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LABORATORY MODELS FOR STUDYING THE HEALTH EFFECTS OF AIR POLLUTION AND CLIMATE CHANGE

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Abstract

The subject of soil microbiology has now entered the age of big data. However, there are still obstacles in connecting laboratory, field, and model-based investigations of ecosystem functioning. The limiting of variables in laboratory tests fails to include the interactions of many environmental forces in their natural settings. This often leads to conflicting results between laboratory and field investigations, which may potentially mislead the creation and predictions of models. Transferring soil microbiology research from the lab to ecosystems is a significant issue for environmental scientists. However, it has the potential to provide valuable information to policymakers in order to create climate-smart and resource-efficient ecosystems. The process of upscaling involves not just scaling up, but also the need to separate and understand the functional links and activities at each level. There are three possible explanations for the differences between studies conducted in laboratories and those conducted in the field. These explanations include the dynamics of space and time, disturbances in sampling, and the interactions between plants, soil, and microbes. Additionally, there are three important considerations to keep in mind when connecting observations with model predictions. These considerations include the effects that occur across different scales, the complex relationships between different processes, and the regulation of multiple factors. Field-based research is only able to investigate a restricted range of environmental variation. To fully understand the underlying processes, it is necessary to complement these investigations with laboratory and mesocosm manipulation experiments. The lack of information in scaling up soil microbiology from laboratory to ecosystems should encourage multidisciplinary cooperation including experimental, observational, theoretical, and modeling research.

Keywords: Laboratory, ecosystem, soil microbiology, review.

1. Introduction

The fast progress in technology for high-throughput sequencing and omics analysis has allowed soil microbiology to enter a big data age, covering larger temporal and geographical scales. This is shown by studies conducted by Chen & Sinsabaugh (2021), Lui et al. (2021), and Xia et al. (2020). The rapid collection of data has greatly enhanced our knowledge of how soil microbial communities develop in different environmental situations and their ecological activities (Luo et al., 2016; Smercina et al., 2021). Recent research has shown that include microbial activities in mechanistic modeling has greatly improved predictions of soil carbon and nutrient cycling, resulting in more accurate estimates and lower model uncertainties (Wang, Gao, et al., 2021; Wieder et al., 2015). These investigations have stimulated study at both laboratory and field scales to investigate the patterns and processes of soil microbial communities, their roles, and the ecological consequences.

2. Laboratory and field research

Laboratory and field research possess distinct benefits and drawbacks due to significant differences in boundary conditions, such as drivers, sizes, complexity, and specifically soil structure and its interactions with plants (Lui et al., 2021; Standing et al., 2007). Consequently, results obtained from experiments conducted in laboratories and in real-world settings do not consistently align and may exhibit conflicting outcomes (Feng et al., 2017; Jian et al., 2020). The discrepancies between laboratory-based and field-based investigations have posed significant obstacles in scaling up these studies to regional and global levels. Nevertheless, several contemporary models fail to sufficiently account for these problems, potentially resulting in erroneous forecasts by the models.

The discrepancy between laboratory and field studies arises when incorporating N-cycling microbial guilds to forecast soil N_2O emission, despite a growing body of research demonstrating the pivotal role of soil microorganisms in regulating soil N_2O emission in both laboratory and field settings (Shi et al., 2021; Zhang et al., 2022). Zhang et al. (2022) conducted field-based investigations on a worldwide scale and found that the addition of nitrogen (N) had a considerable impact on the abundance of microbial guilds involved in nitrogen cycling and the emission of nitrous oxide (N_2O) from the soil. However, they could not establish unambiguous causal links between these two factors. In contrast, laboratory- and mesocosm-based investigations have revealed strong associations between the abundances of N-cycling microbial guilds and the emission of soil N_2O (Shi et al., 2021).

These inconsistencies indicate that using just laboratory-based model frameworks may result in an overestimation of the microbial impact on in situ soil N2O emission variations. An explanation for this phenomenon is the inadequate depiction of crucial environmental elements in laboratory-based investigations (Zhang et al., 2022). These parameters include precipitation, soil pH, soil C:N ratio, ecosystem type, and the interactions with plants.

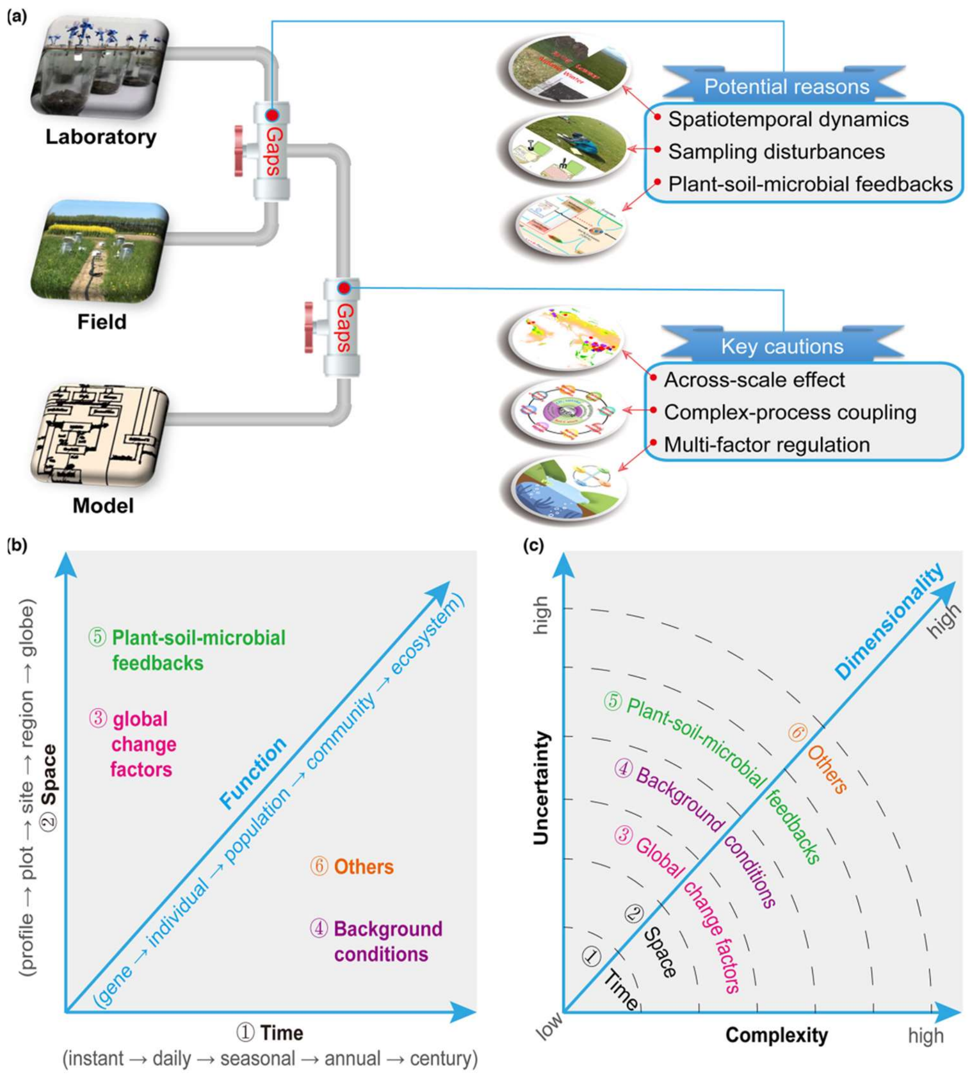
Difficulties arise when trying to combine laboratory, field, and model-based investigations to demonstrate the role of microorganisms in soil carbon cycling. Jian et al. (2020) used short-term laboratory-incubations to optimize microbial parameters and estimated that soil organic carbon (SOC) will decrease by 8% due to warming. Their modeling findings, however, lack support from field-based investigations on unaltered soil organic carbon (SOC) (van Gestel et al., 2018). In addition, Jian et al. (2020) made a forecast that there would be a little increase of 2% in soil organic carbon (SOC) when adjusting microbial parameters using long-term laboratory incubations. This prediction contradicts the model projections that were based on short-term laboratory incubations. Therefore, the length of the investigation might be a significant factor in connecting laboratory, field, and modeling studies. For instance, a 26-year study conducted in the Havard forest shown that the effects of warming on soil respiration over a long period of time are different from those seen in the short term (Melillo et al., 2017).

There are existing issues about soil phosphorus (P) cycling across laboratory, field, and model-based investigations. According to Liebig's law of minimum, some laboratory-based studies have indicated that there would be an increase in plant and microbial phosphorus restriction after the greater deposition of nitrogen in the atmosphere (Luo et al., 2022). In contrast, a comprehensive study of 668 field-based observations conducted globally revealed that increased nitrogen (N) input had a substantial short-term effect of exacerbating phosphorus (P) restriction. However, the long-term continuous addition of N may not always lead to an overall rise in P limitation (Chen et al., 2020).

One possible reason is that nitrogen-induced phosphorus limitation in field-based studies is gradually reduced over time due to the initial increase in soil microbial metabolic activity, soil phosphatase activity, and interactions between plants, soil, and microbes. This ensures a sufficient supply of phosphorus to support the growth of plants and microbes (Chen et al., 2020). Earth System Models predict that without accounting for the interactions between plants, soil, and microbes, the addition of nitrogen would lead to an increase in phosphorus restriction. This change is expected to cause ecosystems to shift from being net absorbers of CO2 to net emitters.

Nevertheless, Fleischer et al. (2019) demonstrated that ecosystems may consistently function as net CO2 sinks over time with the addition of nitrogen, when taking into account the plant-soil-microbial interactions. Undoubtedly, the difficulties in connecting laboratory, field, and model-based research are often noticed in the area of soil microbiology. However, these issues are just beginning to be acknowledged, and they provide significant obstacles in scaling up findings and generating dependable evidence for policymakers.

Three factors contribute to the mismatch between laboratory and field investigations (Figure 1): (1) Spatiotemporal dynamics refer to the patterns and changes that occur in both space and time. Laboratory investigations are carried out in controlled settings that are different from field research, particularly when taking into account the significant daily, seasonal, and yearly fluctuations, as well as random occurrences, of various environmental elements (Feng et al., 2017; Jian et al., 2020). (2) Sampling errors.



The soils used for laboratory experiments undergo significant disruption and homogenization processes, such as sifting. These procedures might potentially expedite the release of enclosed resources and nutrients (Feng et al., 2017). More precisely, the combination of places with high microbial activity and areas with low activity is likely to result in an underestimating of microbial metabolic processes, even if this relationship is not straightforward. (3) Interactions between plants, soil, and microorganisms that influence each other's growth and development. The lack of external resource inputs in laboratory-based investigations leads to a rapid decline in microbial metabolic activities and process rates. This is expected to result in unexplored feedback loops between plants and microorganisms, which have not been well examined (Mariotte et al., 2018).

Ye et al. (2019) conducted a study on soil heterotrophic respiration using 110 field dryland observations worldwide. They found that the best way to predict soil heterotrophic respiration was by considering a positive correlation between CUE (carbon use efficiency) and temperature. This finding contradicts laboratory-based studies, such as the one conducted by Wang, Qu, et al. (2021), which showed a decrease in CUE as temperature increases.

It is important to exercise caution when applying information obtained from research conducted in controlled environments to larger ecosystem investigations. Additionally, incorporating this knowledge into models that can accurately forecast the consequences of changing environmental circumstances at the appropriate ecological sizes requires careful consideration (Figure 1). The across-scale effect refers to the variations in underlying processes and related mechanisms across different geographical and temporal scales. Processes examined at a local scale may not be significant when considering the whole ecosystem. This is because the processes being researched are less relevant compared to other factors controlled by large-scale environmental variables. Furthermore, the application of findings from short-term observational research to long-term circumstances may lead to complex-process coupling concerns owing to the inadequate representation of elements that influence microbial adaptation and acclimation.

For instance, Jian et al. (2020) anticipated divergent impacts of warming on soil carbon store, depending on whether model parameters were adjusted using short- or long-term research. The third issue is to the combined impact of microbial activity under multi-factor control, making it challenging to isolate the individual impacts of different biotic and abiotic variables (Matchado et al., 2021; Standing et al., 2007). It becomes more difficult when examining the effects of numerous global change drivers, since most current field-based modification research are mostly done under just one component.

Although there are challenges in integrating laboratory and field-based investigations, they provide unique benefits in enhancing our understanding of soil microbiology (Lui et al., 2021). Laboratory-based research are capable of successfully investigating microbial sensitivities and the underlying processes in response to experimental stimuli under highly controlled circumstances. This may greatly contribute to the advancement of mechanistic knowledge. Field-based research provide the ability to observe and document the many environmental and climatic changes, as well as the interactions between plants and soil. This allows for a more accurate representation of how the whole ecosystem responds.

Nevertheless, field-based observations often include a restricted spectrum of environmental circumstances, necessitating the inclusion of laboratory or mesocosm investigations to enhance our comprehension of the underlying mechanisms. For instance, when studying the impact of temperature on soil respiration, laboratory experiments provide a high level of control over soil moisture at different temperatures. However, in field-based experiments, even a slight increase in temperature can lead to unavoidable changes in soil moisture levels (Feng et al., 2017).

Laboratory-based investigations may provide insights into underlying processes and mechanisms that are not well represented in existing model frameworks. However, it is important to carefully assess the limitations and restrictions associated with combining data from various sources. Hence, it is essential for future study to explore efficient approaches to address the challenges in connecting laboratory, field, and model-based investigations, and to enhance the integration of data from diverse sources.

Researchers are now working on creating tools that can combine various research at different levels of analysis in order to get a more precise comprehension and ability to make predictions, despite the inherent differences between studies conducted in laboratories, in the field, and via computer models. Data assimilation is an illustrative case where model frameworks are systematically adjusted by including new data and procedures to align with the most recent observations. However, it is important to note that this data integration is only suitable if the data adequately span the desired range.

Chen et al. (2019) created a data-driven enzyme model by including data assimilation. This model is based on the latest findings from a meta-analysis (Chen et al., 2018), which established novel connections between soil extracellular enzymes and SOC dynamics. The data assimilation strategy effectively replicates the observed connections between enzymes and SOC, leading to substantial improvements in the model's predictions of SOC dynamics in response to increased N addition at Duke Forests. Despite its initial lack of inspiration, the enhancement of observational networks, such as those focused on global changes, biodiversity, and C-N fluxes, has been achieved across many environmental circumstances. This will enable the evaluation of models that reflect novel mechanistic insights over a wide array of real-world scenarios. One way to do this is by using current extensive network observations and conducting long-term ecological studies (Wieder et al., 2015).

3. Conclusion

Investigating effective indicators (such as genes, enzymes, and other functional characteristics) for the diverse soil microbial communities (Treseder et al., 2012; Trivedi et al., 2013). Wang, Gao, et al. (2021) significantly enhanced the accuracy of soil carbon and nitrogen cycle simulations in the Microbial-Enzyme Decomposition model by including different enzyme-mediated activities related with carbon and nitrogen into the model as a representation of microbial processes. Utilizing cutting-edge data-analytic methods such as hierarchical random-matrix, eco-evolutionary dynamics, machine learning, and ecological networks to combine our understanding of fundamental microbial processes with data from various levels of analysis (Matchado et al., 2021; Zhang et al., 2022).

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