

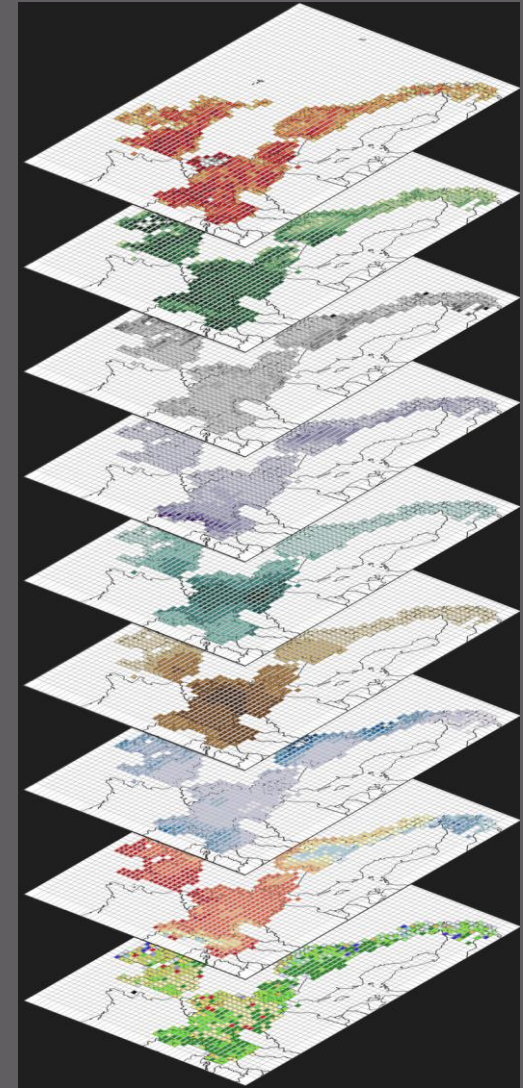
What drives European fungal biogeography?

Connecting digital data to temporally static and dynamic environmental predictors to explain climate, pollution and urbanization impacts on fungi

Carrie Andrew (PhD 2009)

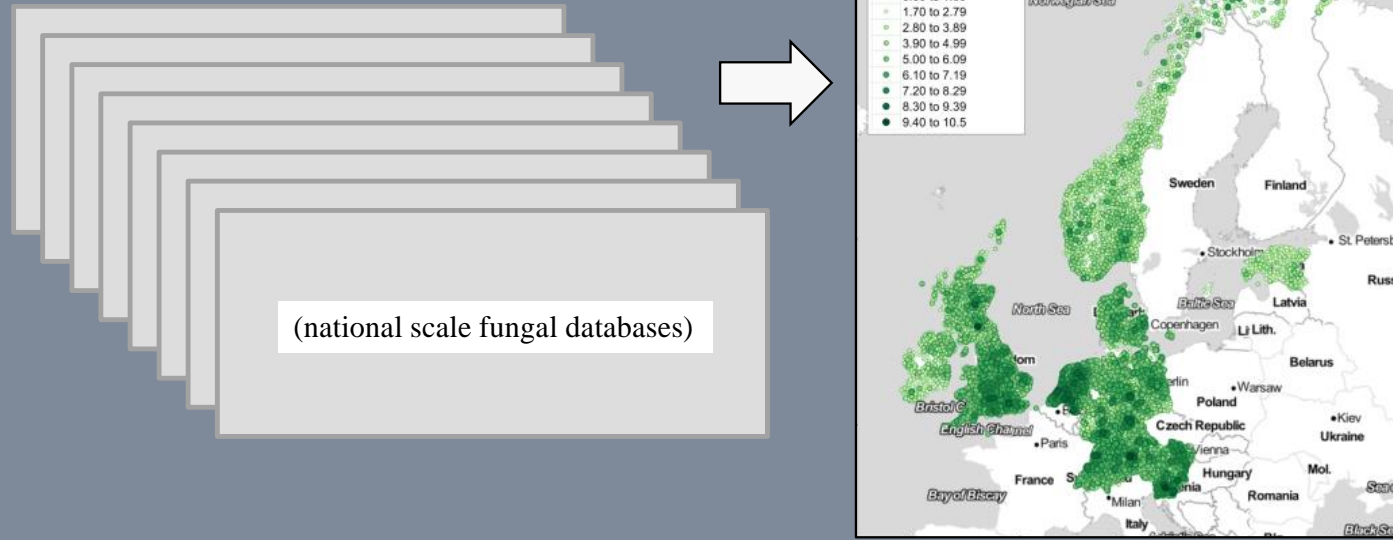
Swiss Federal Research Institute WSL; University of Oslo, Norway

Ulf Büntgen, Univ. of Cambridge, Swiss Fed. Res. Inst. WSL, Global Change Res. Centre & Masaryk Univ.; **Simon Egli**, Swiss Fed. Res. Inst. WSL; **Einar Heegaard**, Norwegian Inst. of Bioeconomy Res.; **Rune Halvorsen**, Natural Hist. Museum, Univ. of Oslo; **Paul M Kirk**, Royal Bot. Garden, Kew; **Klaus Høiland**, Univ. of Oslo; **Claus Bässler**, Bavarian Forest Nat'l. Park, Tech. Univ. of Munich; **Alan C Gange**, Royal Holloway, Univ. of London, Egham; **Jacob Heilmann-Clausen**, Natural Hist. Museum, Univ. of Copenhagen; **Irmgard Krisai-Greilhuber**, Univ. of Vienna; **Thomas W Kuyper**, Wageningen Univ.; **Beatrice Senn-Irlet**, Swiss Fed. Res. Inst. WSL; **Lynne Boddy**, Cardiff Univ.; **Håvard Kauserud**, Univ. of Oslo



The current 'ecological era': **big data**

- massive amounts gathered quickly through the digitization of museum, herbaria records, plus citizen science projects (molecular 'big data', too)
- combining data allows even greater scientific potential, does it not?



Fungal fruiting records, compiled from European databases, into one unified **ClimFun 'meta-database'**

- 6 million total records
- 3-4 million commonly utilized
- For most analyses: 1970-2010
- A collaboration of 18+ scientists

Andrew et al. 2017. Big data integration: Pan-European fungal species observations' assembly for addressing contemporary questions in ecology and global change biology. *Fun. Bio. Rev.*, 31: 88-98

* further information on the data and results are presented in a poster this evening

What can be addressed with fungal fruitbody records?

Past to present impacts to fungi,

- our only historical source

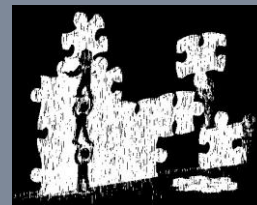
...at **extensive spatiotemporal** coverage(s),

- representative of continuous environmental gradients (when aggregated) more than field samples can be (to this date)

...of **global change** (climate, land-use, pollution).

- reproductive structures might respond more to climatic conditions than vegetative structures

All data have limitations.
All data are also 'pieces of the puzzle'.



Ephemeral
Sporadic
Reproductive
Presence-only
Non-mycelial

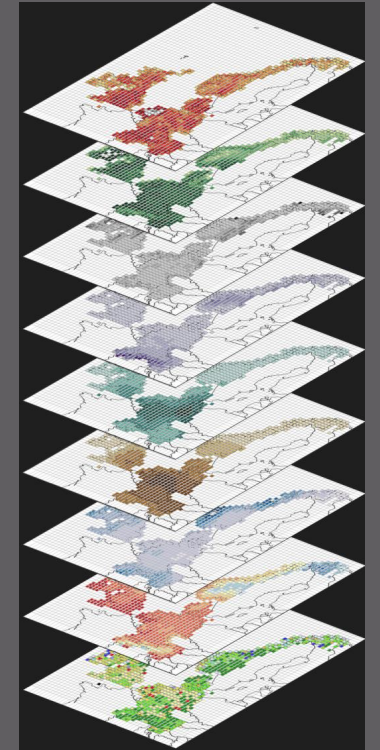


(wikimedia commons)

Linking **biological data** to the **changing environment**: varied sources and formats of explanatory variables

Not a simple task. Many potential issues:

- **applied** (file formats; geocoordinate formats; availabilities of the data; how were the data created (field observations or models) and what is their reliability(-ies); must be available for country(-ies) of interest)
- **spatial** (continuity of data points; sample intensity(-ies); spatial resolution(s))
- **temporal** (past, present, or future; static or dynamic covariates; (non-)matching timescales; temporal resolution(s) and extent(s))
- **aggregating** (point-based or gridded; values based on sample intensity or spatial extent; variability; mean; min.; max.)
- **interpretability** (interpolation; transference; projection; reliability)
- **ecological use and meaning**

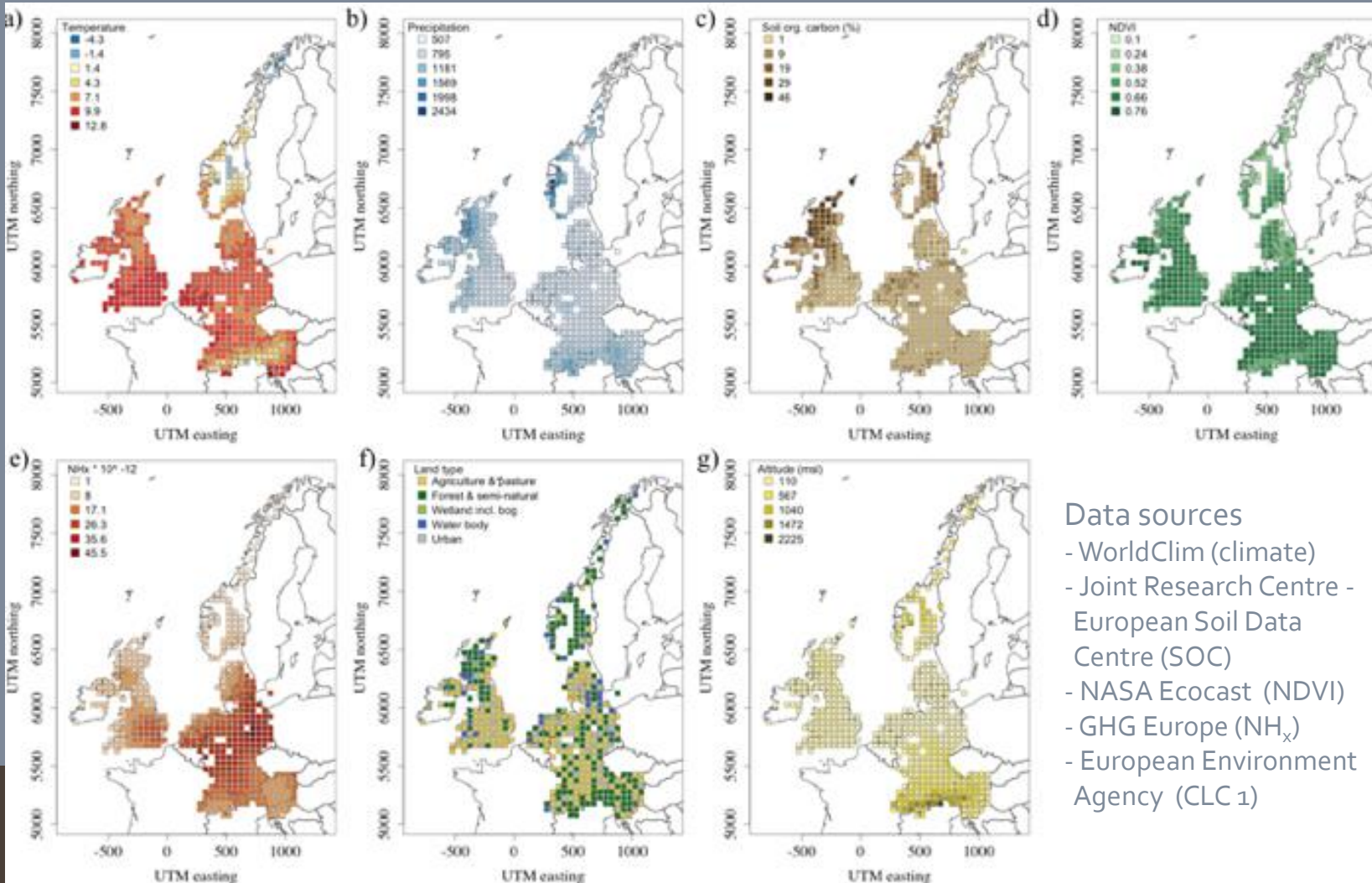


... a balance between **what we would like** to address, and **what we can** address given the available data

Example 1: static covariates to explain fungal assemblages and their environmental correlates at the European scale

Fungal species assemblages: what drives their large-scale patterns?

- 50x50 km resolution
- Explanatory variables: single time point [aggregations] that best matched fungal data
- Fungal data: single time point (1990-2010) and two time points (1970-1990 vs. 1991-2010)
- Means within a grid based on locations of collections (thus relatable to actual fruiting conditions) instead of spatial uniformity across each grid



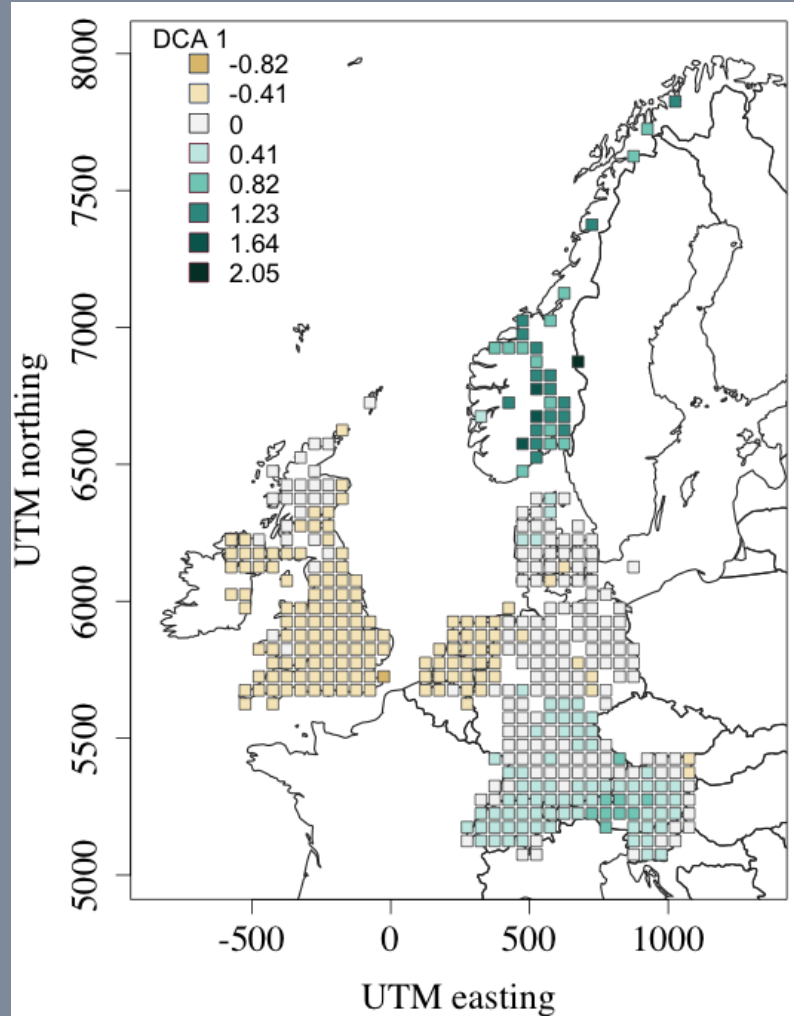
Data sources

- WorldClim (climate)
- Joint Research Centre - European Soil Data Centre (SOC)
- NASA Ecocast (NDVI)
- GHG Europe (NH_x)
- European Environment Agency (CLC 1)

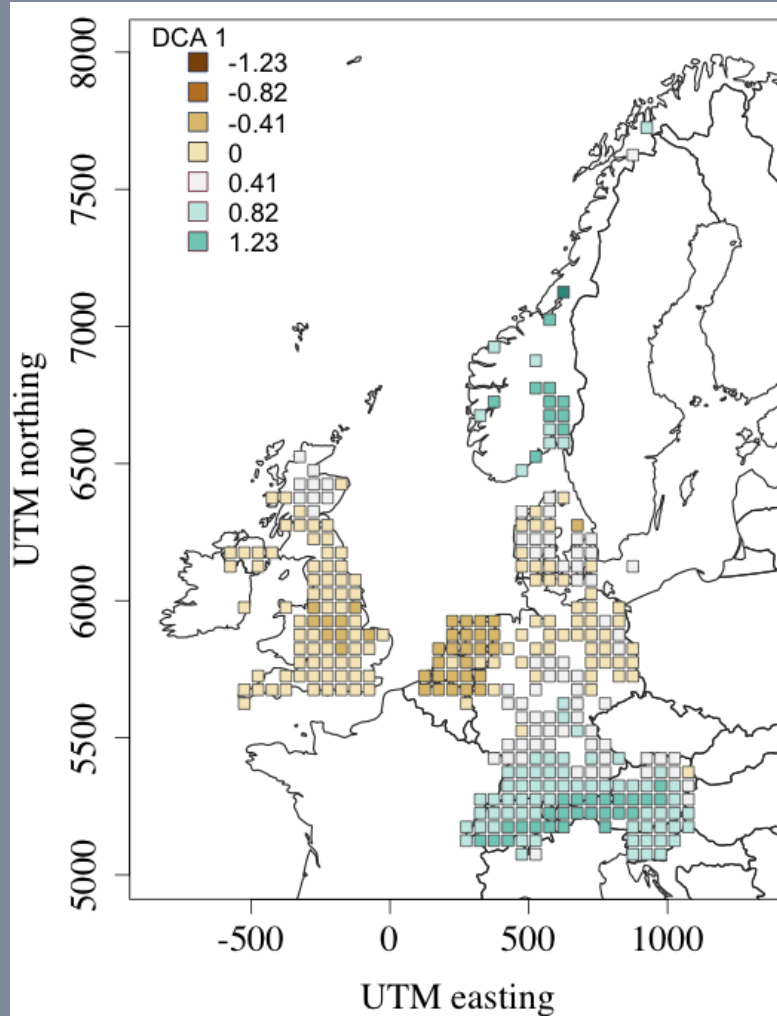
(winter) temp. ↔ altitude ↔ longitude



Saprotrophic assemblies



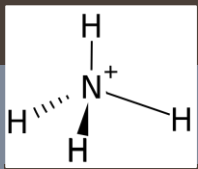
Ectomycorrhizal assemblies



Mean annual temperature: most important correlate of the first compositional gradient for both saprotrophic and ectomycorrhizal fungi

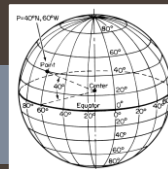
Andrew et al. Continental-scale macro-fungal assemblage patterns correlate with climate, soil carbon and nitrogen deposition. *Journal of Biogeography*, accepted 23 Apr 2018.

nitrogen ↔ continentality

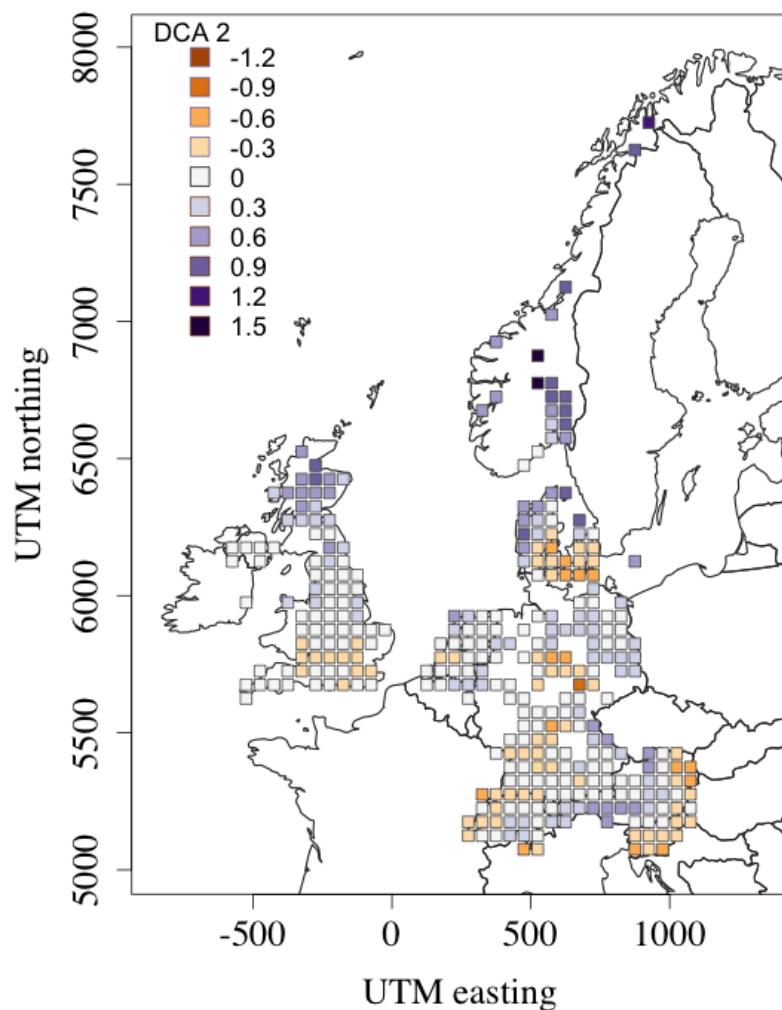
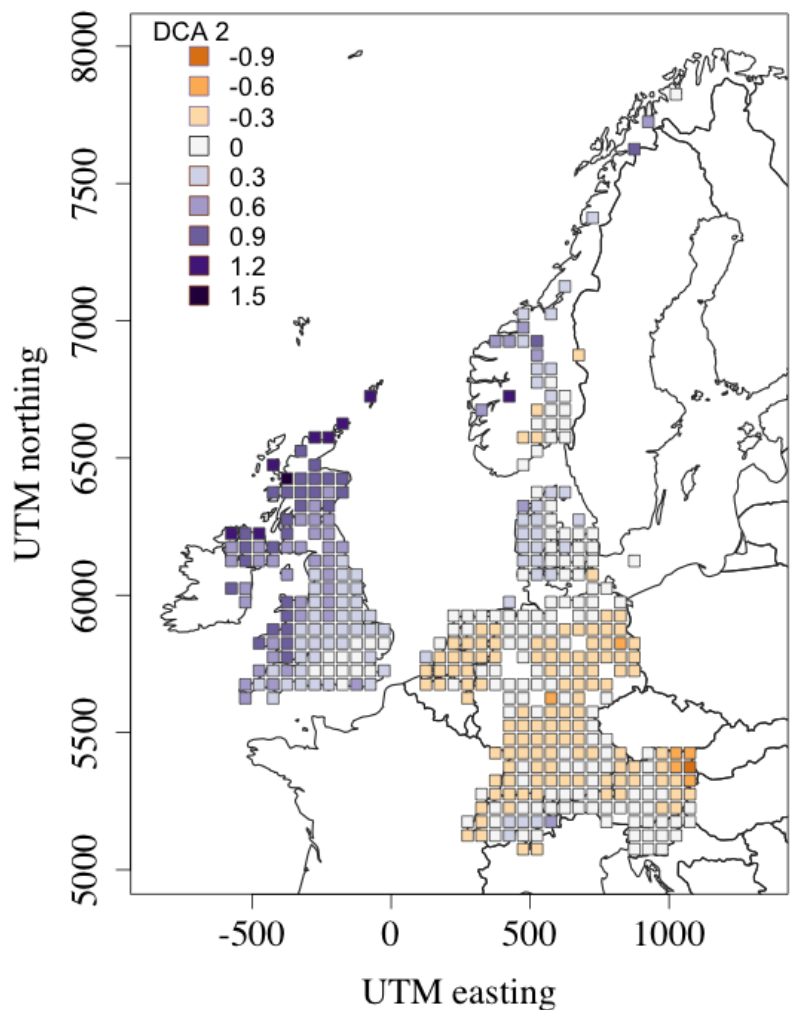


Saprotrophic assemblages

soil org. C ↔ sum. temp. ↔ latitude



Ectomycorrhizal assemblages



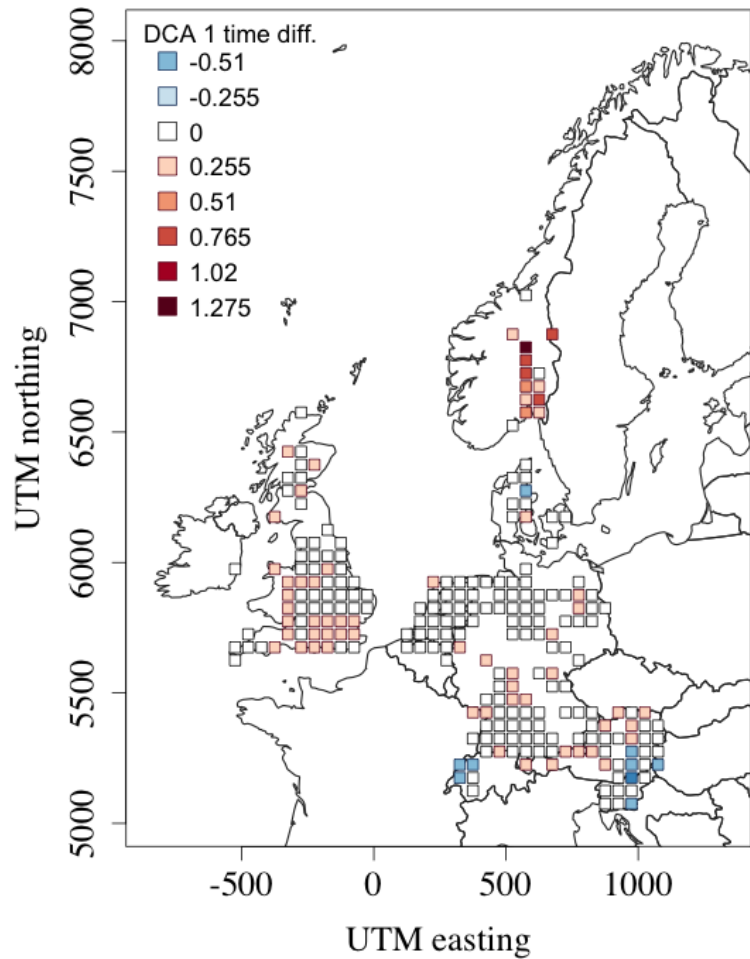
Second gradient structuring assemblages differs:

Nitrogen deposition highest correlate for **saprotrophic** fungi

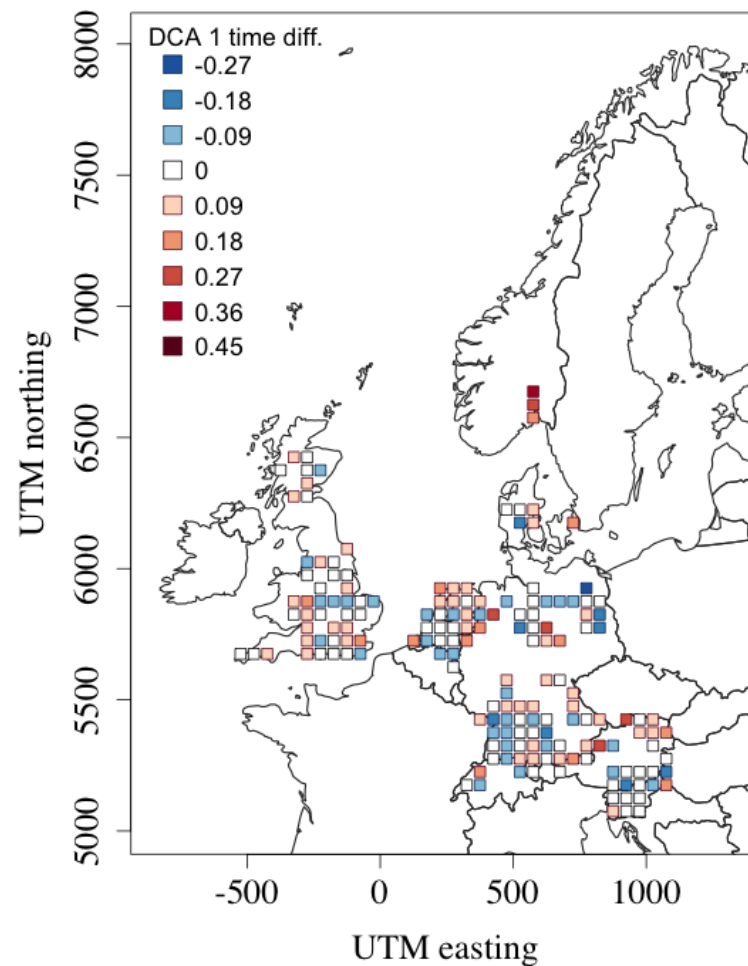
Soil organic carbon highest correlate for **ectomycorrhizal** fungi.

Andrew et al. Continental-scale macro-fungal assemblage patterns correlate with climate, soil carbon and nitrogen deposition. *Journal of Biogeography*, accepted 23 Apr 2018.

Saprotrophic assemblies



Ectomycorrhizal assemblies



Compositional change by time
(1970-1990 vs. 1991-2010)
suggests targeting higher latitudes and altitudes for a better understanding of fungal dynamics, especially related to climate change.

Andrew et al. Continental-scale macro-fungal assemblage patterns correlate with climate, soil carbon and nitrogen deposition. *Journal of Biogeography*, accepted 23 Apr 2018.

Describing actual **global change** consequences via digital data can be a challenge

The **biological (records) data**, temporally-speaking, are either

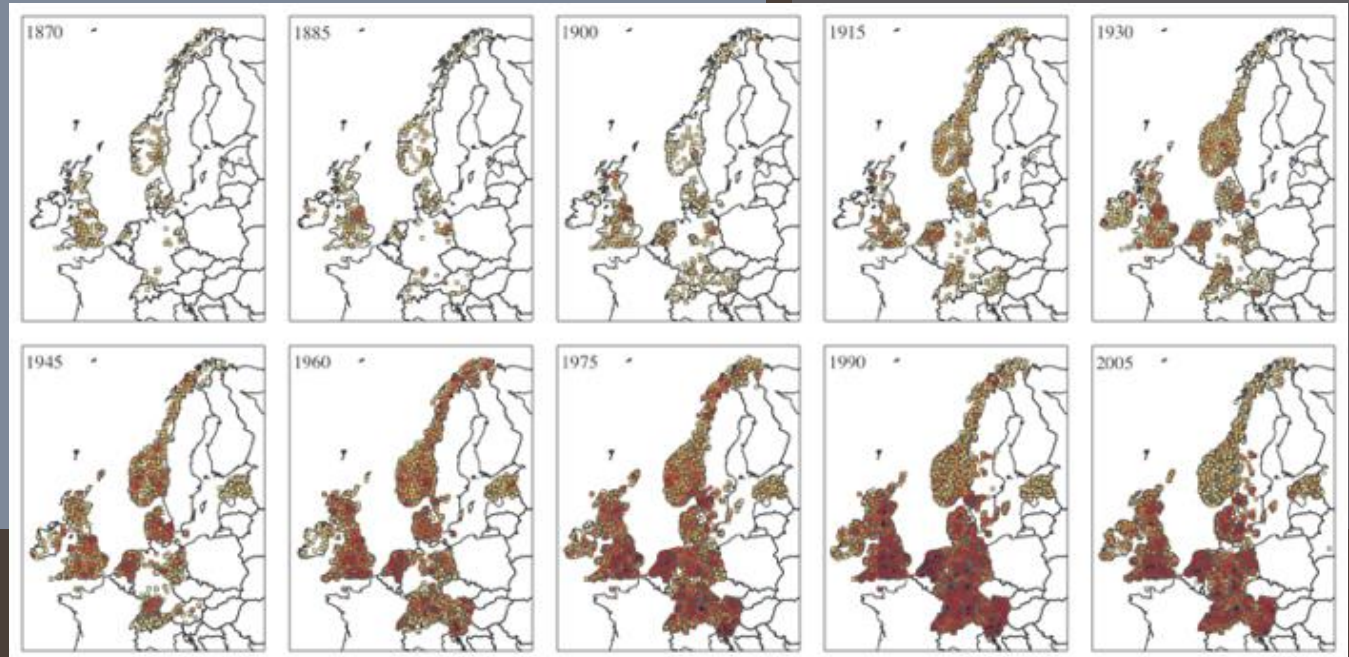
- **static** (a single time period)

- funding/sampling/processing logistics prevent collecting further data
- cannot readily fix this issue; projections or temporal-based interpolations/transference are possible go-arounds

- **dynamic** (available at multiple time periods; ideally daily to annually)

- likely spatiotemporally patchily distributed, especially at large spatial scales
- can aggregate for some measures (e.g., total counts; eg. 15 year intervals)
- sampling biases might require aggregation to one to or a few time periods (time 1 vs. time 2) (e.g., richness; species-specific responses)
- i.e., the ClimFun fungal records

Challenges to putting the *change* in global change research



The explanatory, environmental data, likewise,

- are often temporally static

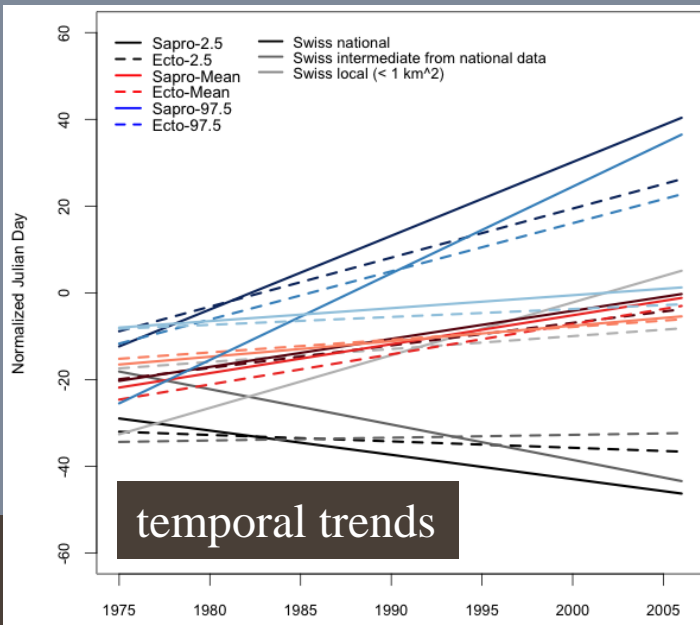
- infer correlational impacts due to temporal changes (from past to present); don't use explanatory data in this case

- utilize static covariates, comprising a gradient across the spatial range of the data, to demonstrate likely future impacts based on differences along the gradients (climate, land-use/vegetation type)

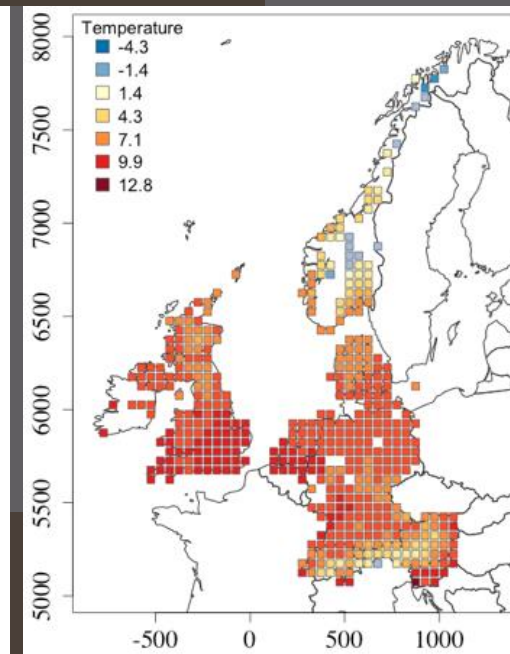
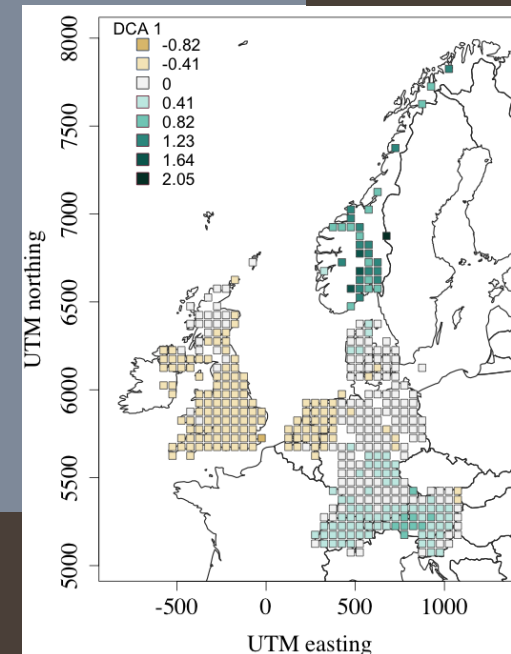
- analyse projected, modelled covariates (for future conditions)

Challenges to putting the *change* in global change research

static env. correlations



Andrew et al. 2018.
Congruency in fungal phenology patterns across dataset sources and scales.
Fun. Ecol., 32: 9-17



The **explanatory, environmental data**

- can be **dynamic** (available at multiple time periods)
 - if the wrong time period and cannot parse data to match, may have to aggregate to a static measure, but perhaps still more accurate than a single time-point

how to **connect the data**?

- most ideal, but least likely: analyse temporally-based change in both the biological and environmental data

Challenges to putting the *change* in global change research

The **explanatory, environmental data**

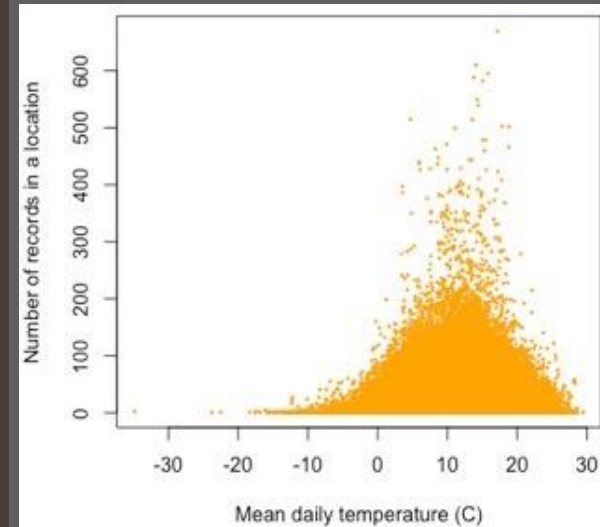
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how to **connect the data?**

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- but if need to aggregate the biological data, **link up the records first to the dynamic, temporally variable environmental data to better address global change questions.**

EOBS daily temperature data linked up to date of fruit body collection ----->

Challenges to putting the *change* in **global change research**



The **explanatory, environmental data**

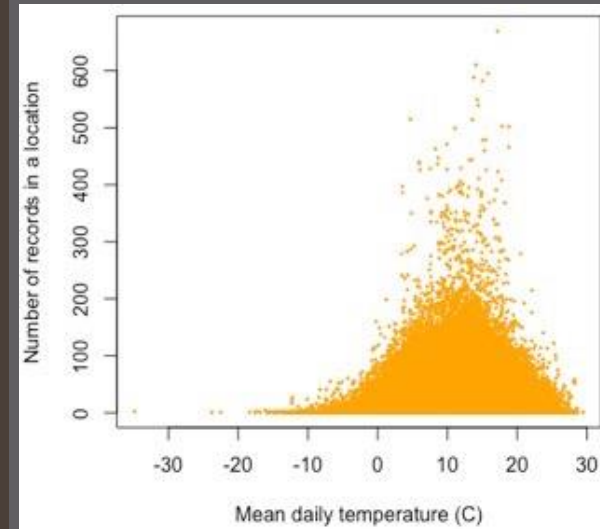
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how to **connect the data?**

- most ideal, but least likely: analyse temporally-based change in both the biological and environmental data
- but if need to aggregate the biological data, **link up the records first to the dynamic, temporally variable environmental data to better address global change questions.**
- **compare the predictive power of static versus dynamic covariates, and what they biologically mean**

EOBS daily temperature data linked up to date of fruit body collection ----->

Challenges to putting the *change* in **global change research**



Example 2: static + dynamic covariates to explain fungal diversity patterns – in a global change context

Working around the challenges to putting the *change* in global change research

Example 2: static + dynamic covariates to explain fungal diversity patterns – in a global change context

Add temporally dynamic environmental covariates (as available)
... may better demonstrate how fungal richness patterns are impacted by changes in:

- a) climate
- b) land-use / land-cover / urbanization
- c) pollution amounts (NH_x , NO_y)

...also bring in **tree species observational data**, given the connection between them and fungi

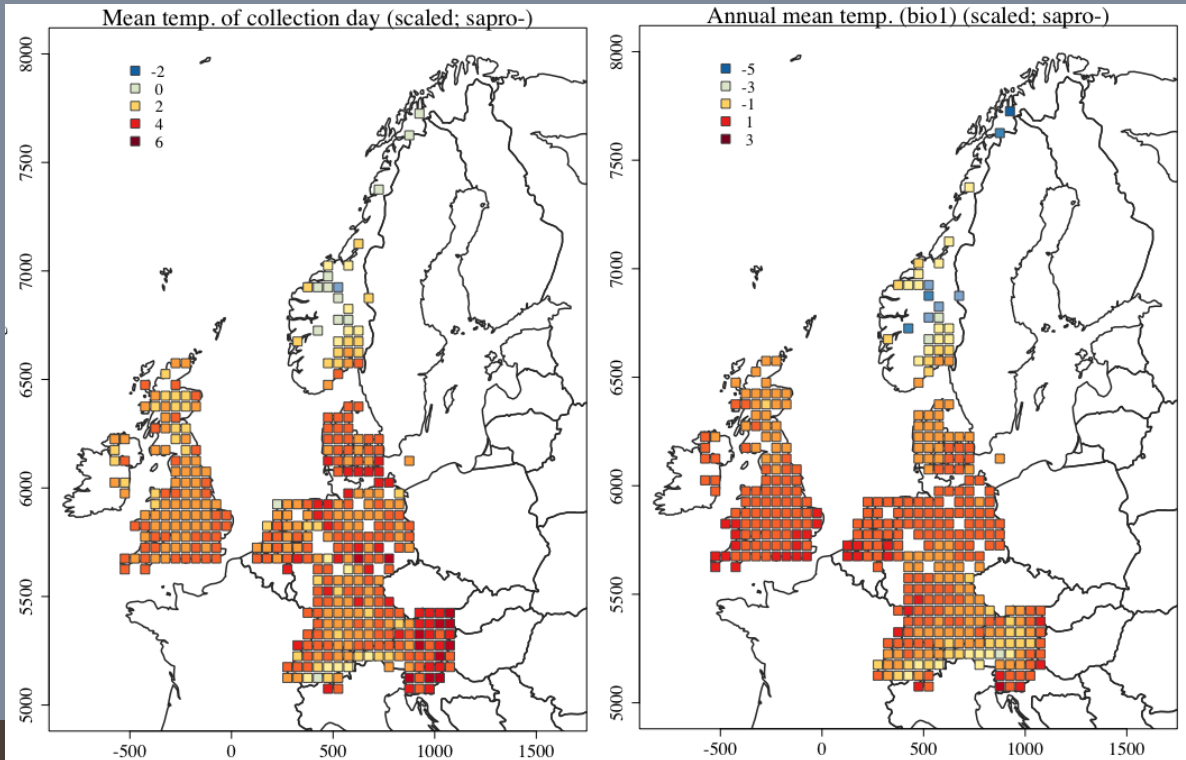
impacts of the shorter- versus longer-term environment to the responsiveness of fungi

Example 2: static + dynamic covariates to explain fungal diversity patterns – in a global change context

(for saprotrophic fungi)

Collection day temp.

Mean annual temp.



range: -2 to 6

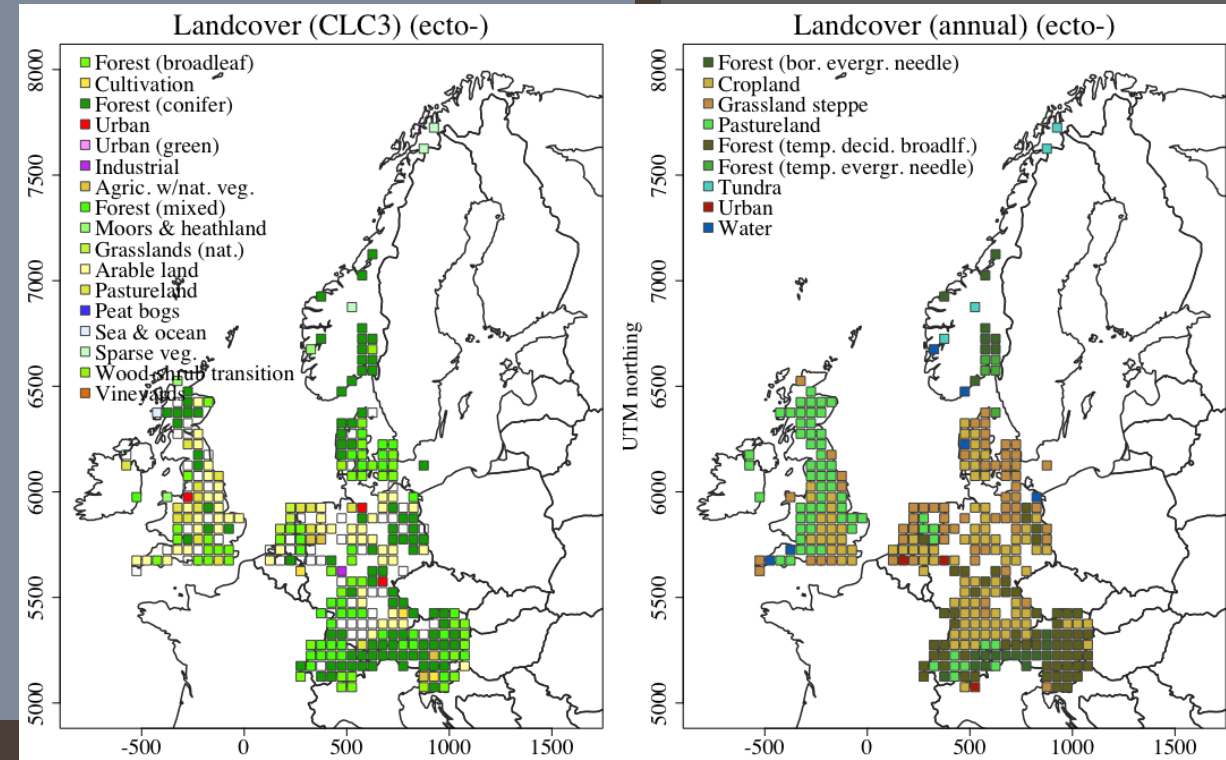
range: -5 to 3

(scaled values)

(for ectomycorrhizal fungi)

Static landcover

Annual land-cover

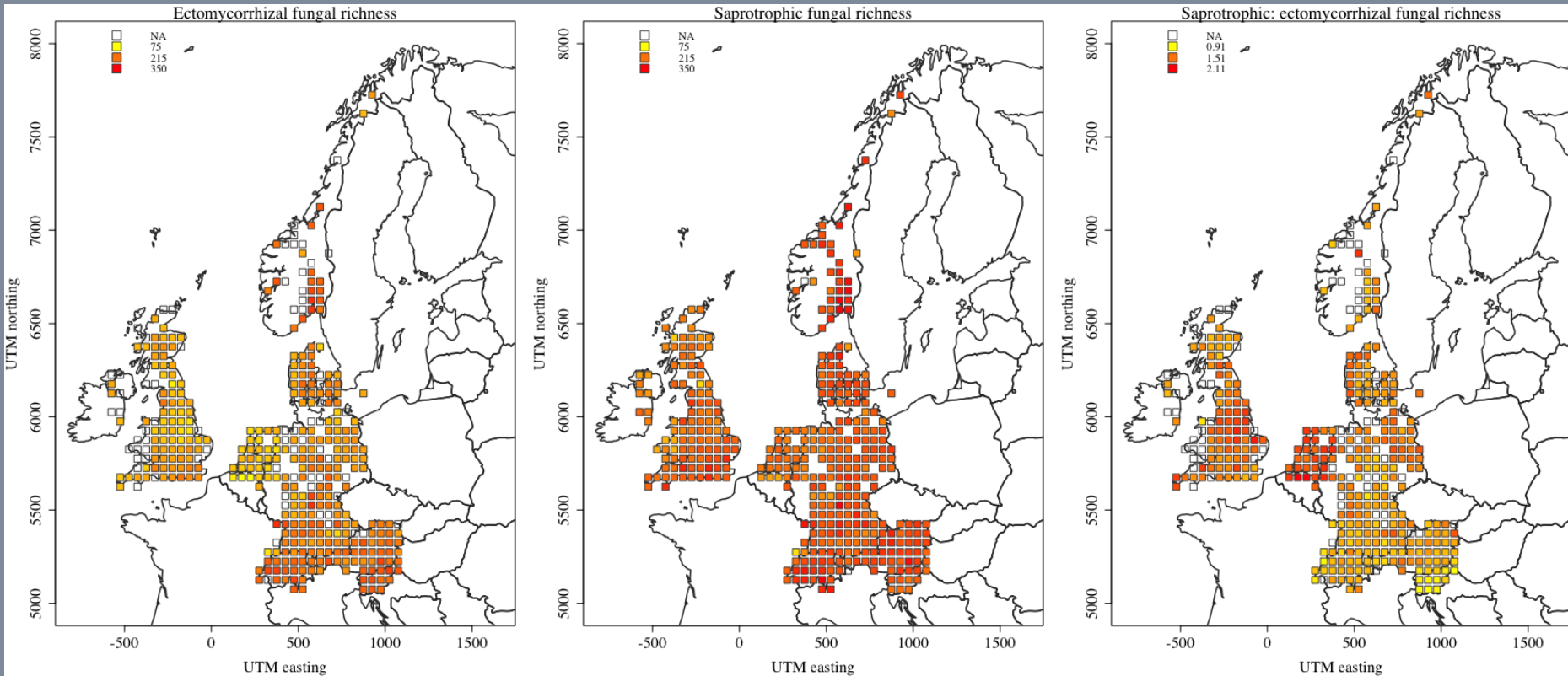


ectomycorrhizal

saprotrophic

saprotrophic: ectomycorrhizal

Fungal richness patterns, on the same colour scale, for ectomycorrhizal and saprotrophic fungi, as well as the ratio of saprotrophic to ectomycorrhizal fungal species



Andrew et al. Temporally static and dynamic environmental predictors demonstrate sensitivity of fungal phenology diversity to climate, pollution and urbanization. *Appl. Plant Sci.*, special issue, 'Emerging Frontiers in Plant Phenology.' *In prep.*

Temperature affects fungal richness:

Saprotrophic

overall temp. related to seasonality important

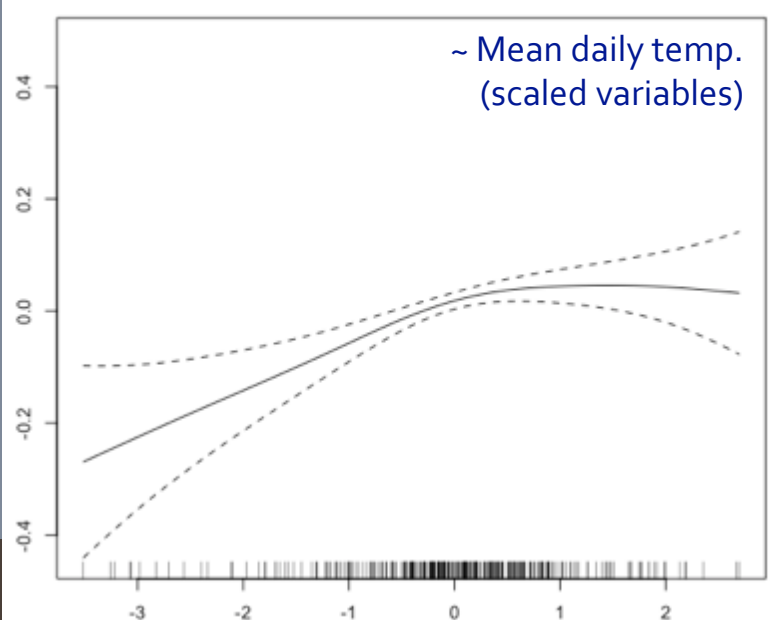
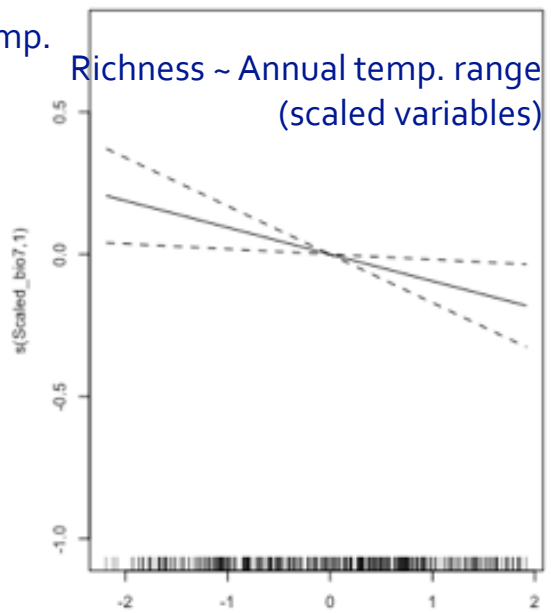
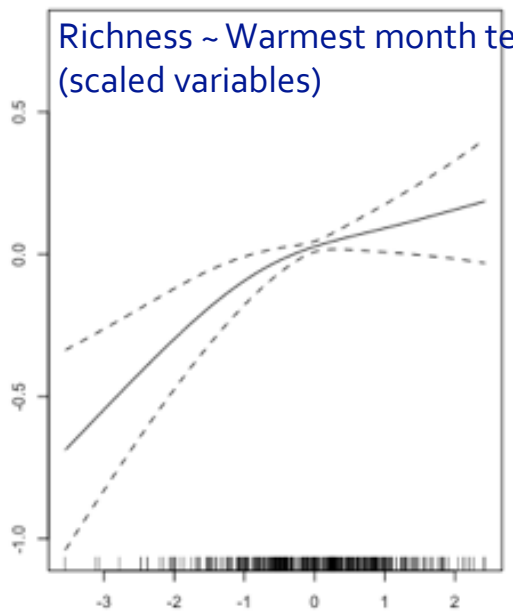
easting * northing	1.16e-09	***
altitude	0.013942	*
Temp. (warmest month)	7.92e-05	***
Temp. (annual range)	0.013385	*
NHx (annual max)	0.000565	***
R-sq. (adj) =	0.403	

Ectomycorrhizal

daily temp. important; greater climatic sensitivity?

easting * northing	< 2e-16	***
Altitude	0.006674	**
NHx (annual max)	0.037692	*
Temp. (mean daily)	0.000962	***
R-sq. (adj) =	0.581	

** Preliminary results; subject to change with model finalization; but the point holds that static and dynamic temporal variables provide unique information that are helpful to understand sensitivities of organisms to climate, pollution and land-use change



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Impact of atmospheric pollution to fungal richness:

diversity decline

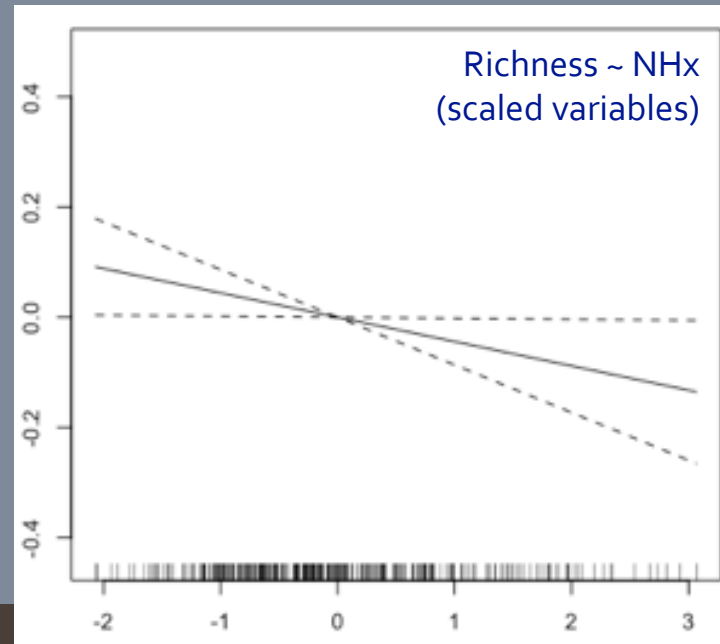
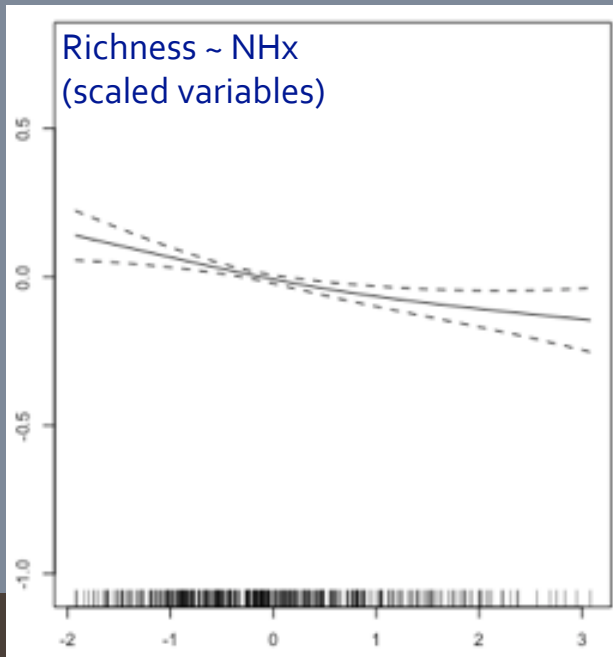
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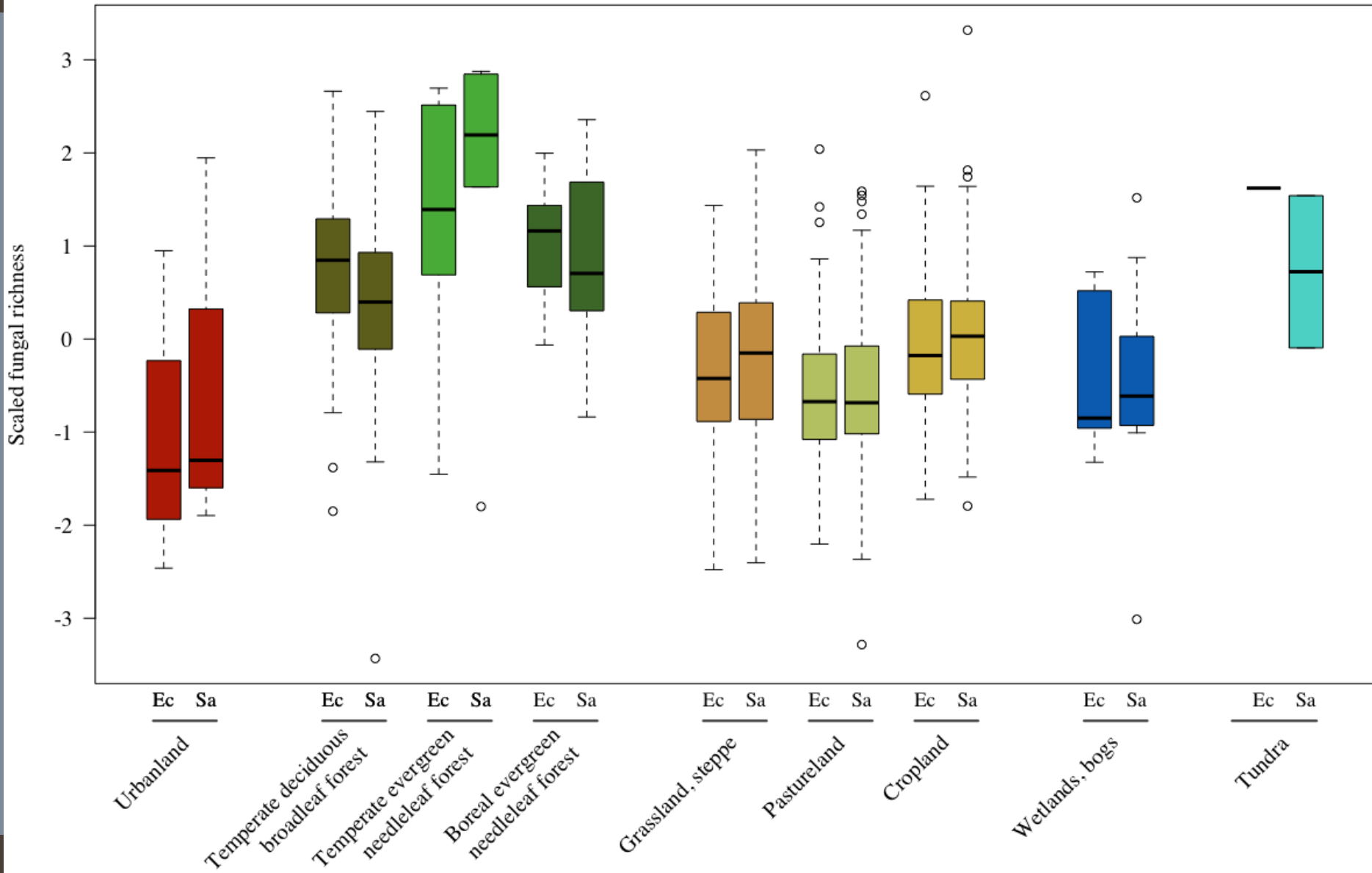
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Richness for ectomycorrhizal (Ec) and saprotrophic (Sa) fungi is statistically **different** ($p < 2.2e-16$) by **land-type**

Lowest mean **diversity** in **urban** areas

Highest mean **diversity** in **forests** (temperate evergreen needleleaf forests)

Andrew et al. Temporally static and dynamic environmental predictors demonstrate sensitivity of fungal phenology diversity to climate, pollution and urbanization. Appl. Plant Sci., special issue, 'Emerging Frontiers in Plant Phenology.' *In prep.*

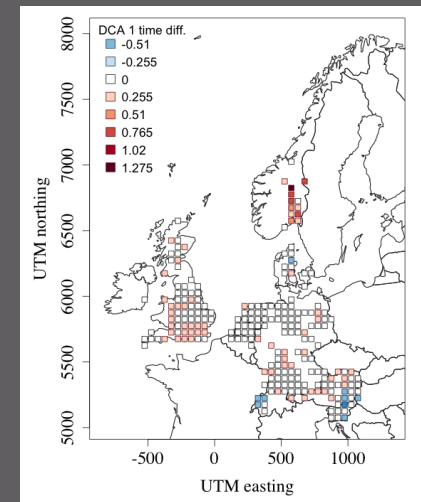
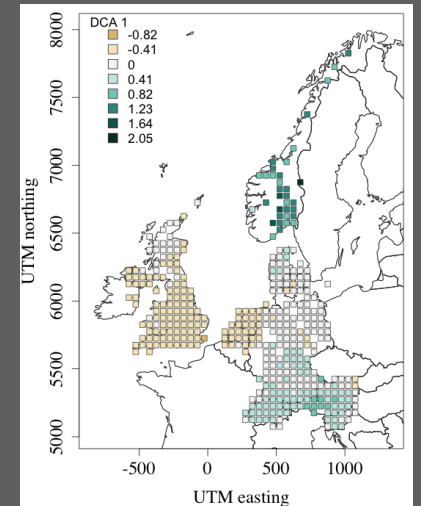
In conclusion

Some patterns are similar across functional groups, e.g., the correlation of annual temperature and the primary gradient structuring fungal assemblages; a decline in richness with increased nitrogen deposition

Other patterns deviate, for example, fungal richness for saprotrophic and ectomycorrhizal fungi correlating with temperature at differing temporal scales.

In terms of temporal linkages between climate change and fungi, our results suggest targeting higher latitudes and altitudes for greater impacts.

Given the patterns presented here, we demonstrate the **power of multi-source observational records data to advance knowledge in global change biology, and through connection with a variety of available meta-data at both static and dynamic temporal scales.**



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