Soil nitrogen mineralisation simulated by crop models across different environments and the consequences for model improvement

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Introduction

Crop models are the state-of-the-art tool to predict crop yields in the context of climate change and food security. The uncertainty associated with their use can be partly overcome by using multi-model ensembles (*mme*), though model improvement is still an important consideration (Rötter et al., 2011). Model intercomparison identifies processes that are well represented by some models, but insufficiently simulated by others. The initial concept relies on testing against high-quality field data under the assumption that the observed crop was grown without limitations. In the case of nitrogen (N) supply to the crop, unlimited growth of the simulated crop can be easily assured if sufficient mineral N fertiliser is applied. However, in low-N systems, N supply to the virtual crop highly depends on how the model simulates soil organic matter turnover and subsequent N release.

Materials and Methods

We revisited the crop growth simulations of *mme*s for wheat (Asseng et al., 2013) and maize (Bassu et al., 2014) and analysed the simulated N mineralisation dynamics for eight different sites. The simulated N supply is discussed in the context of existing observations for N mineralisation from soils of different environments and of the consequences for model improvement.

Results and Discussion

Analysis reveals that within the *mme*s the simulated N mineralisation courses produce a range of N supply levels from 24 to 160 kg N ha^{-1} at a site in Argentina. Here, 120 kg N ha^{-1} additional fertiliser was given, but a considerable number of models still simulated N stress of the grown wheat crop. A subsequent crop parameter adjustment under the assumption of unlimited N supply may have failed in some of these cases due to violation of the precondition (Table 1). The simulation of N stress, when none occurred, would have contributed to the variability between models. Investigating the N-related processes seems promising to further improve the models, leading to reduced uncertainty in *mme*s.

Table 1. Preconditions for crop parameter optimisation arising from observed vs simulated soil conditions.

	Observed crop	
	N limited	Not N limited
N stress simulated	Simulation reflects the site conditions well. However, basic assumption for the simulation study violated (non-optimal conditions for plant growth).	N supply underestimated. Crop parameter adjustment probably the wrong handle. Site conditions match the basic assumption of optimal growth.
N stress not simulated	N supply overestimated. Model assumes optimal growth, which is not the case. Crop parameter adjustment may go astray.	Site conditions match the basic assumption (optimal growth). Crop parameter adjustment feasible according to the study's objective.

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