Projected increases in precipitation are expected to reduce nitrogen use efficiency and alter optimal fertilisation timings in agriculture

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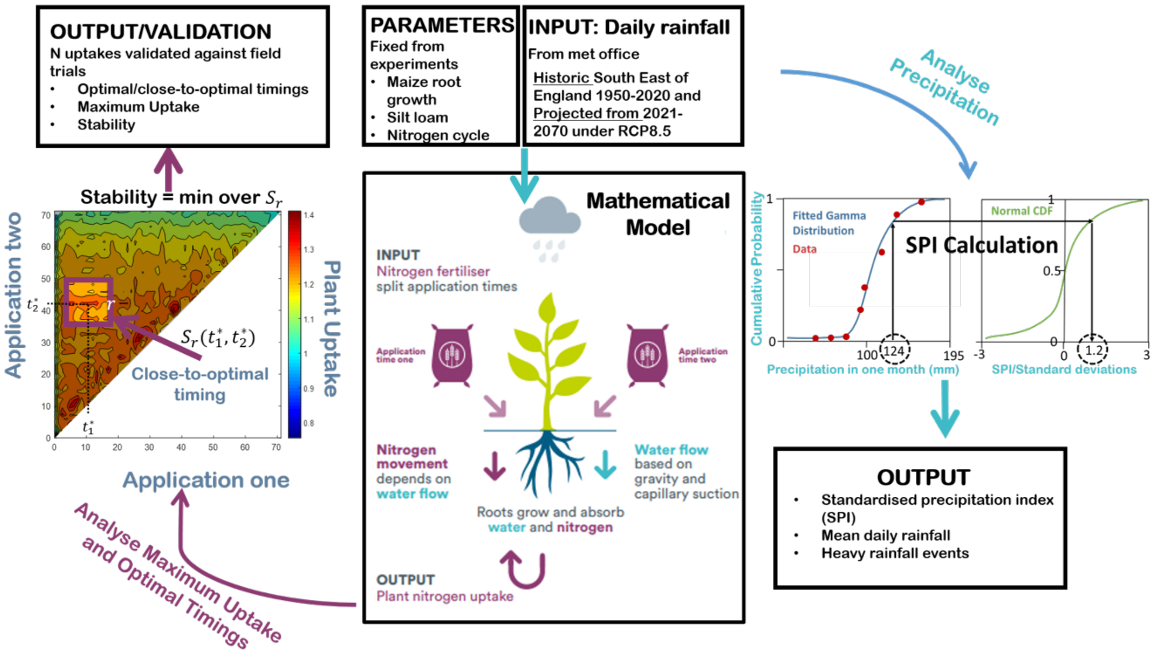
Abstract

Nitrogen fertilisation is vital for productive agriculture and efficient land use. However, globally, approximately 50% of the nitrogen we apply is lost to the environment causing inefficiencies, pollution, and greenhouse gas emissions. Rainfall and its effect on soil moisture are the major components controlling nitrogen losses in agriculture. Thus changing rainfall patterns could accelerate nitrogen inefficiencies. We used a mechanistic modelling platform to determine how precipitation-optimal nitrogen fertilisation timings and resulting crop nitrogen uptake have changed historically (1950-2020) and how they are predicted to change under the RCP8.5 climate scenario (2021-2069) in the South East of England. We found that historically, neither precipitation-optimal fertilisation timings nor resulting plant uptake changed significantly. However, there were large year-to-year variations in both. In the 2030s, where it is projected to get wetter, precipitation-optimal fertilisation timings are predicted to be later in the season and the resulting plant uptake noticeably lower. After 2040 the precipitation-optimal uptakes are projected to increase with earlier precipitation-optimal timings closer to historical values, corresponding to the projected mean daily rainfall rates decreasing to the historical values in these growing seasons. It seemed the inter-annual variation in precipitation-optimal uptake is projected to increase. Ultimately, projected changes in precipitation patterns will affect nitrogen uptake and precipitation-optimal fertilisation timings. We argue that the use of bespoke fertilisation timings in each year can help recuperate the reduced N uptake due to changing precipitation.

Synopsis: Future precipitation changes will affect crop nitrogen uptake; fertiliser application timings should adapt and stay flexible to maintain fertiliser efficiency.

Keywords: nitrogen use efficiency, precipitation, modelling, plant modelling

Graphical Abstract



1 INTRODUCTION

Insufficient levels of available soil nitrogen (N) is a major limiting factor for crop yields globally[1]. Soil replenishment of N occurs *via* a number of anthropogenic and natural processes[2]. While biotic N fixation, *i.e.* converting atmospheric N to plant-available species, is one major pathway for soil N replenishment, synthesized N fertilisers *via* the Haber-Bosch process[3] are necessary to support the current global food demand. 50% of food production relies on synthesised fertilisers. However, their synthesis is energy intensive, requiring 1.2% of global primary energy production[4].

Besides N fertiliser production, fertiliser application can also contribute to environmental issues. Transformations between N species can result in the release of potent greenhouse gases such as nitrous oxide (N_2O)[5,6]. N added to fields can be flushed through the soil to deeper sections and/or into the water table (*i.e.* 'leaching'), thus becoming inaccessible to the crops and causing eutrophication[7,8]. Furthermore, N leached from fields into the groundwater has the potential to be denitrified into N_2O in aquatic and marine environments[9]. Additionally, ammonium in the soil can be volatized and the N released as ammonia gas; this can be significant (up to 60% of applied N) when the fertiliser isn't incorporated into the soil and depends on temperature, soil texture, moisture and pH[10,11].

Soil moisture controls both N leaching and crop N uptake[8,12-14]. High rainfall rates flush N through the soil resulting in increased leaching. However, low soil moisture limits N mobility, resulting in poorer plant N uptake[11,15,16]. It remains unclear how precipitation patterns, soil type, crop and growth stage influence uptake. However, it is clear precipitation patterns are closely linked to Nitrogen Use Efficiency (NUE)[17,18] defined in this paper as the ratio of N taken up by the crop to the amount of N applied, i.e., NUE = (Quantity of plant assimilated N)/(Quantity of N input into the system).

Several studies have correlated cumulative rainfall with measures of N loss or plant N uptake[13,17]. In field trials in England, Powlson et al.[16] found that N loss correlated positively with total rainfall 3 weeks post fertilisation, which explained 55% of the variation. This indicated that in this region, more rainfall results in lower NUE provided water is not limiting for crop growth. In a mechanistic-modelling study, McKay Fletcher et al.[18] found that cumulative rainfall post-fertilisation explained 40% of the variation in N loss by only varying precipitation patterns between simulations (*i.e.* soil type, root growth *etc.* were kept constant). The positive correlation between cumulative precipitation and N loses is only valid provided there is enough water to support healthy crop development. In fact, in drier regions, NUE increases with cumulative precipitation, likely due to increased N mobility and enhanced crop growth, until a certain amount, from which it decreases due to enhanced leaching[17].

Efforts to maximise N uptake focus on the Four Rs of fertiliser efficiency: 'right source, right rate, right time, right place'[19]. However strategies depend on the individual farms, meteorological condition, crop and soil[20]. 'Right time' typically concerns timing the fertiliser application to ensure N is available when the crop demand is the highest[21]. Fertilisation timing in agriculture is often based on crop growth stage[22,23]. Typical guidance for nutrient management in the UK can be found in Roques, et al. [23]. Wallace, et al. [24] found that delaying fertilisation until the end of tillering increased NUE except in very dry seasons where late fertilisation decreased NUE. The physics based model of

McKay Fletcher et al.[18] mirrored these results, finding that reduced N-uptake in drier seasons with late application was due to low N mobility. Delaying fertiliser application beyond the onset of stem-elongation in wheat can also decrease yields[25], a feature which was also present in the model results[18]. There are few studies that specifically investigate precipitation-optimal fertiliser timings, defined here as application timings that achieve maximum crop N uptake with respect to the precipitation. Typically, fertiliser timings are based on growth stage in scientific experiments, the effect of rainfall is only mentioned to help explain anomalous results and not the primary control variable for fertilisation timing (e.g. Dharmakeerthi, et al. [26] and references above). It is clear that better timing of N fertilisation with respect to rainfall patterns (known as precipitation-optimal timings in the current article) can improve NUE in addition to timing with respect to crop demand[24]. The former approach is the least studied but most volatile due to changing local climates but both play an import role in plant N uptake.

The impact of climate change on N fertilisation is becoming increasingly studied due to the sensitive dependence on weather[13]. Changing weather, specifically heavy rainfall events, can increase N leaching and denitrification resulting in increased N_2O and N_2 emission, and lower crop NUE and water pollution[27]. In response, farmers need to adapt to ensure profitable production (i.e. enough crop N uptake) while minimising adverse environmental impacts. Researchers have found moderate success in current approaches for mitigating N loss[20]. Interviews with maize farmers in mid-western USA revealed that they primarily responded to increased heavy rainfall events with increased fertiliser application[28]. Although this maintains production, it also increases pollution. To enable sustainable N farming strategies, it will be necessary to demonstrate the strategies maintain high yields, lower pollution and incentivise farmers with reductions in net fertiliser costs[28]. However, there are few studies that quantify the outcome of fertilisation strategies in a changing climate on N use efficiency or how optimal strategies may need to change.

Here we studied precipitation-optimal N fertilisation timings through a number of historic and predicted growing seasons in the South East of England using a mathematical model. We considered modelled crops of maize on a silt loam soil sown in spring. We used historic daily rainfall data from 1950-2020 and predicted daily rainfall data for 2021-2069 under the RCP8.5 climate scenario[29]. Precipitation-optimal split fertilisation timings (two fertilisation days per growing season) were determined for each year by monitoring every possible fertilisation day pair in the model and the resulting final modelled crop uptake. With this approach we addressed the following questions for the South East of England climate scenario:

- Have precipitation-optimal fertilisation timings and corresponding NUE changed historically?

- Are they projected to change?
- Do precipitation metrics correlate with precipitation-optimal fertilisation times and/or NUE?

By answering these questions we can inform how N fertilisation strategies may be adapted and demonstrate the positive economic and environmental impact, in terms of NUE, of adapting to mitigate the effects of changing precipitation patterns. Finally, we argue that advanced computational tools can become valuable as support tools for farmer/agronomist decision.

2 METHODS

2.1 PRECIPITATION DATA

We simulated a growing season from the 1st of March to the 30th of June and used the precipitation data from the same period as an input to the model. Historic (1950-2020) daily precipitation data from the administrative region of South East of England was obtained from the Met Office using an average over weather stations in the region[30]. Additionally, predicted daily precipitation data (2021-2069) for the same region under the RCP8.5 climate scenario was obtained from the UK Climate Projections User Interface (https://ukclimateprojections-ui.metoffice.gov.uk). The RCP8.5 climate scenario assumes a 3.2-5.4 °C increase in global mean surface temperatures averaged over years 2081-2100 compared to the preindustrial averages from years 1850-1900. The climate model used to predict the daily precipitation rates was HadGEM3-GC3.05 collected through the UK Climate Projections User Interface[31]. The details of the configuration to access the data can be found in Williams, et al. [32].

2.2 PRECIPITATION ANALYSIS

A number of precipitation metrics were used to infer how NUE and precipitation-optimal fertilisation timings may correlate with precipitation patterns. The mean daily precipitation rate for the growing season was calculated. When it was necessary to account for the large variations in precipitation from year-to-year and capture long time-scale changes, measurements and averages were taken over decades (inter-decadal analysis). When referring to a specific year we write it non-plural, *e.g.* 2020, when referring to the decade we write it plural, *e.g.* 2020s.

Precipitation variability is expected to increase, resulting in increased heavy rainfall events and droughts[33]. In the context of N fertilisation, a heavy rainfall event over one day or less can have a large impact on N leaching. To account for this we define a “heavy rainfall event” as days with high rainfall rates relative to a reference period[27]. The period 1950-1979 (March to June) is used as a reference period and the daily rainfall rate which marks the top one percentile in this reference period is calculated. A heavy rainfall event is then defined as any day which is equal to or above this top one percentile rainfall rate[27]. Since one day without any precipitation is common and has much less impact on soil moisture than a heavy rainfall event, defining lack of rainfall in the context of N fertilisation requires a longer time scale. A common approach to measure drought is the Standardized Precipitation Index (SPI)[34]. The SPI measures standard deviations from the mean over aggregated time-periods, typically 1,3,6,18,24 months depending on the context in which drought is defined. To calculate the SPI a probability density function (gamma distribution in this paper) is fitted to the aggregated rainfall data using the maximum-likelihood approach (find distribution-parameters in which the data is most probable when drawn from that distribution). The fitted cumulative density function is then calculated and transformed to standardized normal cumulative density function to determine the SPI as standard deviations from the mean, see the SPI calculation in Figure 1 for a visual description of this index. SPI measurements of drought are thus relative to the region. Since precipitation-optimal fertilisation timings depend on changes in soil moisture, we chose the shortest viable time aggregation of one month for this study. Thus, 4 SPIs were given per growing season in the simulations. The classification of relative droughts using the SPI are: $0 \geq SPI > -1$ mild drought, $-1 > SPI > -1.50$ moderate drought, $-1.5 \geq SPI > -2$ severe drought, and $SPI \leq -2$ extreme drought[34]. For each decade, we calculate the percentage of months which are moderate drought and above or severe drought and above. SPI was calculated in Python3 (Python Software Foundation, https://www.python.org/) using the standard_precip package (https://github.com/e-baumer/standard_precip).

2.3 MODELLING

The modelling framework follows that of McKay Fletcher, et al. [18]. Here we summarise the approach and highlight important assumptions in the model that are required to interpret the results in the relevant context. We aim to simulate spring sown maize on a silt loam in the South East of England. Split fertilisation timings will then be varied for each year from 1950-2059. The model couples the advection-diffusion reaction equation for N transport and the N cycle in soil to Richards' equation for water flow in the soil. Importantly, the advective N transport is governed by the soil saturation profile to accurately capture the effect of soil moisture and precipitation on N dynamics. The crops are represented by a root length density function and a root depth function that evolves in time according to logistic root growth equations with parameters that match the growth of maize. The crops absorb the N species and water in soil. Growth stage dependent crop N uptake is not explicitly considered in the model as our emphasis is on precipitation pattern variation. However, N demand is a function of root length density which itself is a proxy for plant size. Thus, the growth stages happen at the same time each year. Figure S1 shows the performance of the model against the experimental data of Powlson, et al. [16] by correlating N leaching with cumulative rainfall 3 weeks post fertilisation. The model data in this figure uses daily rainfall rates drawn from a distribution which was fit to rainfall data in the South East of England. We refer the reader to McKay Fletcher, et al. [18] for a full description of the model. It is important to note that the root depth and length density functions are independent of water and N uptake *i.e.* plant growth is never water or N limited. This might become relevant when interpreting the results regarding the drier years where water may be limiting. However, the region of study, the South East of England, is a temperate region and is rarely water limited for grain production. Additionally, gaseous losses of N (e.g. N_2O, N_2 and NH_3) from the system are not explicitly included in the current version of the model. Typically only fractions of a percent of ammonium is transformed into nitrous oxide during denitrification in agriculture[35]. Although we judged this to have little effect on crop N uptake and omitted it from the model for parsimony, nitrous oxide is a potent greenhouse gas and should be included in future models considering greenhouse gas emissions. Ammonia volatilisation can contribute a significant amount of N loss from soil systems, however for ammonium nitrate, the fertiliser simulated in this study, losses are typically between 2-3% of the applied N which we judged to be small enough compared to leaching to omit from the model [11]. Therefore, N loses calculated by the model only include leaching and any link between N losses and NUE is an approximation.

The experimental variables, namely the precipitation pattern and the two N fertilisation applications are boundary conditions on the soil surface for the Richards' equation and the N advection-diffusion-reaction equation, respectively. The applications of N fertiliser are modelled as pulses of ammonium nitrate at user controlled fertilisation times t_1 and t_2. The fertiliser is applied at a yearly rate equivalent to 144 kg ha^{-1} (a typical recommendation for maize to maximize yield and reduce leaching[8]), with one third being applied at t_1 and the remaining two thirds applied at t_2. One instance of the model refers to a specific growing season's precipitation pattern and a fertilisation timing pair (t_1, t_2), from the solution of the model the plant N uptake can be calculated by integrating the root uptake soil sink over space and time. The fertilisation timings are limited to the first 70 days of the growing season with $t_1 \leq t_2 \leq 70$ days. For each growing season (*i.e.* precipitation pattern) the fertilisation timing pair (t_1, t_2) that achieves the maximum crop N uptake is calculated by directly. Specifically, the model is solved for every possible fertilisation timing pair with 1.2 day resolution in fertilisation timing, and the total N uptake is calculated. This results in data demonstrated in the heat map in Figure 1 for each year. The fertilisation timing pair that achieves the maximum plant N uptake relative to the growing season is referred to as the precipitation-optimal timing and the associated N uptake is referred to as the maximum uptake. Each model instance was solved numerically using a finite element method in Comsol 5.3a (COMSOL AB, Stockholm, Sweden).

2.4 MODELLING ANALYSIS

To determine the precipitation-optimal timing for all growing seasons, 111,600 instances of the model were solved numerically. As with the precipitation analysis, the results are presented in both yearly and decadal groupings to determine both short and long time-scale trends. The use of an exhaustive approach as opposed to an optimisation method enabled the calculation of fertilisation timing pairs in the growing season that achieve close-to-maximal N uptake relative to the growing season. A fertilisation timing pair is said to be close-to-optimal if it achieves an N uptake within 5% of the precipitation-optimal timing in that growing season. A growing season with many close-to-optimal timings is advantageous as fertilisation strategies can be less accurate and the farmer can choose when to fertilise based on other factors besides precipitation, *e.g.* growth stage.

It is possible that close-to-optimal timings follow or pre-date timings that achieve low N uptakes. Ideally, close-to-optimal timings are surrounded by fertilisation timings that achieve relatively high uptakes so that the farmer has a buffer zone to fertilise in. We developed a metric to quantify this feature and determine how this has changed and is predicted to change: For a given a close-to-optimal timing pair, (t_1^*, t_2^*) in a particular growing season, denote the set of all timings within radius r days each side of (t_1^*, t_2^*) by $S_r(t_1^*, t_2^*)$. The 'Stability' of (t_1^*, t_2^*) is defined as the minimum uptake achieve by the fertilisation timing pairs in $S_r(t_1^*, t_2^*)$ as a proportion of the uptake achieved by fertilising on (t_1^*, t_2^*), see Figure 1 for a visual description of Stability. The 'Stability' of a growing season is then defined as the mean Stability over all close-to-optimal timings in the growing season. For example, a growing season with a Stability of 0.75 means that, on average, a farmer is guaranteed to get within 75% of the close-to-optimal timing if they miss the close-to-optimal timing by r days either side. We present analysis of Stability with $r = 2.4$ days. All analysis of the model results was computed in Python3[36].

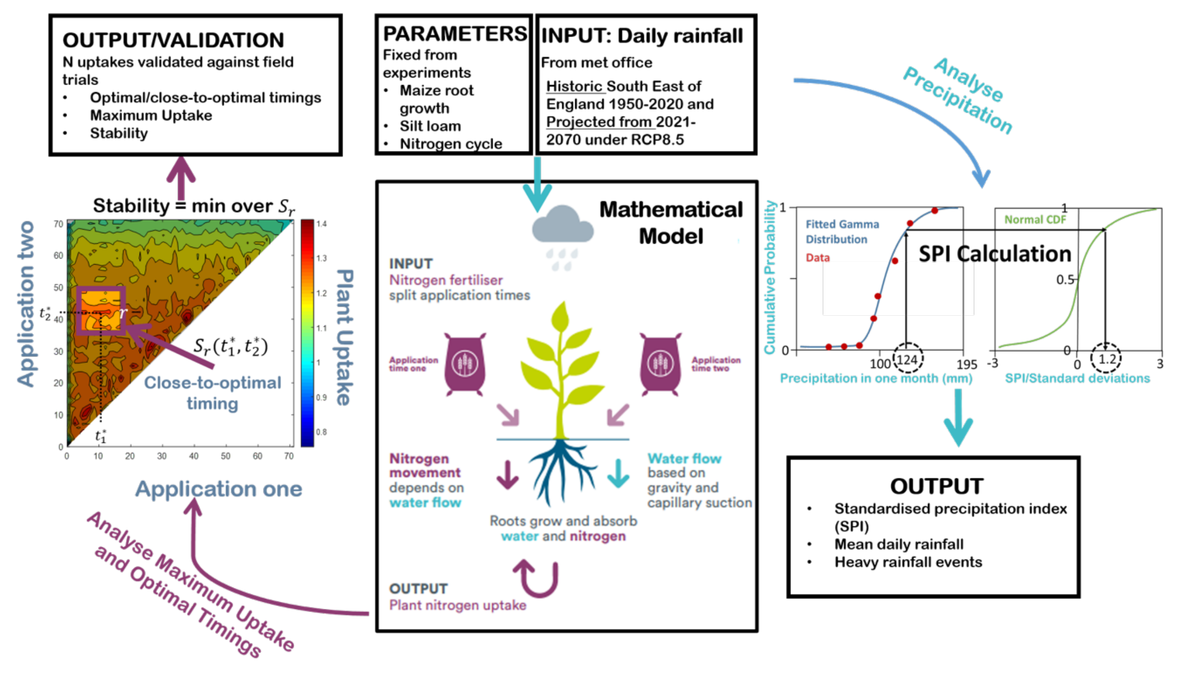


Figure 1: Explanation of modelling and processing of model outputs and rainfall data. Historic and projected rainfall data is an input to the mechanistic model. The model is solved for every possible split fertilisation timing and the results are analysed, including 'Stability', maximum uptake and optimal fertilisation timings. In addition, the rainfall data is analysed using a one-month aggregated standardised precipitation index, heavy rainfall events and means.

3 RESULTS AND DISCUSSION

3.1 PRECIPITATION HISTORY AND PROJECTIONS

We found a large inter-annual variability in the mean daily rainfall rate, Figure 2a. From 1950-2021 the rolling mean (width 11 years) hovered around 1.7 mm day^{-1}. After 2021, the rolling mean is projected to monotonically increase until it reached a maximum in 2032, where the raw values are projected to reach 3.71 mm day^{-1}. The rolling mean was then projected to decrease until 2045 and then hover around 1.9 mm day^{-1}. From 1980s to 2010s the heavy rainfall days stayed close to 1%, suggesting there was little change from the reference years in this period, Figure 2b. In the 2030s there was a steep jump to 3.1% of heavy rainfall days, after which the heavy rainfall events were projected to decrease back to the values of the 2020s. The number of moderate drought months from 1950s to 2020s stayed between 13% and 22%, Figure 2c. The 2020s, 2030s and 2040s were projected to have noticeably lower amounts of Moderate Drought months, Figure 2c, which is unsurprising given the projected high daily rainfall rates, Figure 2a. This analysis suggests that the growing season had consistently drier months historically, while in the future, under this climate scenario, we expect these months to be interrupted by more heavy rainfall events.

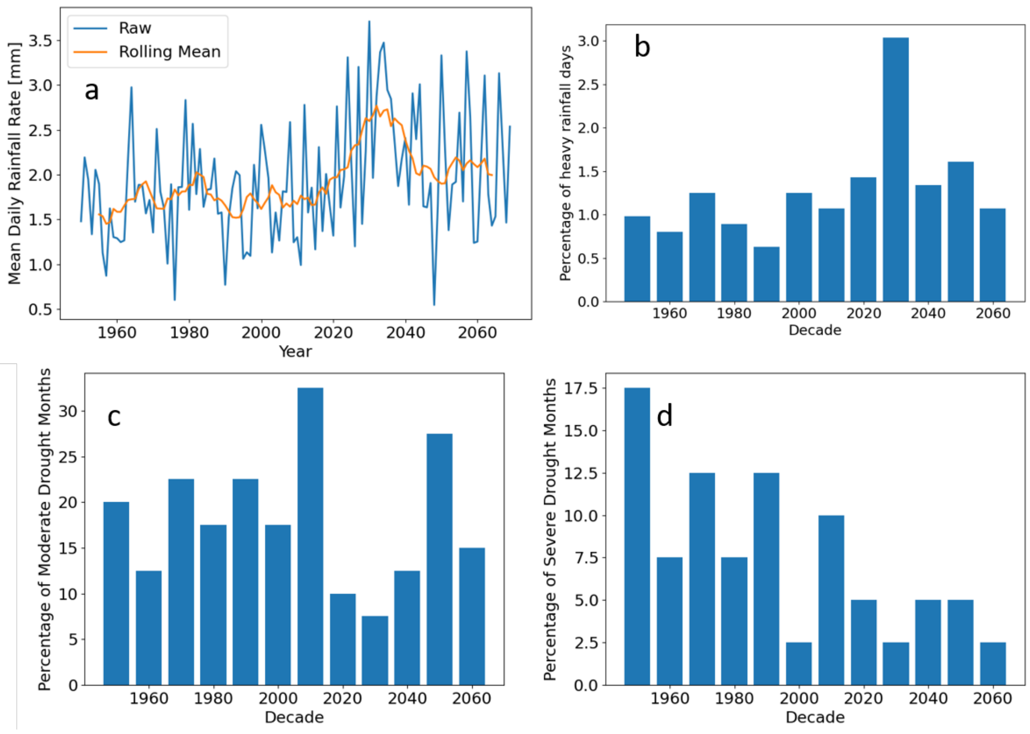


Figure 2: Analysis of precipitation data within the growing seasons. ***a****) Yearly mean March-June daily rainfall. The rolling mean with width 11 years is also shown in yellow.* ***b****) Percentage of heavy days classified as heavy rainfall event in each decade. A heavy rainfall event is a day higher than the top percentile of daily rainfall rates from 1950-1979.* ***c****) Percentage of months in the decade moderate drought or worse decade, SPI≤-1.0.* ***d****) Percentage of months in the decade severe drought or worse decade, SPI≤-1.5.*

3.2 A Computational History and Projection of Nitrogen Uptake and Precipitation Optimal Fertilisation timings.

Nitrogen uptake

The year on year maximum modelled N uptake is shown in Figure 3a. All 'N uptake' results from this point onwards are modelled values. For historic years (1950 to 2020) the model predicted the maximum N uptake to be around 204 kg N ha^{-1} (see the rolling mean in Figure 3a). However, there was large inter-annual variability. For example, in 1951 the maximum N uptake was 191.4 kg N ha^{-1}. In the following year this increased by 12% to 213.8 kg N ha^{-1}. The rolling mean of N uptake started decreasing towards the end of the 2010s, where in 2030 it is predicted to reach a minimum of 190.0 kg N ha^{-1}, with some specific years reaching lows of 169.1 kg N ha^{-1} (2030). This corresponds to increased mean projected rainfall and increased percentage of heavy rainfall events in the same period, Figure 2a and b. After 2034 the rolling mean is predicted to increase rapidly until 2043 to reach values similar to the historical maximum uptake , which aligns with the mean projected rainfall rate decreasing in this period, Figure 2a. However, from 2053 to 2069 the rolling means of maximum N uptakes are predicted to fall below that of the historical data. In the projected years the inter-annual variability in maximum uptake can be larger than the historical variability. For example, in 2030 the maximum uptake was 169.1 kg N ha^{-1} which increases by 25.6% to 212.4 kg N ha^{-1} in 2031. The maximum-uptake over all of the years is predicted to be in 2051, achieving 226.35 kg ha^{-1}. The model predicted crop N uptakes are consistent with field trial measurements for maize. Ciampitti and Vyn [37] found that mean N uptake for maize over a number of varieties and fertilisation quantities was 152 kg N ha^{-1} with a maximum and minimum of 387 and 33 kg N ha^{-1} respectively. Our model predicted mean N uptake over all fertilisation timings ranged from 158-163 kg N ha^{-1}, Figure S2.

Figure 3b illustrates a decadal analysis and considers the median over all close-to-optimal uptakes in each decade. This approach monitored and predicted longer time scale changes. Additionally, median values over close-to-optimal (N uptakes within 5% of the maximum) values are reported to account for the fact that the true maximum is unlikely to be achieved in practice. Historically, there were only small changes from decade to decade. However, in the projected wetter decades of 2020s and 2030s the median close-to-optimal uptake is predicted to drop dramatically before reaching the historical values again in the 2040s-2060s.

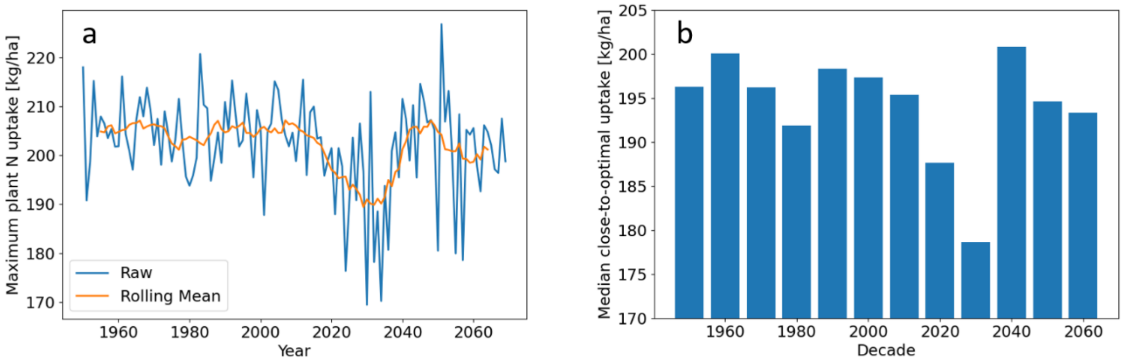


Figure 3: Modelled maximum nitrogen uptakes based on historical and projected climate data. ***a****) Maximum nitrogen uptake possible in each year from 1950 to 2069. The rolling mean with a windows size of 11 years is also shown in red.* ***b****) Median of all close-to-optimal uptakes in each decade. A close-to-optimal uptake is a plant nitrogen uptake within 5% of the maximum in its growing season.*

Fertilisation timings

The median close-to-optimal first and second fertilisation timings year-on-year can be seen in Figure 4a. As with the maximum N uptakes, there was large inter-annual variability both in the historic and the projected years. For example, in 1982 the precipitation-optimal first fertilisation day was 12 days after germination while in 1983 it was day 35. Additionally, there seemed to be more inter-annual variability in the second fertilisation day than the first, which could be explained by the fact that twice as much fertiliser was applied in the second day. The rolling mean of the two fertiliser application timings were positively correlated (Pearson r = 0.86), *e.g.* when one was later the other was also later. In general the same was true for the raw data, but the correlation was not as strong (Pearson r = 0.66), showing that different alterations in fertilisation timings were required for each application during certain years. From 2015 the rolling mean for both timings is predicted to be increasingly later until 2030. For the first application, the rolling mean was predicted to be the latest around 2030, but the raw values are not predicted to exceed the historic values. After 2030, the rolling mean for both timings is predicted to become earlier and comparable to historic values. This corresponds with projected high rainfall followed by low rainfall in the same period, Figure 2a.

There was little change in Stability year-on-year (see the rolling mean in Figure 4b). Stability can vary, with some years being as low as 0.76 and some as high as 0.94, however, this feature of precipitation-optimal fertilisation timings has not, nor is it expected to, change significantly.

Decadal analysis for precipitation-optimal fertilisation timings shows that, based on projected rainfall, by the 2030s the timings will be significantly later than the historic timings, with the median optimal second application predicted to be at day 43 compared to around day 26 historically; see Figure 4c. Figure 4c also displays the number of close-to-optimal fertilisation day pairs per growing season in each decade, which varies decade to decade. The 1960s only had 8 close-to-optimal fertilisation day pairs per growing season while the 2030s (the wettest decade according to projections) had 22. Ideally, there would be many close-to-optimal fertilisation day pairs per growing season so the farmer has many chances to time their fertilisation successfully. Although the 2030s are predicted to have the most close-to-optimal fertilisation day pairs per growing season, the 2030s also had the lowest max uptake, 178.9 kg N ha^{-1}, Figure 3b. This means the 2030s is predicted to have many chances to achieve a low maximum uptake relative to other decades.

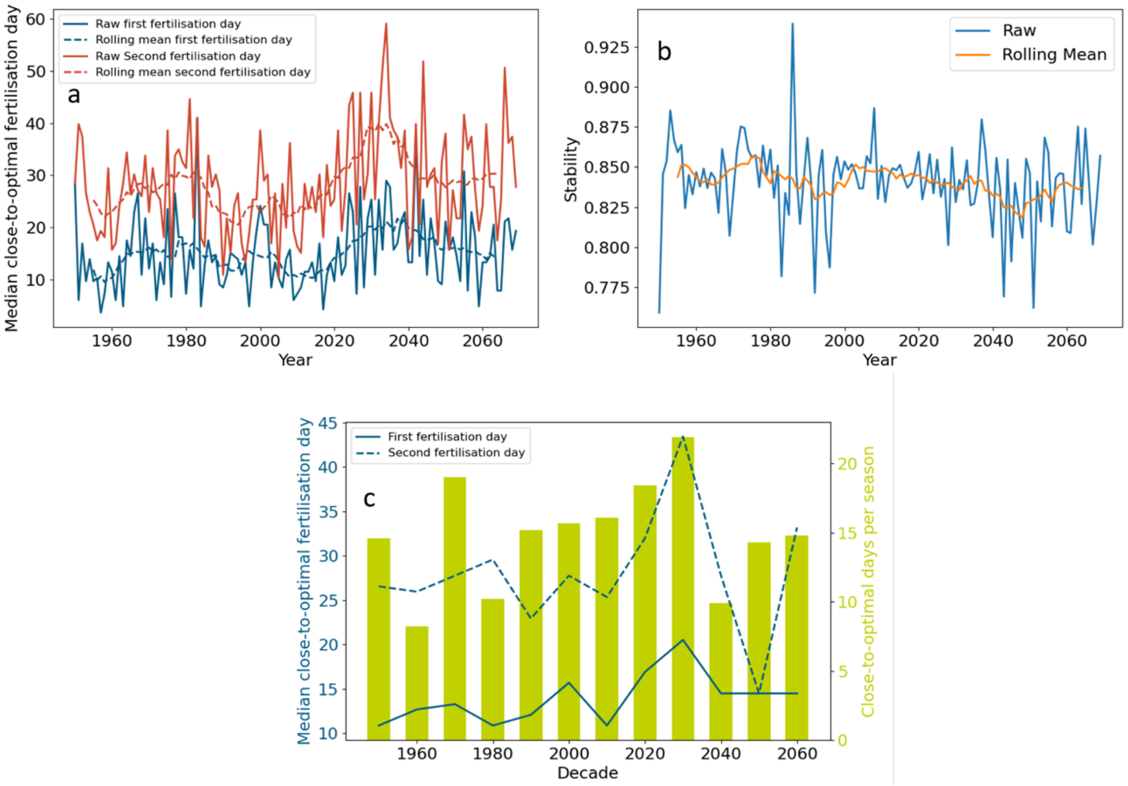


Figure 4: A history and projection of precipitation-optimal fertilisation timings and their Stability. ***a****) Yearly analysis of the median close-to-optimal first and second fertilisation timings. The rolling mean with a window size of 11 years is also shown.* ***b****) The yearly Stability with a 2.4 day window. Note, a growing season with a Stability of 0.75 means that, on average, a farmer will get within 75% of the close-to-optimal timing if they miss the close-to-optimal timing by* 2.4 *days either side. The rolling mean with a window size of 11 years is also shown.* ***c****) Decadal analysis of median precipitation-optimal fertilisation days and number of close-to-optimal fertilisation day-pairs per season. A close-to-optimal fertilisation day-pair is defined as those fertilisation day pairs which achieve a nitrogen uptake within 5% of the maximum of that growing season. The median close-to-optimal first and second fertilisation days and close-to-optimal uptake are taken over all close-to-optimal fertilisation day pairs in that decade or year.*

3.3 PRECIPITATION METRICS VERSUS MAXIMUM NITROGEN UPTAKE AND PRECIPITATION-OPTIMAL FERTILISATION TIMINGS

Since projected precipitation patterns were speculative, correlations between precipitation metrics and maximum N uptakes or precipitation-optimal fertilisation timings can help guide fertilisation strategies in an uncertain future climate. We found that the mean daily rainfall rate correlated negatively with maximum N uptake, Figure 5a. However, the best fit line $y = -0.065x + 1.52$ had an R value of only 0.35. Mean daily rainfall rates between 1.15 and 2.35 mm day^{-1} could achieve the highest maximum N uptakes, although rates above 2.15 mm day^{-1} could also result in low maximum

N uptakes. Mean daily rainfall rates above 2.85 mm day^{-1} always had low maximum N uptake. The mean (one month aggregated) SPI of the growing season explained less of the variance in maximum N uptake than mean daily rainfall rate, Figure 5b. However, a mean SPI above 0.75 consistently resulted in low uptakes, while a mean SPI between -0.75 and 0.65 could result in high uptakes. Mean daily rainfall rate correlated positively with both the first and second precipitation-optimal fertilisation timings, Figure 5c. The best fit line for the precipitation-optimal second application timing $\mathrm{y} = 10.91\mathrm{x} + 7.26$ had a more positive correlation and higher R value (0.56) than the best fit line for the first fertilisation day $\mathrm{y} = 6.66\mathrm{x} + 2.19$ (R=0.39). This is because the second application contained twice as much fertiliser as the first, suggesting that the greater amount of fertiliser applied the greater dependence of precipitation-optimal timing on precipitation. Similar to the maximum N uptake, mean SPI showed a similar trend, but it explains less variation than mean daily rainfall rate for precipitation-optimal fertilisation timings, Figure 5d.

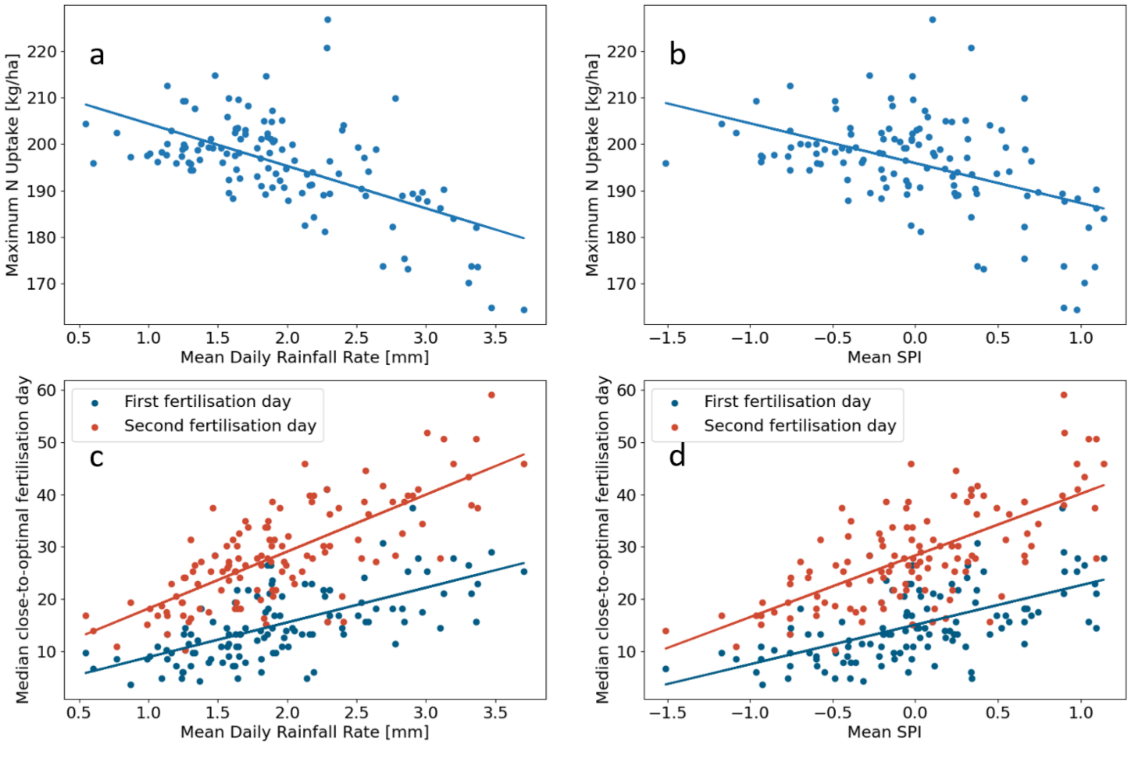


Figure 5: Correlations of yearly precipitation metrics with maximum nitrogen (N) uptake and precipitation-optimal fertilisation days. ***a****) Maximum N uptake vs mean daily rainfall rate in the growing season (March-June), each dot is an individual year. The best fit line is described by* $y = -0.065x + 1.52$ *and explains 35% of the variance.* ***b****) Maximum N uptake vs mean standardized precipitation index (SPI) in the growing season. The one month aggregated SPI is calculated for each of the 4 months in the growing season and the mean is taken for each year. The best fit line is described by* $y = -0.061x + 1.40$ *and explains 22% of the variation.* ***c****) Median close-to-optimal first and second fertilisation day vs mean daily rainfall rate. A fertilisation day is close-to-optimal if it achieves an N uptake within 5% of the maximum in that year. The first fertilisation day best fit line (blue) is described by* $y = 6.66x + 2.19$ *and explains*

39% of the variance. The second fertilisation day best fine line (red) is described by $y = 10.91x + 7.26$ *and explains 56% of the variance.* ***d****) Median close-to-optimal first and second fertilisation day vs mean SPI. The fist fertilisation day best fit line (blue) is described by* $y = 7.57x + 15.01$ *and explains 35% of the variance. The second fertilisation day best fit line (red) is described by* $y = 11.82x$ *+28.33 and explains 46% of the variance.*

3.4 DISCUSSION

Recently the dependence of N leaching on soil moisture/precipitation has been in the spotlight due to changing local precipitation patterns[13,28,38]. Researchers have pointed out the importance of demonstrating both the environmental and economic benefit of adapting fertilisation strategies to changing precipitation patterns[28]. However, to our knowledge there have been no attempts to directly quantify how changing precipitation patterns might affect crop N uptake or how fertilisation strategies may need to change in future to ensure high NUE in arable farming. Here we used a well-established mechanistic soil physical modelling approach[39,40] to study the effect of precipitation patterns on precipitation-optimal split fertilisation timings to maximise plant N uptake. Importantly, N dynamics was coupled to water movement in the soil so the effect of precipitation could be studied directly. As a case study, we modelled maize grown in spring on silt loam in the South East of England, thus our results would likely change given a different soil texture or crop type. By using historic and projected (RCP 8.5) precipitation data in the model we could determine how the precipitation-optimal timings and maximum uptakes have changed and might change in the future for these conditions.

Historically, the mean daily rainfall in the South East of England had little change in the rolling mean. There was, however, large inter-annual variability which was more pronounced for projected years. From 2021 the rainfall is projected to increase until reaching a peak in the 2030, Figure 2a. This was projected to be accompanied by more heavy rainfall events and less severe droughts, Figure 2. These predictions are in agreement with previous studies regarding precipitation in temperate regions such as the South East of England. A warmer climate will accelerate the global water cycle which is thought to increase extreme precipitation events, i.e, more heavy rainfall events, but less rainy days[41]. However, this is not the case for regions in the subtropics where precipitation is expected to decrease due to climate change[42]. Thus, our results are only relevant to the region reported and future studies should consider other climates with contrasting predicted future precipitation patterns. To apply the same approach to drier regions, where climate change is expected to have a big impact on NUE and water use efficiency[43], it would be important to include additional mechanisms in the model. In particular, the root growth model should be extended to include water and nitrogen limited growth. The assumption of water- and nitrogen-independent growth was valid for arable fields in the South East of England where crops are rarely water or nitrogen deficient. However, in drier regions crops may produce less biomass due to water deficiency and therefore have lower N demand which will affect N uptake and leaching. In the drier cases it would be important control fertilisation amount as well as timing to account for the possibility of low biomass[43,44]. Additionally, water scarcity would affect the nitrogen cycle in the soil and soil saturation dependent reaction rates may need to be included to accurately capture this[45].

Only one realisation of the climate model was used in the simulations. However, the behaviour of the climate realisation used in this study was representative of the ensemble average of multiple climate realisations, but the particular variability may not be exactly representative of all possible future trends. Our approach still provides a more realistic example of fluctuations in rainfall patterns that could be expected and how these fluctuations will impact N acquisition by crops in these conditions. We also note that the RCP 8.5 climate scenario (business as usual) is hopefully not the guaranteed scenario. However, this is expected to be the scenario that most perturbs trends that follow from the historic data set. This scenario is also currently serving as the basis for global policies[29]. As such, the selection of the RCP 8.5 projection is likely to be a useful representation of the projected precipitation trends used in this study.

The historic inter-annual variability in N uptake increased in the projected years, Figure 3a. However, only the wettest decade of the 2030s was projected to have notably lower maximum N uptake on the decadal scale (Figure 3b). This result has severe implications for NUE, as crop yields in this period are not expected to grow well under the current application strategy. Historically, practitioners have compensated for this by applying more fertiliser in response to reduction in crop yields[28,38]. While this might be a necessary strategy to sustain production for this decade, there will likely be enhanced N leaching and increased N_2O emissions in this period. Furthermore, our predictions suggest that maintaining a compensatory strategy past this decadal dip would be suboptimal, as precipitation rates are expected to reduce back to their pre 2030s trends. As such, our model results can help inform strategies for insuring practitioners during suboptimal times.

Both precipitation-optimal fertilisation timings were predicted to become noticeably later in the 2030s, Figure 4c. In addition, there were predicted to be more close-to-optimal fertilisation day pairs in the 2030s, Figure 4c. It seems that if the weather is wetter, maximum N uptake is reduced, precipitation-optimal fertilisation timings become later and the number of close-to-optimal fertilisation day pairs per growing season increases, Figure 4. However, this only means there are predicted to be more days to achieve this lower maximum, Figure 3. This is confirmed by correlating precipitation metrics with precipitation-optimal timings and maximum N uptakes and is true for many wet growing seasons, Figure 5, not just those in the 2030s. This is attributed to the wetter years having increased chance of leaching[46], thus fertilising later gives the roots as long as possible to establish before fertiliser application to intercept the N[18]. However, applying fertiliser too late means there is less time in the growing season for the crop to take up and utilise the applied N[18,24]. The precipitation-optimal timings for wet years find the balance between mitigating leaching and ensuring enough time for crop uptake. The driest years did not have the highest maximum N uptakes, Figure 5a, but were higher than the wettest years. This is attributed to low mobility of N with low soil moisture limiting crop uptake[18]. To account for the low mobility, the precipitation-optimal fertilisation timings in dry years are predicted to be earlier than wetter years Figure 5c; in these years there was predicted to be less risk of leaching. However, the model did not account for reduced root growth in very dry conditions, thus the maximum uptake for the driest years (if they were water limited) may be an over estimate.

The current model assumes constant temperature and does not account for the effect of global warming in order to carefully study the effect of changing precipitation; a scenario relevant to South East England. However, changing temperature would alter important processes in the model, including evaporation, root growth[47] and transpiration, and N transformation rates in soil[38] which may ultimately affect the results. Including these processes would introduce many additional unknown parameters introducing further uncertainty to the model. Furthermore, changing precipitation is thought to have a larger impact than temperature on controlling crop N uptake in temperate regions[13] which was why precipitation was the initial study for our model[14]. However, temperature can strongly affect gaseous N loses. Ammonia volatilization increased 3-fold when the temperature increased from 25 to 45˚C in a lab experiment[48]. Thus, future models should certainly consider gaseous N losses when modelling the effect of warming on crop N uptake. However, temperature increases are unlikely to be this extreme in the South East of England. Temperature and precipitation act in tandem to affect cropping systems and both need to be studied to fully understand the impact of climate change on NUE. The model assumptions regarding temperature should be reconsidered in future modelling studies to refine the current predictions, expand them to include a wider geographical area, and have holistic understanding of the effect of climate change on worldwide crop N uptake.

Mean daily rainfall rate explained more of the variation in maximum N uptakes and precipitation-optimal fertilisation timings than the mean one-month aggregated SPI, Figure 5. This suggests that N fertilisation is more sensitive to short time-scale variations in precipitation. SPI is judged to be a poor indicator of N uptake compared to mean daily rainfall rate. While SPI provides a more intuitive presentation of precipitation patterns (*i.e.* relative drought, flood), it obscures the detail required to capture precipitation-optimal fertilisation. Additionally, since the calculation of SPI requires fitting a distribution to the local precipitation data, the correlations may not generalise to other regions. The full detail in the rainfall pattern was used directly as a boundary condition for the model output, and, although more complicated, may be required to predict NUE.

Our analysis assumes farmers find precipitation-optimal or close-to-optimal fertilisation day pairs for each growing season. In fact, most timings achieve poor N uptakes in each decade (Figure S2) and finding the timings that achieve high uptakes is not a trivial task. If in the future farmers decided to use the mean precipitation-optimal timings based on historic data, on average they would achieve 87.7% of the potential maximum uptake in the projected years (but the potential maxima are projected to be lower in the future). By comparison, the same strategy in the historic years would achieve 89.3% of the potential maximum on average. Thus, not only are the precipitation-optimal N uptakes projected to decrease due to increased precipitation in the future, but timing fertilisations based on the status-quo will further increase N losses. There is little an individual farmer can do to directly stop climate change, but by adapting N fertilisation timings for each year based on crop growth stage[23] *and* precipitation they could recuperate some of the reduced N uptake caused by changing precipitation. This adaptation would also reduce the quantity of N fertiliser required to produce high yields, as well as reducing leaching and greenhouse gas emissions which would help mitigate the climate impact of agriculture. Currently, there is no decision support tool available to guide farmers on when to fertilise based on the forecasted weather. Ideally, field trial data would be used to create such a tool but the model data presented in this paper provides the starting point to create tools that can use the past and forecasted weather to guide farmers with a good time to fertilise[49].

To conclude, simulation results show that there has been little change in crop N uptake or precipitation-optimal fertilisation timings historically due to changing precipitation patterns. However, there has been notable variation year-to-year. In the 2030s, simulations project N uptake to reduce and precipitation-optimal timings to become later in the season in response to wetter weather and, in particular, increased occurrence of heavy rainfall events. In addition, the year-to-year variation in crop N uptake increases due to climate change. Fertilisation strategies should stay flexible since simulations project optimal-fertilisation timings to become earlier and N uptake to reduce in the 2040s to figures similar to the historic in response to a reduction in precipitation.

4 ACKNOWLEDGEMENTS

D.M.F., S.R. and T.R. are funded by BBSRC SARIC BB/P004180/1. T.R. is also funded by ERC Consolidator grant 646809 (Data Intensive Modelling of the Rhizosphere Processes), BBSRC SARISA BB/L025620/1. D.L.J. and D.R.C. are supported by BBSRC SARIC BB/P004539/1 and the UK-China Virtual Joint Centre for Agricultural Nitrogen (CINAg, BB/N013468/1), which is jointly supported by the Newton Fund, via UK BBSRC and NERC, and the Chinese Ministry of Science and Technology. CP and KW are funded by European Research Council Consolidator grant 646809 (Data Intensive Modelling of the Rhizosphere Processes).

The authors acknowledge the use of the IRIDIS High Performance Computing Facility, and associated support services at the University of Southampton, in the completion of this work.

5 SUPPORTING INFORMATION

Supplementary file with two additional figures is available online to provide extra information on model-data comparison and further uptake rates presented for decadal analysis.

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