroRIVERS: River ATLAS_v10_lev12; HydroBASINS: BasinATLAS_v10_lev12) for either river reaches or corresponding subwatersheds, though all variables were not populated for all sub-watersheds. We excluded variables from HydroBASINS that were composite measures where we already included confounded variables (e.g., biome, human development index, and human footprint). We recorded temperature data with loggers for a subset (*n*=360) of the 514 rivers to determine the mean daily temperature of the river water during the cotton-strip incubation period.

Litter decomposition data

We used a global dataset of 3,216 unique estimates of litter-decomposition rates (as K_d using the equation above except that mass rather than tensile strength was used) for 125 plant genera and multiple experimental conditions (27) to independently validate whether our cellulose-decomposition model could explain rates of litter decomposition. These data are an

expanded version of the data published by LeRoy et al. (2020) (see data repository for complete data)(27). For each unique river reach sampled in the dataset, we averaged K_d estimates by each unique combination of leaf condition (i.e., leaves picked from the trees while still living or collected from the ground after senescence), plant genus, and direct feeding by detritivorous invertebrates (i.e., coarse-mesh which included invertebrates or fine-mesh litter bags which excluded invertebrates). We excluded any data for which we had 3 or fewer measurements of decomposition for a genus. The final dataset included 895 unique observations of 35 genera from 559 river reaches. All but 7 estimates of litter decomposition also included mean temperature during deployment, which we included as a predictor variable.

Leaf- and litter-trait data sources

We downloaded 384,252 records from 21,100 plant species and 4,557 genera of leaf traits related to nutrient, micronutrient, and structural compounds for leaves from the TRY plant-trait database (31). After filtering for traits describing the chemical constituency of plant leaves that we felt were most relevant for decomposition, the resulting database included average values for 7 traits representing 64 genera. Litter traits were assembled from 114 studies comprising 602 litter deployments of 172 genera in rivers (43). These trait values were joined by genus to the aforementioned empirical data on leaf litter. All genera for which we had litter-decomposition rates had data regarding either leaf or litter traits, and most included complete values for both. Details on filtering, aggregating, and variable selection as well as full datasets can be found in the data repository (43).

Data Analysis

Environmental data processing

At each river sampling location in the CELLDEX dataset, we combined temperature recorded during the experiment, extracted values from nutrient yield and deposition rasters, and attributes from HydroBASINS summarized by upstream watershed as well as the containing sub-watershed. For HydroBASINS fields that were additionally available as monthly summaries (e.g., air temperature, potential evapotranspiration, snow coverage), we used both annual summaries and those from the month of deployment at each site as predictors in the BRT model. Variables from HydroBASINS were back-transformed into original units, and predictors with log-normal distributions were log₁₀ transformed. In total, we had 101 predictor variables for our cellulose-decomposition model.

Boosted-regression tree models

The choice between boosted regression tree (BRT) and other modeling techniques, such as Generalized Additive Models (GAMs) or neural networks depends on the specific characteristics of the data and the goals of the analysis. For our purposes, BRTs were an appropriate tool to answer our questions while addressing some of the complexity in our data. BRTs are recognized for their predictive accuracy, particularly in managing nonlinear relationships and interactions among predictors. The method is appropriate for handling missing data and outliers and processing large datasets. As the BRT constructs trees, it selects the most informative variables at each step, and assigns lower importance to the variables that contribute less to predictive performance. BRT is also resilient to irrelevant variables, as the boosting process assigns diminished weights to less informative variables and reduces their impact on the final model. BRTs can also capture interactions between variables and because the boosting process is adaptive, it allows the algorithm to focus on the most important variables and their interactions. Therefore, it reduces the risk of overfitting and improves the generalization of the model when challenged with new data. The learning rate of the BRT imposes a penalty on overfitting. Learning rates are often set to between 0.01 and 0.1, and ours was set to 0.001. Smaller learning rates put a penalty on the contribution of each tree, a technique that prevents the model from fitting the training data too closely.

In BRTs, "importance" refers to the degree of influence each predictor variable has on the predictive performance of the model and is normalized so the sum of all explanatory variable importance is 100. Variable importance in BRT is calculated based on how often a given variable is selected for: 1) splitting across all the trees, and 2) how much it contributes to the reduction in the model's loss function. Variables that are frequently chosen and contribute to improving model performance are considered more important. Higher importance values indicate features that have a greater impact on making accurate predictions. Detailed descriptions of the BRT approach are found in (*50*).

We used the gbm package in R (version 4.3.2) to build BRT models (51, 52) for cellulose decomposition and leaf-litter decomposition. Both BRT models were fitted with Gaussian distributions, learning rates of 0.001, and an interaction depth of 5. We initially used 20,000 trees in the cellulose model and the cross-validation determined the optional number of trees was 9,497. For the litter model, we initially ran 50,000 trees, and the optimal number was identified as 40,853. While BRT models handle variables with broad ranges, we ln-transformed K_d to facilitate the interpretation of results. The cellulose model used 101 explanatory variables (table s1) and the leaf-litter model used 17 explanatory variables (table s2). We assessed model explanatory power by calculating a pseudo- R^2 for each model and determined variable importance via permutation tests (53) (table 1). Explanatory variables with importance values greater than $1/n_{variable} *100$ ($n_{variable} = total number of explanatory variables in the model$) were included in trees more than would be expected from random chance and identified for further discussion (54). The importance threshold was 0.99 for the cellulose model and 5.88 for the leaflitter decomposition model. For the leaf litter model, two highly correlated explanatory variables (litter C:N and litter N content) fell just below the importance threshold but were discussed further because they each exceeded the threshold in other model runs and are well known to correlate with litter decomposition rates.

Output rasters of predicted cellulose-decomposition rates

Using the BRT models and data from the assembled spatial data layers, we predicted river K_d at the extent and at the resolution of the WorldClim rasters (global with 30 arc-second resolution; https://www.worldclim.org) using the raster package in R (55). In these output rasters, we did not predict K_d for sub-watersheds with ≤ 10 ha of sub-basin area, nor for Antarctica, which is not included in HydroATLAS. Importantly, we predicted K_d using a BRT model that included variables measured at each site in the original CELLDEX experiment (i.e., water temperatures and month of deployment), but those variables were not included in the generation of the global K_d map.

Validation of cellulose and leaf-litter BRT models

The spatial structure of the cellulose and leaf-litter datasets are quite different; therefore, we used different validation approaches for the cellulose and leaf-litter models. Because of the smaller dataset and hierarchical spatial structure of the cellulose-decomposition data (i.e., multiple streams measured by each partner), we performed a "leave-one-out" validation of the BRT by running 131 iterations of the model, each excluding one partner from the dataset. The goal was to assess the model's ability to predict the data of the omitted partner, measured through the calculation of root mean square error (RMSE). The average RMSE for the leave-one-out partner analysis was 1.08; in comparison, the BRT's cross-validation, which optimizes the number of trees directly in the code, yielded an RMSE of 0.93. The range of cellulose decomposition rates was 5.1 natural log units (K_d range 0.0012–0.20 d⁻¹). This analysis indicates that the model can predict cellulose decomposition rate with an accuracy of approximately +/- 1 natural log unit and predictions in unsampled locations have similar accuracy to the model with all data included. For the larger, leaf-litter dataset compiled from published literature (n=895 decomposition rates), we randomly selected 80% of the data and used that to train the model, and we tested the model with the remaining 20% of the data. The average RMSE for the 80/20 analysis was 0.75 (n=20 random splits). In comparison, the BRT's cross-validation, which optimizes the number of trees directly in the code, yielded an RMSE of 0.76. The range of leaf litter decomposition rates was 5.9 natural log units (K_d range 0.005–0.18), which is much greater than the RMSE, indicating that the model is sufficiently accurate to make predictions of litter decomposition.

Data. All data and code for analyses and figures are available on GitHub (43).

Supplemental Acknowledgements: Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

Table S1.

Boosted-regression tree model importance values for cellulose decomposition rates $(\ln[K_d]))$, their description and the source of data. Importance values greater than 0.99 indicate that the variable was selected more than expected from random chance. The detailed information from the predictor variables derived from HydroBASINS can be found on their website. Variables that have similar names are typically referring to differences in the spatial or temporal characteristics of the variable. For example, air temperature tmp_dc_uyr is the annual average temperature for the total watershed upstream of sub-basin pour point, whereas tmp_dc_smx is the annual average temperature at the sub-basins pour point. If data were log transformed, "log", is written before the predictor variable text. The "Source" column denotes the origin of the data.

Boosted-regression tree - explaining cotton decomposition rate $(\ln[K_d])$			
\mathbb{R}^2	0.81		
Predictor variable	Relative importance	Description	Source
mean_mean_daily_t emp	14.02	mean_mean_daily_temp	CELLDEX (19)
log10lka_pc_sse	6.94	Limnicity (Percent Lake Area): Category = Hydrology; Spatial Extent = {s} at sub-basin pour point; Dimensions = {se} spatial extent (%)	HydroBASINS
log10NO3c	6.7	NO3 yield	McDowell et al. 2021 (46)
log10DRPc	4.89	DRP yield	McDowell et al. 2021 (46)
AETmonth	4.4	AET month of deployment	HydroBASINS
tmp_dc_uyr	2.48	Air Temperature: Category = Climate; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {yr} annual average	HydroBASINS
snowmonth	2.26	Snow cover month of deployment	HydroBASINS
tmp_dc_smx	2.25	Air Temperature: Category = Climate; Spatial Extent = {s} at sub- basin pour point; Dimensions = {mx} annual maximum	HydroBASINS
soc_th_uav	2.16	Organic Carbon Content in Soil: Category = Soils & Geology; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {av} average	HydroBASINS
run_mm_syr	2.1	Land Surface Runoff: Category = Hydrology; Spatial Extent = {s} at	HydroBASINS

		sub-basin pour point; Dimensions =	
		{yr} annual average	
crp_pc_sse	2.03	Cropland Extent: Category = Landcover; Spatial Extent = {s} at sub-basin pour point; Dimensions = {se} spatial extent (%)	HydroBASINS
log10dis_m3_pmn	1.94	Natural Discharge: Category = Hydrology; Spatial Extent = {p} at sub-basin pour point; Dimensions = {mn} annual minimum	HydroBASINS
gdp_ud_sav	1.71	Gross Domestic Product: Category = Anthropogenic; Spatial Extent = {s} at sub-basin pour point; Dimensions = {av} average	HydroBASINS
slp_dg_sav	1.54	Terrain Slope: Category = Physiography; Spatial Extent = {s} at sub-basin pour point; Dimensions = {av} average	HydroBASINS
pet_mm_uyr	1.44	Potential Evapotranspiration: Category = Climate; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {yr} annual average	HydroBASINS
log10sgr_dk_sav	1.3	Stream Gradient: Category = Physiography; Spatial Extent = {s} at sub-basin pour point; Dimensions = {av} average	HydroBASINS
log10dor_pc_pva	1.29	Degree of Regulation: Category = Hydrology; Spatial Extent = {p} at sub-basin pour point; Dimensions = {va} value	HydroBASINS
log10pop_ct_usu	1.29	Population Count: Category = Anthropogenic; Spatial Extent = {u} in total watershed upstream of sub- basin pour point; Dimensions = {su} sum	HydroBASINS
tempmonth	1.28	Air temp month of deployment	HydroBASINS
tmp_dc_syr	1.28	Air Temperature: Category = Climate; Spatial Extent = {s} at sub- basin pour point; Dimensions = {yr} annual average	HydroBASINS
crp_pc_use	1.24	Cropland Extent: Category = Landcover; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {se} spatial extent (%)	HydroBASINS

ele_mt_smx	1.22	Elevation: Category = Physiography; Spatial Extent = {s} at sub-basin pour point; Dimensions = {mx} maximum	HydroBASINS
log10dis_m3_pyr	1.09	Natural Discharge: Category = Hydrology; Spatial Extent = {p} at sub-basin pour point; Dimensions = {yr} annual average	HydroBASINS
snd_pc_uav	1.09	Sand Fraction in Soil: Category = Soils & Geology; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {av} average	HydroBASINS
log10rdd_mk_uav	1.07	Road Density: Category = Anthropogenic; Spatial Extent = {u} in total watershed upstream of sub- basin pour point; Dimensions = {av} average	HydroBASINS
tmp_dc_smn	1.01	Air Temperature: Category = Climate; Spatial Extent = {s} at sub- basin pour point; Dimensions = {mn} annual minimum	HydroBASINS
TNdep	0.95	TN deposition	Ackerman et al. 2019 (47)
pac_pc_sse	0.9	Protected Area Extent: Category = Landcover; Spatial Extent = {s} at sub-basin pour point; Dimensions = {se} spatial extent (%)	HydroBASINS
pre_mm_uyr	0.89	Precipitation: Category = Climate; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {yr} annual average	HydroBASINS
aet_mm_uyr	0.88	Actual Evapotranspiration: Category = Climate; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {yr} annual average	HydroBASINS
log10gdp_ud_usu	0.88	Gross Domestic Product: Category = Anthropogenic; Spatial Extent = {u} in total watershed upstream of sub- basin pour point; Dimensions = {su} sum	HydroBASINS
log10lkv_mc_usu	0.85	Lake Volume: Category = Hydrology; Spatial Extent = {u} in total watershed upstream of sub-basin pour point: Dimensions = {su} sum	HydroBASINS

pre_mm_syr	0.85	Precipitation: Category = Climate; Spatial Extent = {s} at sub-basin pour point; Dimensions = {yr} annual average	HydroBASINS
TPdep	0.79	TP deposition	Brahney et al. 2015 (48) & Mahowald 2008 (49)
log10ppd_pk_uav	0.78	Population Density: Category = Anthropogenic; Spatial Extent = {u} in total watershed upstream of sub- basin pour point; Dimensions = {av} average	HydroBASINS
cly_pc_sav	0.77	Clay Fraction in Soil: Category = Soils & Geology; Spatial Extent = {s} at sub-basin pour point; Dimensions = {av} average	HydroBASINS
moist_indexmonth	0.77	moist_indexmonth	HydroBASINS
nli_ix_sav	0.7	Nighttime Lights: Category = Anthropogenic; Spatial Extent = {s} at sub-basin pour point; Dimensions = {av} average	HydroBASINS
ele_mt_sav	0.68	Elevation: Category = Physiography; Spatial Extent = {s} at sub-basin pour point; Dimensions = {av} average	HydroBASINS
ari_ix_uav	0.67	Global Aridity Index: Category = Climate; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {av} average	HydroBASINS
soc_th_sav	0.66	Organic Carbon Content in Soil: Category = Soils & Geology; Spatial Extent = {s} at sub-basin pour point; Dimensions = {av} average	HydroBASINS
snw_pc_uyr	0.65	Snow Cover Extent: Category = Climate; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {yr} annual average	HydroBASINS
log10rev_mc_usu	0.63	Reservoir Volume: Category = Hydrology; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {su} sum	HydroBASINS
log10gdp_ud_ssu	0.62	Gross Domestic Product: Category = Anthropogenic; Spatial Extent = {s} at sub-basin pour point; Dimensions = {su} sum	HydroBASINS

PETmonth	0.61	PET month of deployment	HydroBASINS
log10rdd_mk_sav	0.59	Road Density: Category = Anthropogenic; Spatial Extent = {s} at sub-basin pour point; Dimensions = {av} average	HydroBASINS
slt_pc_sav	0.59	Silt Fraction in Soil: Category = Soils & Geology; Spatial Extent = {s} at sub-basin pour point; Dimensions = {av} average	HydroBASINS
pac_pc_use	0.58	Protected Area Extent: Category = Landcover; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {se} spatial extent (%)	HydroBASINS
slp_dg_uav	0.57	Terrain Slope: Category = Physiography; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {av} average	HydroBASINS
for_pc_use	0.56	Forest Cover Extent: Category = Landcover; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {se} spatial extent (%)	HydroBASINS
gwt_cm_sav	0.55	Groundwater Table Depth: Category = Hydrology; Spatial Extent = {s} at sub-basin pour point; Dimensions = {av} average	HydroBASINS
log10inu_pc_ult	0.55	Inundation Extent: Category = Hydrology; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {lt} long- term maximum	HydroBASINS
ele_mt_uav	0.52	Elevation: Category = Physiography; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {av} average	HydroBASINS
cly_pc_uav	0.51	Clay Fraction in Soil: Category = Soils & Geology; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {av} average	HydroBASINS
for_pc_sse	0.5	Forest Cover Extent: Category = Landcover; Spatial Extent = {s} at sub-basin pour point; Dimensions = {se} spatial extent (%)	HydroBASINS

log10ria_ha_ssu	0.5	River Area: Category = Hydrology; Spatial Extent = {s} at sub-basin pour point; Dimensions = {su} sum	HydroBASINS
precipmonth	0.48	Precipitation month of deployment	HydroBASINS
pst_pc_use	0.47	Pasture Extent: Category = Landcover; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {se} spatial extent (%)	HydroBASINS
snd_pc_sav	0.47	Sand Fraction in Soil: Category = Soils & Geology; Spatial Extent = {s} at sub-basin pour point; Dimensions = {av} average	HydroBASINS
log10pop_ct_ssu	0.45	Population Count: Category = Anthropogenic; Spatial Extent = {s} at sub-basin pour point; Dimensions = {su} sum	HydroBASINS
aet_mm_syr	0.43	Actual Evapotranspiration: Category = Climate; Spatial Extent = {s} at sub-basin pour point; Dimensions = {yr} annual average	HydroBASINS
snw_pc_smx	0.43	Snow Cover Extent: Category = Climate; Spatial Extent = {s} at sub- basin pour point; Dimensions = {mx} annual maximum	HydroBASINS
log10ero_kh_sav	0.38	Soil Erosion: Category = Soils & Geology; Spatial Extent = {s} at sub- basin pour point; Dimensions = {av} average	HydroBASINS
ari_ix_sav	0.36	Global Aridity Index: Category = Climate; Spatial Extent = {s} at sub- basin pour point; Dimensions = {av} average	HydroBASINS
log10ero_kh_uav	0.35	Soil Erosion: Category = Soils & Geology; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {av} average	HydroBASINS
swc_pc_syr	0.35	Soil Water Content: Category = Soils & Geology; Spatial Extent = {s} at sub-basin pour point; Dimensions = {yr} annual average	HydroBASINS
log10dis_m3_pmx	0.33	Natural Discharge: Category = Hydrology; Spatial Extent = {p} at sub-basin pour point; Dimensions = {mx} annual maximum	HydroBASINS

		-	
cmi_ix_uyr	0.32	Climate Moisture Index: Category = Climate; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {yr} annual average	HydroBASINS
slt_pc_uav	0.32	Silt Fraction in Soil: Category = Soils & Geology; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {av} average	HydroBASINS
log10ppd_pk_sav	0.31	Population Density: Category = Anthropogenic; Spatial Extent = {s} at sub-basin pour point; Dimensions = {av} average	HydroBASINS
ele_mt_smn	0.3	Elevation: Category = Physiography; Spatial Extent = {s} at sub-basin pour point; Dimensions = {mn} minimum	HydroBASINS
pet_mm_syr	0.29	Potential Evapotranspiration: Category = Climate; Spatial Extent = {s} at sub-basin pour point; Dimensions = {yr} annual average	HydroBASINS
log10lka_pc_use	0.26	Limnicity (Percent Lake Area): Category = Hydrology; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {se} spatial extent (%)	HydroBASINS
log10riv_tc_usu	0.26	River Volume: Category = Hydrology; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {su} sum	HydroBASINS
soilwatermonth	0.26	Soil water % month of deployment	HydroBASINS
log10ria_ha_usu	0.21	River Area: Category = Hydrology; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {su} sum	HydroBASINS
log10riv_tc_ssu	0.2	River Volume: Category = Hydrology; Spatial Extent = {s} at sub-basin pour point; Dimensions = {su} sum	HydroBASINS
nli_ix_uav	0.18	Nighttime Lights: Category = Anthropogenic; Spatial Extent = {u} in total watershed upstream of sub- basin pour point; Dimensions = {av} average	HydroBASINS
kar_pc_sse	0.17	Karst Area Extent: Category = Soils & Geology; Spatial Extent = {s} at	HydroBASINS

		sub-basin pour point; Dimensions =		
		{se} spatial extent (%)		
		Pasture Extent: Category =		
net no see	0.17	Landcover; Spatial Extent = $\{s\}$ at	HydroBASINS	
psi_pc_sse	0.17	sub-basin pour point; Dimensions =	IIyulobAsins	
		{se} spatial extent (%)		
		Inundation Extent: Category =		
		Hydrology; Spatial Extent = $\{u\}$ in		
log10inu_pc_umx	0.16	total watershed upstream of sub-basin	HydroBASINS	
		pour point; Dimensions = $\{mx\}$		
		annual maximum		
		Urban Extent: Category =		
urb nc sse	0.16	Anthropogenic; Spatial Extent = {s}	HydroBASINS	
uro_pe_sse	0.10	in reach catchment; Dimensions =	Trydrob/ton to	
		{se} spatial extent (%)		
		Inundation Extent: Category =		
log10inu pc smx	0.14	Hydrology; Spatial Extent = $\{s\}$ at	HydroBASINS	
10810110_P•_51111		sub-basin pour point; Dimensions =	11) 01 0 2 1 1 0 11 1 0	
		{mx} annual maximum		
	0.14	Snow Cover Extent: Category =		
snw pc svr		Climate; Spatial Extent = $\{s\}$ at sub-	HydroBASINS	
		basin pour point; Dimensions = $\{yr\}$		
		annual average		
	0.12	Irrigated Area Extent (Equipped):		
ire pc sse		Category = Landcover; Spatial Extent	HydroBASINS	
		$= \{s\}$ at sub-basin pour point;		
		$Dimensions = \{se\} \text{ spatial extent (\%)}$		
		Karst Area Extent: Category = Soils		
1	0.10	& Geology; Spatial Extent = $\{u\}$ in		
kar_pc_use	0.12	total watershed upstream of sub-basin	HydroBASINS	
		pour point; Dimensions = $\{se\}$ spatial		
		extent (%)		
		Soll water Content: Category = Solls θ_{1} Cools and Sustial Entant (m) in		
	0.12	& Geology; Spatial Extent = $\{u\}$ in	II. Induc DA CINIC	
swc_pc_uyr	0.12	total watershed upstream of sub-bash	HydrodASINS	
		pour point, Dimensions – {yi} annual		
		Climata Maistura Inday: Catagory –		
cmi_ix_syr		Climate Moisture Index: Category = $Climate Spatial Extent = \{a\}$ at an		
	0.1	Climate, Spatial Extent $-\{s\}$ at sub-	HydroBASINS	
		annual average		
		Irrigated Area Extent (Equipped):		
		Category – Landcover: Spatial Extent		
ire_pc_use	0.1	$= \{u\}$ in total watershed unstream of	HydroBASINS	
		sub-basin pour point. Dimensions –		
		$\{se\}$ snatial extent (%)		
		{se} spatial extent (%)		

log10inu_pc_slt	0.1	Inundation Extent: Category = Hydrology; Spatial Extent = {s} at sub-basin pour point; Dimensions = {lt} long-term maximum	HydroBASINS
wet_pc_ug1	0.1	Wetland Extent: Category = Landcover; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {g1} Wetland class grouping; see https://www.worldwildlife.org/pages/ global-lakes-and-wetlands-database	HydroBASINS
urb_pc_use	0.08	Urban Extent: Category = Anthropogenic; Spatial Extent = {u} in total watershed upstream of sub- basin pour point; Dimensions = {se} spatial extent (%)	HydroBASINS
log10inu_pc_umn	0.07	Inundation Extent: Category = Hydrology; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {mn} annual minimum	HydroBASINS
wet_pc_ug2	0.07	Wetland Extent: Category = Landcover; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {g2} Wetland class grouping; see https://www.worldwildlife.org/pages/ global-lakes-and-wetlands-database	HydroBASINS
log10inu_pc_smn	0.06	Inundation Extent: Category = Hydrology; Spatial Extent = {s} at sub-basin pour point; Dimensions = {mn} annual minimum	HydroBASINS
wet_pc_sg1	0.05	Wetland Extent: Category = Landcover; Spatial Extent = {s} at sub-basin pour point; Dimensions = {g1} Wetland class grouping; see https://www.worldwildlife.org/pages/ global-lakes-and-wetlands-database	HydroBASINS
prm_pc_use	0.02	Permafrost Extent: Category = Landcover; Spatial Extent = {u} in total watershed upstream of sub-basin pour point; Dimensions = {se} spatial extent (%)	HydroBASINS
wet_pc_sg2	0.01	Wetland Extent: Category = Landcover; Spatial Extent = {s} at sub-basin pour point; Dimensions =	HydroBASINS

{g2} Wetland class grouping; s		{g2} Wetland class grouping; see		
		https://www.worldwildlife.org/pages/		
		global-lakes-and-wetlands-database		
		Glacier Extent: Category =		
ala na caa	0	Landcover; Spatial Extent = $\{s\}$ at		
gia_pc_sse	0	sub-basin pour point; Dimensions =	HYDRODASINS	
		{se} spatial extent (%)		
	0	Glacier Extent: Category =		
		Landcover; Spatial Extent = $\{u\}$ in		
gla pc use		total watershed upstream of sub-basin	HydroBASINS	
		pour point; Dimensions = {se} spatial		
		extent (%)		
	0	Permafrost Extent: Category =		
prm_pc_sse		Landcover; Spatial Extent = $\{s\}$ at	HydroBASINS	
		sub-basin pour point; Dimensions =		
		{se} spatial extent (%)		

Table S2.

Boosted-regression tree model importance values for leaf-litter decomposition rates $(\ln[Kd])$, their description and the source of data. Importance values greater than 5.88 indicate that the variable was selected more than expected from random chance. Additional information about plant traits can be found in the data repository (43) in the file "Litter_trait_review.csv" and more details about the TRY database are contained in (31).

Boosted-regression tree - explaining leaf litter decomposition rate $(\ln[K_d])$					
\mathbb{R}^2	0.70				
Predictor variable	Relative	Description	Source		
	importance				
ln_pred_k _d	39.47	Model predicted cotton k _d	This study		
Mesh.size		Mesh size	LeRoy et al.		
	20.84		2020 (27)		
Lignin_Litter_Mn		Litter lignin content	Literature		
	11.96		values (43)		
CtoN_Litter_Mn		Litter C:N	Literature		
	5.45		values (43)		
N_Litter_Mn		Litter N content	Literature		
	5.23		values (43)		
	2.50		Literature		
P_Litter_Mn	3.59	Litter P content	values (43)		
	0.07	L'H C I I	Literature		
C_Litter_Mn	2.37	Litter C content	values (43)		
Callulasa Littan Ma	2.20	Litter cellulose content	Literature (42)		
	2.20		TDV database		
Ca_Leaf_Mn	2.03	Leaf Ca content	TRT database		
NtoP_Leaf_Mn	1.19	Leaf N:P	TRY database		
Thick_Mn	1.04	Leaf thickness	TRY database		
Leaf.condition	1.03	Leaf condition	TRY database		
			Literature		
NtoP_Litter_Mn	0.95	Litter N:P	values (43)		
P_Leaf_Mn	0.76	Leaf P content	TRY database		
CtoN_Leaf_Mn	0.69	Leaf C:N	TRY database		
C_Leaf_Mn	0.66	Leaf C content	TRY database		
N_Leaf_Mn	0.53	Leaf N content	TRY database		



Fig. S1.

Correlation plots of the relationship between the magnitude of predicted change in litterdecomposition rates in pine-dominated forests invaded by the pine bark beetle and watershed soil water content (A) and AET (B). Greater values indicate a higher magnitude increase in litter decomposition upon canopy replacement. Our forecasts predict insect-induced canopy replacement from pine to oak would approximately double mean decomposition rates (see main text). Though the relationships are highly variable, the associations between the predicted magnitude of change in decomposition and soil water and AET indicate drier subwatersheds are expected to have a larger change in decay rates than wetter sites.

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