Soil net nitrogen mineralisation (N$_{\text{min}}$), the conversion of organic into inorganic N, is important for productivity and nutrient cycling. The balance between mineralisation and immobilisation (net N$_{\text{min}}$) varies with soil properties and climate. However, because most global-scale assessments of net N$_{\text{min}}$ are laboratory-based, its regulation under field-conditions and implications for real-world soil functioning remain uncertain. Here, we explore the drivers of realised (field) and potential (laboratory) soil net N$_{\text{min}}$ across 30 grasslands worldwide. We find that realised N$_{\text{min}}$ is largely explained by temperature of the wettest quarter, microbial biomass, clay content and bulk density. Potential N$_{\text{min}}$ only weakly correlates with realised N$_{\text{min}}$, but contributes to explain realised net N$_{\text{min}}$ when combined with soil and climatic variables. We provide novel insights of global realised soil net N$_{\text{min}}$ and show that potential soil net N$_{\text{min}}$ data available in the literature could be parameterised with soil and climate data to better predict realised N$_{\text{min}}$. 

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Soil nitrogen (N) availability is one of the most important drivers of ecosystem productivity\(^1-3\) and microbial decomposition\(^4\), and is key in regulating N cycling. During the breakdown and depolymerisation of organic material to monomers and inorganic N, plants and microbes compete for these N resources\(^5-7\). The net balance of N mineralisation and immobilisation (soil net N\(_{\text{min}}\)) is mediated by soil physicochemical properties, aboveground and belowground litter input, plant and microbial nutrient demand and climatic factors\(^5-13\), and is regarded as a good index of overall soil N availability\(^5\). Soil net N\(_{\text{min}}\) usually is greater in well-aerated soils from more humid climates at lower latitudes\(^14-16\), reflecting the controls of soil temperature, moisture and oxygen content over microbial activity. However, climatic conditions also shape soil properties over long time-scales\(^17,18\), so understanding the impact of climate and soil properties for soil net N\(_{\text{min}}\) is crucial to achieve robust estimates of soil N availability, and ultimately, productivity in terrestrial ecosystems.

Soil net N\(_{\text{min}}\) is commonly estimated either in the field or laboratory. Field measures represent realised soil net N\(_{\text{min}}\) constrained by site macro-climatic and micro-climatic conditions (Fig. 1) and are typically collected at local to regional scales\(^12\). In contrast, studies at the continental\(^15,16\) or global scale\(^14,19\) generally rely on laboratory incubations that estimate potential soil net N\(_{\text{min}}\). Laboratory incubations use homogenised soil samples incubated under optimised and controlled temperature and moisture conditions to allow the comparison of samples collected from different locations in a standardised way. Yet, homogenisation disrupts the soil structure and removes plant residues, which may affect these estimates\(^20,21\). Laboratory measures also fail to account for soil micro-climatic differences found under field conditions. Although potential may in some cases effectively predict realised soil net N\(_{\text{min}}\) we do not know whether, or under what conditions this is the case. Successfully identifying the environmental drivers connecting the two indices could greatly enhance the use of potential soil net N\(_{\text{min}}\) data to model and predict global patterns in realised soil net N\(_{\text{min}}\). This would facilitate our understanding of how global soil N availability may respond to future global anthropogenic influences such as climate change or eutrophication\(^22,23\).

We conducted coordinated measurements of realised and potential soil net N\(_{\text{min}}\) and assessed soil properties and climatic variables across 30 grasslands on six continents that span a globally relevant range of climatic and edaphic conditions (Fig. 2; Supplementary Tables 1 and 2). We focused on grassland ecosystems because they cover approximately one-third of the Earth’s terrestrial landscape\(^24,25\), are threatened by global change\(^22,23,26\), and provide important ecosystem services intricately linked with N\(_{\text{min}}\). Notably, they store 20–30% of the terrestrial C, mostly in the soil\(^24,25,27\). Here, we describe the global spatial patterns in realised and potential soil net N\(_{\text{min}}\) and the relationship between them. We then explore the key drivers of each soil net N\(_{\text{min}}\) index.
separately. Finally, we use structural equation modelling (SEM) to build a system-level understanding of how these specific climate and soil variables together with potential soil net N\textsubscript{min} could be used to predict realised soil net N\textsubscript{min}. This final step provides a basis upon which extensively available data on potential soil net N\textsubscript{min} could be leveraged to improve predictions of realised soil net N\textsubscript{min} at a global scale.

First, we expect opposite global spatial patterns in realised and potential soil net N\textsubscript{min}: Namely, decreasing realised soil net N\textsubscript{min} with increasing distance to the equator due to colder growing season temperatures and therefore lower mineralisation. Concurrently, we expect increasing potential soil net N\textsubscript{min} with increasing distance to the equator, because higher amounts of labile organic material accumulated under colder conditions are mineralised when incubated under standardised conditions in the laboratory. Second, climate variables and the presence of plant residues should predict realised soil net N\textsubscript{min} through their effects on soil properties and the activity of soil biota\textsuperscript{11-13}. In contrast, soil chemical properties, soil texture and the activity/abundance of soil biota may be more important for potential soil net N\textsubscript{min} than climatic variables\textsuperscript{11-13}. Nonetheless, as climatic conditions impact soil formation\textsuperscript{17,18}, we expected that climate provides additional predictive information to explain potential soil net N\textsubscript{min}. Third, we expect that realised soil net N\textsubscript{min} can be estimated by combining key environmental drivers with potential soil net N\textsubscript{min}.

All 30 sites (Fig. 2, Supplementary Tables 1 and 2) are part of the Nutrient Network globally distributed experiment (NutNet [https://nutnet.umn.edu/])\textsuperscript{28}. We incubated one soil sample per plot in the field to assess realised soil net N\textsubscript{min} (Fig. 1)\textsuperscript{29} and collected additional samples to measure potential soil net N\textsubscript{min} and soil properties, i.e., water holding capacity, bulk density, C and N content, texture, pH, pore space, microbial biomass, and archaeal (AOA) and bacterial (AOB) ammonia oxidiser abundance using identical materials and methods at each site. The field incubation averaged 42 days (range 36–57) and ended at peak plant biomass at each site. Soil moisture was kept at 60% of the field capacity of each sample and 20 °C for the 42-day laboratory incubations. Climate data for each site were obtained from global data sets\textsuperscript{30}.

We dropped correlated variables prior to analyses\textsuperscript{31}, calculated the correlation between realised and potential soil net N\textsubscript{min} and then explored the global spatial patterns in realised and potential soil net N\textsubscript{min} with linear mixed effects models (LMMs). Then, we used LMMs and multilevel inference\textsuperscript{32} to determine the drivers of realised and potential soil net N\textsubscript{min}. Based on the LMMs and existing literature, we developed a conceptual model of causal relationships among environmental drivers, potential soil net N\textsubscript{min} and realised soil net N\textsubscript{min} (Fig. 3)\textsuperscript{33}. Here, we find that realised correlates only weakly with potential soil net N\textsubscript{min} and that different environmental parameters drive the two measures. However, potential soil net N\textsubscript{min} contributes to explain realised N\textsubscript{min} when combined with soil and climatic variables. We provide new insights for realised soil net N\textsubscript{min} and show how potential soil net N\textsubscript{min} data could be parameterised to better predict realised N\textsubscript{min} in global grasslands.

**Results and discussion**

**Global patterns and drivers of soil net N mineralisation.** Across our 30 grassland sites, realised and potential soil net N\textsubscript{min} were weakly positively correlated ($r = 0.21$, $p = 0.052$, $df = 83,$...
The variability in temperature alone or in combination with precipitation affect microbial biomass across large scales \cite{19,60,61}. The best LMMS revealed that temperature variability had a positive, and temperature of the wettest quarter a negative effect on potential soil net $N_{\text{min}}$ (Table 2). These two direct effects likely stand for surrogates of missing direct drivers influenced by climate parameters that we could not identify in this current study. Thus, temperature variability and temperature of the wettest quarter represent a legacy effect of long-term climatic properties on soils in a global context.

The top LMMS in this study revealed that temperature of the wettest quarter has a positive effect on realised soil net $N_{\text{min}}$ (Table 2) across global grasslands. Clay content positively affects microbial biomass on a global scale \cite{14,16}. Clay content positively affects potential and realised $N_{\text{min}}$ \cite{14,16}. Microbial biomass has a positive effect on soil mineralisation rates $N_{\text{min}}$\cite{19}. The goal of this study was to determine whether knowledge about the potential of a soil to mineralise N can predict realised $N_{\text{min}}$, but we only found a weak correlation between potential and realised $N_{\text{min}}$ (see main text, Supplementary Figure 1). However, the potential of soil microbes to mineralise N may be revealed when we include several climatic as well as soil biotic and abiotic predictors simultaneously into a model as done here. Thus, higher potential $N_{\text{min}}$ measured in the laboratory should result in higher realised $N_{\text{min}}$ in the field across global grasslands.

### Table 1: Potential relationships between variables derived from the literature and the linear mixed effects model results (see Table 2)

| Path # | Pathway | Proposed relation |
|--------|---------|-------------------|
| 1, 2   | Temperature variability or temperature of the wettest quarter $\rightarrow$ microbial biomass | The variability in temperature alone or in combination with precipitation affect microbial biomass across large scales \cite{19,60,61}. |
| 3, 4   | Temperature variability or temperature of the wettest quarter $\rightarrow$ potential $N_{\text{min}}$ | The best LMMS revealed that temperature variability had a positive, and temperature of the wettest quarter a negative effect on potential soil net $N_{\text{min}}$ (Table 2). These two direct effects likely stand for surrogates of missing direct drivers influenced by climate parameters that we could not identify in this current study. Thus, temperature variability and temperature of the wettest quarter represent a legacy effect of long-term climatic properties on soils in a global context. |
| 5      | Temperature of the wettest quarter $\rightarrow$ realised $N_{\text{min}}$ | The best LMMS revealed that temperature variability had a positive, and temperature of the wettest quarter a negative effect on potential soil net $N_{\text{min}}$ (Table 2). These two direct effects likely stand for surrogates of missing direct drivers influenced by climate parameters that we could not identify in this current study. Thus, temperature variability and temperature of the wettest quarter represent a legacy effect of long-term climatic properties on soils in a global context. |
| 6      | Clay content $\rightarrow$ microbial biomass | Clay content positively affects microbial biomass on a global scale \cite{14,16}. |
| 7, 8   | Clay content $\rightarrow$ potential and realised $N_{\text{min}}$ | Clay content positively affects potential and realised $N_{\text{min}}$ \cite{14,16}. |
| 9, 10  | Microbial biomass $\rightarrow$ potential and realised $N_{\text{min}}$ | Microbial biomass has a positive effect on soil mineralisation rates $N_{\text{min}}$\cite{19}. |
| 11     | Potential $N_{\text{min}}$ $\rightarrow$ realised $N_{\text{min}}$ | The goal of this study was to determine whether knowledge about the potential of a soil to mineralise N can predict realised $N_{\text{min}}$, but we only found a weak correlation between potential and realised $N_{\text{min}}$ (see main text, Supplementary Figure 1). However, the potential of soil microbes to mineralise N may be revealed when we include several climatic as well as soil biotic and abiotic predictors simultaneously into a model as done here. Thus, higher potential $N_{\text{min}}$ measured in the laboratory should result in higher realised $N_{\text{min}}$ in the field across global grasslands. |

### Fig. 4: Global patterns in realised and potential soil net N mineralisation (soil net $N_{\text{min}}$).

**a** Realised soil net $N_{\text{min}}$ at 30 NutNet sites ordered according to increasing realised soil net $N_{\text{min}}$. **b** Potential soil net $N_{\text{min}}$ at the 30 NutNet sites. Order of sites according to **a**. The box represents the median (50th percentile), 25th and 75th percentile of the data for each site. The whiskers represent 1.5 times the inter-quartile range. Source data are provided in the source data file.
Table 2 Model selection results for realised soil net $N_{\text{min}}$ and potential soil net $N_{\text{min}}$ starting with the full model including all explanatory variables (Supplementary Table 5) followed by multi-model inference to select the simplest models that explained the most variation in realised and potential soil net $N_{\text{min}}$

| Top models | Exp. vars incl. | Estimate | SE | $p$ | df | AICc |
|------------|----------------|---------|----|----|----|-----|
| **Realised soil net $N_{\text{min}}$** | | | | | | |
| Model 1 | Intercept | 0.521 | 0.037 | <0.001 | 5 | 23.44 |
| | T.q.wet | 0.106 | 0.038 | 0.01 | | |
| | Microbial biomass | 0.142 | 0.037 | <0.001 | | |
| Model 2 | Intercept | 0.520 | 0.033 | <0.001 | 4 | 23.50 |
| | T.q.wet | 0.125 | 0.039 | 0.002 | | |
| | Microbial biomass | 0.125 | 0.039 | 0.002 | | |
| Model 3 | Intercept | 0.521 | 0.041 | <0.001 | 4 | 24.04 |
| | Clay content | 0.121 | 0.039 | 0.003 | | |
| | Microbial biomass | 0.125 | 0.039 | 0.002 | | |
| Model 4 | Intercept | 0.518 | 0.036 | <0.001 | 5 | 24.73 |
| | T.q.wet | 0.122 | 0.039 | 0.004 | | |
| | Bulk density | −0.133 | 0.036 | <0.001 | | |
| **Potential soil net $N_{\text{min}}$** | | | | | | |
| Model 5 | Intercept | 0.587 | 0.042 | <0.001 | 6 | 68.64 |
| | AOB | 0.123 | 0.039 | 0.003 | | |
| | T.q.wet | −0.194 | 0.045 | <0.001 | | |
| | Tvar | 0.125 | 0.045 | 0.010 | | |
| Model 6 | Intercept | 0.587 | 0.046 | <0.001 | 5 | 69.29 |
| | AOB | 0.134 | 0.041 | 0.002 | | |
| | T.q.wet | −0.149 | 0.046 | 0.003 | | |
| Model 7 | Intercept | 0.592 | 0.064 | <0.001 | 4 | 69.45 |
| | Microbial biomass | 0.163 | 0.059 | 0.007 | | |
| Model 8 | Intercept | 0.589 | 0.052 | <0.001 | 5 | 69.47 |
| | T.q.wet | −0.206 | 0.056 | 0.001 | | |
| | Tvar | 0.152 | 0.054 | 0.009 | | |
| Model 9 | Intercept | 0.590 | 0.057 | <0.001 | 4 | 70.58 |
| | T.q.wet | −0.150 | 0.058 | 0.015 | | |

Model selection criteria were set at delta AICc < 2 due to our small sample size. All results are based on linear mixed effects models with site identity as a random factor. Exp. vars. incl. = All explanatory variables included in the respective model. Estimate = parameter estimate, SE = parameter estimate standard error, $p$ = $p$-value related to each variable, df = degrees of freedom of the component model, AICc = corrected Akaike’s information criterion, T.q.wet = temperature of the wettest quarter, AOB = ammonia oxidising bacteria, Tvar = temperature seasonality. The total number of observations in all models = 85, the total number of sites in all models = 30.

with increasing distance to the equator. However, the meta-analyses may not be comparable to our more closely controlled study from a single vegetation type, because they included a wide range of data from different land-use and vegetation types (croplands, wetlands, forests, shrublands, grasslands) and incubation conditions (duration, temperature, and soil moisture).

The variation in realised soil net $N_{\text{min}}$ across our 30 grassland sites was jointly explained by positive effects of temperature of the wettest quarter and microbial biomass (Model 1; Table 2) or by microbial biomass alone (Model 2, Table 2), clay alone (Models 3, Table 2) or by a positive effect of temperature of the wettest quarter combined with a negative effect of soil bulk density (Model 4; Table 2). Many studies consider soil organic C as one of the main drivers of soil net $N_{\text{min}}$. In our study, soil organic C was highly correlated with soil microbial biomass ($r = 0.85$). When replacing microbial biomass with soil organic C the model selection process yielded similar results (Models 1–3; Supplementary Table 3). Together our findings suggest that with higher temperature of the wettest quarter and more microbial biomass (or soil organic C), more organic matter was mineralised by soil microbes. The greater explanatory power of temperature of the wettest quarter, as opposed to MAT or MAP, shows that annual averages may be less useful for predicting ecosystem processes than more temporally specific climatic variables. Higher temperatures may only promote soil biological activity if soil moisture levels are sufficiently high. Our results also suggest that sites with higher soil clay content and lower soil bulk density likely featured more conducive soil micro-climatic conditions for soil microbes to thrive and allowed for higher realised soil net $N_{\text{min}}$. In contrast to microbial biomass, soil clay content and soil organic C, soil bulk density is usually not considered a key predictor of soil N mineralisation. Here, we show that bulk density as a measure of favourable soil structure improved predictions of realised soil net $N_{\text{min}}$. Future soil net $N_{\text{min}}$ studies and simulation studies for soil N cycling may benefit from including bulk density.

Potential soil net $N_{\text{min}}$ was higher when more AOB were present at the start of the incubation (Models 5, 6, Table 2). However, there is no mechanistic link between AOB and potential soil net $N_{\text{min}}$ because AOB only transform ammonium to nitrate but do not drive net production of total inorganic nitrogen in the soil. Yet, AOB abundance was positively correlated with potential net nitrification (Supplementary Fig. 4), which is similar to previous findings. Further, potential soil net $N_{\text{min}}$ was positively influenced by temperature seasonality and was negatively affected by temperature of the wettest quarter (Models 5, 6, 8, 9, Table 2). The same models were selected when we replaced soil microbial biomass with organic C (Models 4–7, Supplementary Table 3). However, higher potential soil net $N_{\text{min}}$ was also explained by higher soil microbial biomass alone (Model 7; Table 2) and microbial biomass was positively correlated with potential soil net nitrification (Supplementary Fig. 5). Our results agree with findings of a recent meta-analysis that identified soil microbial biomass as an important driver of potential soil net $N_{\text{min}}$. In addition, the effect of microbial biomass on potential soil net $N_{\text{min}}$ indicates that a quantitatively improved understanding of the soil microbial community could likely improve soil biogeochemical models. In addition, the selection of the two climate variables rather than the expected individual soil physical and chemical variables as predictors of potential soil net $N_{\text{min}}$ suggests that there is a long-term legacy effect of climate on these grasslands that we were not able to capture with the soil physico-chemical variables that we measured.

Soil C:N ratio is often regarded as an important predictor of soil net $N_{\text{min}}$ as it determines the transition from net N immobilisation to net N mineralisation. However, soil C:N was not important in our study as all but one (temple.us) of our grassland soils had C:N ratios below the critical threshold of 20. Also contrary to our expectations, realised and potential soil net $N_{\text{min}}$ were both partially constrained by climatic variables. Interestingly, temperature of the wettest quarter positively influenced realised soil net $N_{\text{min}}$ but had a negative effect on potential $N_{\text{min}}$ (Table 2, also see Fig. 5). This pattern suggests that N mineralisation may 'acclimatising' along climate gradients. Greater mineralisation occurring in a warmer and wetter climate may lead to the depletion of easily available organic N pools compared to soils from cooler climates. When incubated under constant temperature in the laboratory, mineralisation rates from substrate-depleted soils from warmer climates were less than those from soils of cold regions where labile organic N has accumulated for centuries. Alternatively, physical disturbance and disruption of the soil structure caused by sieving and sample homogenisation may have more profoundly affected the samples from warmer and wetter climates. Finally, it could be that the soil microbes did not perform as well in the laboratory because the 20 °C incubation temperature was considerably lower.
than the field temperatures during peak growing season at the warmer and wetter sites. Thus, the potentials we measured may not have represented full potential mineralisation for these sites.

**Estimating soil net N mineralisation in grasslands worldwide.** By combining the identified main drivers from the LMMs and potential net $N_{\text{min}}$ (Figs. 3 and 5, Table 1), we produced a SEM model that explained 33% (marginal $R^2$) of the variation in realised soil net $N_{\text{min}}$ across these grasslands (Fig. 5a). This is similar to the explained variability in potential soil net $N_{\text{min}}$ measured in other studies\(^ {14,16,19}\). The model revealed a new system-level understanding of the controls on global-scale patterns in realised net $N_{\text{min}}$ by showing that temperature of the wettest quarter, soil microbial biomass, and potential soil net $N_{\text{min}}$ (positive effects) can be directly related to realised soil net $N_{\text{min}}$. Soils with higher clay content, which have higher soil microbial biomass, have higher potential soil net $N_{\text{min}}$ altogether having a positive effect on realised soil net $N_{\text{min}}$ (Fig. 5a, b). The negative effect of temperature of the wettest quarter and the positive effect of temperature variability represent a legacy effect of climate on soil properties that affect potential soil net $N_{\text{min}}$. Again, our findings were very similar when we substituted soil microbial biomass with soil organic C (Supplementary Fig. 6).

This study is the first to directly and simultaneously compare realised and potential soil net $N_{\text{min}}$ across a globally relevant range of biotic and climatic conditions in grasslands. The two indices were only weakly related across these grasslands, highlighting the uncertainty in using laboratory measurements of soil net $N_{\text{min}}$ to predict rates actually occurring in the field. By combining potential soil net $N_{\text{min}}$ with specific climate and soil property data, we produced more robust estimates of realised soil net $N_{\text{min}}$ across our global set of grasslands. Thus, our results provide a first insight into how potential soil net $N_{\text{min}}$ data that is widely available in the literature could be leveraged to learn more about large-scale N mineralisation processes under field conditions. Accurately quantifying realised N mineralisation is crucial for estimating the role of increasing reactive N in ecosystem functioning. Mis-estimation of these processes could lead to errors in predicting how N limitation affects ecosystem functioning. Given the global extent of grasslands\(^ {24,25}\), this could, in turn, substantially affect our predictions of global change-driven impacts on C cycling\(^ {26}\). Overall, our findings suggest that management activities that alter soil compaction, nutrient content, or microbial community function may interact with future changes in temperature and precipitation regimes to severely impact the amount of N that is mineralised in grassland soils\(^ {22,46}\).

**Methods**

**Study sites and experimental design.** The 30 study sites are part of the Nutrient Network Global Cooperative (NutNet [https://nutnet.umn.edu/]; Fig. 2, Supplementary Table 1 and 2). At each site, the effects of nutrient addition and herbivore exclusion treatments are examined via a random-block design\(^ {28}\). This block design is replicated three times at the majority of the sites. For four sites, we only had data from one (1 site) and two blocks, respectively. This study is restricted to data collected from the untreated control plots ($n = 85$). Each 5 m × 5 m plot is divided into four 2.5 m × 2.5 m subplots. Each subplot is further divided into four 1 m × 1 m square sampling plots, one of which is set aside for soil sampling\(^ {28}\). Plots are separated by at least 1 m wide walkways. Mean annual temperature of our sites ranged from −4 to 19 °C, mean annual precipitation from 252 to 1592 mm, and elevations from 6 to 4241 m above sea level (Fig. 2, Supplementary Table 1). Soil organic C varied from 0.32% to 22.30%, soil total N from 0.03% to 1.25% and the soil C:N ratio from 9.07 to 23.64 across our 30 sites. Also soil clay content (3.0–53.3%) and soil pH (3.25–7.71) spanned a large gradient across the 30 sites (Supplementary Table 2). Thus, our 30 sites cover a wide range of grasslands globally that are typical for the respective region (Fig. 2, Supplementary Tables 1 and 2).

**Soil net N mineralisation and soil properties.** Each site received an identical package shipped from the Swiss Federal Institute for Forest, Snow and Landscape Research (WSL) with material to be used for sampling and on-site incubations (steel cores and rings, resin bags, caps, gloves, etc.). For the field incubation, we followed the protocol by Risch et al.\(^ {29}\). Briefly, at randomised locations in each plot we clipped the vegetation and then we drove a 5 × 15 cm (diameter × depth) steel cylinder 13.5 cm deep into the soil so that 1.5 cm on top of the cylinder remained empty. To capture incoming N from run-off and/or deposition, we placed a polyester mesh bag (mesh-size 250 μm) filled with 13.2 ± 0.9 g of acidic and alkaline exchanger resin (1:1 mixture; ion-exchanger I KA/ion-exchanger III AA, Merck AG, Darmstadt) into the upper 1.5 cm space of the cylinder. The bag was fixed in place with a metal Seeger ring (Bruettich-Rüegger Holding, Urdorf, Switzerland). Thereafter, we removed 1.5 cm soil at the bottom of the cylinder and placed another resin bag into the cylinder to capture N leached from the soil column. We
made sure that the exchange resin was saturated with H+ and Cl− prior to filling the bags by stirring the mixture for 1 h in HCl 1.2 M and then rinsing it with deionized water. The electrical conductivity of the water saturated soil was monitored. The cylinders including the soil core and the resin bags were then re-inserted into the soil, at the same location where the sample was collected, flushed with the soil surface, and incubated for 42 days (range 36–57, see also Fig. 1a). Each site coordinator chose the timing of incubation so that it started 6 weeks prior to peak plant growth. The soil core was then weighed and placed on a water saturated soil in 105 °C to 151 °C from the cylinders were separately extracted in a 100 ml PE-bottle with 80 ml M KCl for 1.5 h on an end-over-end shaker and filtered through ashless folded filter paper (DF 5895 150, ALBET LabScience). We measured NO3− (colorimetrically) and NH4+ concentrations (flow injection analysis; FIAS 300, Perkin Elmer) on these filtrates.

At the start of the field incubation, we additionally collected two soil cores of 5 cm diameter and 12 cm depth with a steel core at each sampling point for potential soil net Nmin, soil chemical and biological analyses (see below). We composited the two samples in each core using the steel cylinder to collect one additional sample (5 × 12 cm) to assess soil physical properties. This third sample remained within the steel core and both ends were tightly closed with plastic caps. The capped steel cores were then gently packed to avoid further disturbance and together with the composited soil samples overnight-shipped to the laboratory at WSL. Prior to incubation, we extracted an equivalent of 20 g dry soil with KCl as described above and NO3− and NH4+ concentrations were measured. Realised soil net Nmin was then calculated as the difference between the inorganic N content of samples collected at the end of the incubation (plus N extracted from the bottom resin bag) and the N content at the beginning of the incubation and scaled to represent daily values. We also calculated both realised soil net Nmin with growing season length to assess whether growing season differences among our sites would help to explain latitudinal differences in realised soil net Nmin.

Numerical calculations and variable selection. We examined the distributions of our explanatory variables. Some of them were highly skewed and therefore were log transformed. We centred and scaled all explanatory variables to have a mean of zero and variance of one. We then filtered our variables to avoid collinearity between them. For this purpose, we performed a correlation analysis (Supplementary Fig. 7). If variables were strongly correlated (Pearson’s r | > 0.70)2,61, we excluded either one or both of the ones that allowed us to optimise the model (Supplementary Fig. 7, Supplementary Table 5). In case of the highly correlated variables soil bulk density, soil total C, soil organic C, soil total N, soil pore space and microbial biomass, we chose a soil physical, chemical and biological variable each for use. First, soil bulk density as it is easy and inexpensive to measure and therefore readily available in large datasets, second, microbial biomass as the only soil biological variable of the group, and third, soil organic C as it is most often thought to drive soil net N mineralisation. In summary, temperature of the warmest quarter, temperature of the driest quarter, precipitation of the wettest quarter, soil total C, soil total N, and soil pore space were removed from the dataset (Supplementary Table 5). We also transformed our two response variables realised and potential soil net Nmin (square root transformation) to account for a highly skewed data distribution ($\gamma = \text{sign}(y) \times \text{sqrt}|y|$) negative values in the data set meant log transformation was not possible.

Statistical analyses. To assess the spatial patterns in soil net Nmin we used linear-mixed effect models (LMMs) fitted by likelihood maximisation using the R nlme package30 (version 3.13.1.1) and lme function (R version 3.4.4; R Foundation for Statistical Computing). Realised or potential soil net Nmin respectively, was the dependent variable, distance to the equator the fixed factor and site identity a random effect. To determine global drivers of grassland soil net Nmin we used multi-model inference32 and LMMs. We separately assessed how our variables explained realised soil net Nmin and potential soil net Nmin. Site identity was used as a random effect in these models. We first calculated the full models including all explanatory variables (Supplementary Table 5) and then applied the MuMin package57 (version 1.42.1) to select the simplest models that explained the most variation based on Akaike’s information criterion (AIC; model.avg function). We used the corrected AIC (AICc) to account for our small sample size12,59 and selected the top models that fell within 2 AIC units (delta AIC < 2). We present all our top models rather than model averages. We calculated all our models using either microbial biomass or soil organic C as these two measures represent a very similar soil feature and were highly correlated (r = 0.85). The models with soil microbial
biomass are included in the main text, the ones with soil organic C in the Supplementary Information.

Based on findings from the LMM analyses and the literature we developed an a priori causal conceptual model of relationships among environmental drivers, potential and realised soil net N_{min} to test with SEM using a d-sep approach and potential soil net N_{min}. The direct links between climate properties (Tvar, T_q-wet) and potential soil net N_{min} may represent legacy effects of climate on soil properties that we did not directly measure (see main text). Soil clay content was, in turn, predicted to affect microbial biomass (or soil organic C content), realised and potential net N_{min}. As we determined microbial biomass prior to incubating the samples in the laboratory or field, we assume that microbial biomass impacts N process rates and not vice versa. Further, as it was the goal of this study to explore if potential soil net N_{min} in combination with other properties could be used to predict realised soil net N_{min}, we added a link from potential to realised soil net N_{min}. We tested our conceptual model (Fig. 3, Table 1) following a d-sep approach using the piecewiseSEM package (version 2.0.2) in R (3.4.0), in which a set of linear structured equations are evaluated individually. This approach allows us to account for nested experimental designs and also to overcome some of the limitations of standard structural equation models such as small sample sizes. We first used the lme function of the nlme package to model response variables, including site as a random factor. Good fit was assumed when Fisher’s C values were non-significant (p > 0.05). Although the abundance of AOB explained some of the variability in potential soil net N_{min}, we did not include this variable in our SEMs as there is no mechanistic basis to rationalise that AOB drives the total accumulation of inorganic nitrogen in soil, only its partitioning between ammonium and nitrate. However, we calculated an SEM including AOB to assess if we can predict realised soil net nitrification using our predictors as well as potential soil net nitrification (Supplementary Fig. 8). While we were able to explain potential soil net nitrification well, the model fits rather poorly for realised soil net nitrification (Supplementary Fig. 8).

Reporting summary
Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability
The data will be available at https://doi.org/10.16994/envidakvba. Source data for Figs. 2, 4, 5, Supplementary Figs. 1–8 can be found in the source data file.

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A.C.R., S.Z., M.Sc., F.H. and B.M. developed the idea. A.C.R., R.O.-H. and B.M. analysed the data and M.Sc., J.L.F., F.H., P.B.A. contributed to data analyses. A.C.R. wrote the paper with input of S.Z., R.O.H., M.Sc., B.F., J.L.F., P.A.F., F.H., E.T.B., E.W.S., W.S.H., J.M.H.K., R.L.McC., A.A.D.C., C.J.S., M.L.S., P.B.A., S.B., I.A.R., J.M.B., C.S.B., M.C.C., S.L.C., P.D., A.di V., A.B.N.E., E.L., A.E., N.I.H., Y.I., K.P.K., A.M.Sc.D., J.L.M., S.A.P., S.M.P., C.R., M.Sa., I.S., K.L.S, P.M.T., R.V., L.Y. and M.B.S.Z., R.F. and J.S. analysed the samples. All authors but S.Z., R.O.-H., B.F., F.H., J.S. and B.M. are NutNet site coordinators, collected and shipped the soil data and samples. E.T.B., E.W.S. and W.S.H. are NutNet network coordinators. A detailed listing of author contributions can be found in the author contribution matrix (Supplementary Table 6).

Competing interests

The authors declare no competing interests.

Additional information

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