Title
Adapting agroecosystems to water scarcity: Dry farming and crop rotation as transitions to diversified farming systems in California and the US Midwest

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By

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Professor Timothy Bowles, Chair
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Abstract

Adapting agroecosystems to water scarcity: Dry farming and crop rotation as transitions to diversified farming systems in California and the US Midwest

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As climate change gives rise to water shortages and unstable growing conditions in California and across the United States, agricultural systems must be able to adapt to increasingly extreme environmental stressors. Diversified farming systems, which incorporate biodiversity across multiple temporal and spatial scales to support ecosystem services, offer an alternative to the fragility of the current industrialized regime that dominates US agriculture. When small-scale, thought-intensive, diversified farming systems are supported by research and socio-political movements that defend them and advocate for their wider adoption, food production will transition towards a science, practice, and movement known as agroecology. While many argue that agroecological transitions are necessary to achieve stable food production and climate, economic, and political justice in the US agricultural system, state and federal policies do not reliably support diversified farming systems. In order to craft effective policy interventions, we must have an intimate knowledge of how and why diversified farming practices work to properly support their success and spread. In my dissertation I explore two regional examples of diversified farming practices and their potential for wider adoption given current and possible future policy landscapes. In corn-based crop rotations in the US Midwest and tomato dry farming on California's Central Coast, climate shocks have sparked a need for dramatic change, opening an opportunity for policy to guide agriculture towards an agroecological future. With the help of farmer collaborators, I ask how each of these systems functions, how policy has failed them, and where it may yet succeed.

The first chapter of my dissertation examines the political and physical landscapes in which farmers grow corn-based rotations in the US Midwest, asking what factors lead farmers towards complex vs simplified rotations. I used publicly available, remotely sensed datasets to look at relationships between rotational complexity, and biophysical (land capability, precipitation) and policy-driven (distance to the nearest biofuel plant) factors on 1.5 million fields in the region, using bootstrapped linear mixed models to account for spatial autocorrelation. I found that policy and economic incentives continue to lead farmers towards simplified crop rotations, such as corn-soy and even corn monoculture. In particular, amidst already elevated corn prices from crop insurance structures and livestock feed, I saw that proximity to biofuel plants–where corn prices tend to be higher due to the federal biofuel mandate–encourages farmers to grow corn in as many years as possible. These policy and economic factors then play out in biophysical landscapes as well, where fields with the highest quality soils and precipitation–which can tolerate degradative soil practices without compromising yields in the near term–tend towards the most simplified rotations.

The second and third chapters of my dissertation explore diversified farm management on California's Central Coast in dry farm tomato systems, which rely on diversified farming practices (cover cropping, compost application, organic management, etc.) to build soil water holding capacity and fertility. Dry farming allows farmers to grow produce with little to no irrigation water, relying instead on water held in soils from winter rains to support crops through rain-free summers. As climate change increases water scarcity in California, farmers, advocacy groups and policymakers have begun looking to dry farming as a potential solution to the state's overextended water budget. However, little research has been done on vegetable dry farming in the state, and no coordinated effort has been made to understand the policy conditions that would allow vegetable dry farming to thrive.

In my second chapter, I collaborated with six dry farm operations in a participatory process, coming up with research questions that the farmers who most intimately understand tomato dry farming were eager to answer. After a season of intensive soil and harvest sampling on seven dry farm fields on California's Central Coast, we were able to come to a better understanding of how the system functions, and develop concrete management suggestions for farmers to consider. We found that, due to quickly drying surface soils, harvest outcomes were only impacted by nutrients below 30-60cm in the soil profile, upending soil fertility management paradigms on irrigated fields, where focus is almost entirely on the top 30cm of soil. We were also able to caution against arbuscular mycorrhizal fungal (AMF) inoculants, which have been marketed to farmers with increasing intensity but, if anything, harm harvest outcomes in dry farm systems (as opposed to resident AMF communities, which are fostered through diversified management and typically improve harvest outcomes). Lastly we showed that dry farm soils develop a signature in their fungal communities that supports fruit quality, suggesting that farmers would likely benefit from developing full dry farm rotations where soils are kept irrigation-free for multiple years.

In my third chapter, I conducted semi-structured interviews with the same farmers who participated in the field study to better understand the full context in which tomato dry farming operates on the Central Coast. As farmers, researchers, and policymakers consider an expansion of dry farm vegetable production in California, I wanted to ask how farmers understand the practice and what its environmental and economic constraints are. I emerged with a synthesis of farmer-stated environmental constraints that I used to create a map of California cropland that could be suitable for future dry farm production. As I considered an expansion of dry farming onto these new lands, I drew on farmers' experience to explore how to maintain dry farming's history as an agroecological alternative to the industrial style of farming that dominates the region. Farmers had a clear message about the small operations and direct-to-consumer marketing styles that have been the foundation of dry farming success, and that must serve alongside soil health practices as a model for an agroecological transition towards water savings in California. I identified policies such as publicly funded demonstration farms, participatory breeding programs, and public procurement that could promote dry farm expansion while preserving its fuller context and identity, rather than stoking a shift toward an industrial cooptation of the practice that could edge small growers out of dry farm markets.

Taken together, this dissertation follows on-farm diversification practices–especially those that can help farms guard against water scarcity–through an arc of past and possible future policy. I ask how policy has discouraged crop rotational complexity, and how policy might foster an environment in which dry farming could thrive as a model for an agroecological transition towards water resiliency. I strive to understand dry farming through the eyes of those who practice it to make management and policy recommendations that are grounded in deep knowledge of the system. Through these examples of how complex ecological and policy interactions play out in two separate regions, I highlight the resilience and importance of diversified farm systems, and the possibilities and pitfalls in policy interventions that attempt to prepare our agricultural system for changing climates.

For Grandma, Grandpa, Yaya, and Tata, who never ever failed to be proud of me, and who raised my parents to be brilliant in every way.

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And for baby Pemberton, who will watch the seas rise, overbalance, and–it is my deepest hope–fall.

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Introduction

Amidst an increasingly industrialized food system, farmers and activists the world over have advocated and struggled to move agricultural production towards diversified farming systems[1–6]. Agroecology–a form of agriculture based in small-scale, thought-intensive, diversified farming systems and the socio-political movements necessary to defend them and advocate for their wider adoption–has emerged as a combination of science, practice, and movement that can lead farming systems towards ecological, economic, and social sustainability[7–9]. As climate, economic, and political injustices accelerate in the food system, transitions towards agroecology are increasingly urgent; however, these transitions have been slow to gain traction in dominant political and economic regimes[10,11].

The current era of climate change is creating shocks that open windows for food systems transition, forcing farmers, researchers, and policy makers to consider new approaches to farming and food production. My own work has focused on water scarcity, which is perhaps the most salient climate shock in California where my home institution is located, and a key agricultural concern across the nation and globe[12–14]. In California, the 2020–2022 drought caused the estimated loss of 15,000 jobs and $3 billion in agricultural output, and followed a similarly devastating drought in 2011-2016, calling attention to an urgent need to address future water scarcity in the state[15,16]. Meanwhile, 60% of US farms experienced drought in 2012, with extreme drought in the Midwestern US causing price spikes and yield declines, followed by extensive flooding in 2019[17,18]. In response, local, state, and national advocacy groups and policymakers have begun to call for and implement policy with the intention of making farm systems more resilient to water shortages[19,20]. For example, the Sustainable Groundwater Management Act in California now calls for groundwater basin water budgets to be balanced by 2042; however, there is considerable debate surrounding how to achieve such a goal. Given the complexities of the systems in which these policies operate, implementation can be difficult, and even the best-intended policies can act to either create or curtail opportunities for transitions towards agroecology[21].

In my own work, I have seen climate-motivated policies in the US–in this case the biofuel mandate–lead farmers in the Midwest towards degradative soil practices, while farmers in California respond to water scarcity by growing the tastiest tomatoes chefs have ever encountered. As farmers navigate a complex web of physical, biological, political, and economic environments, they arrive at a wide array of outcomes that reflect both a unique local context and influences that act on entire regions and nations[22]. Yet current economic and political structures have overwhelmingly led US farmers to make choices that have moved agricultural towards the input-intensive, large-scale production that now defines the country's dominant agriculture[1,23].

Two key questions exist when designing policy to target agricultural water resiliency. First, what are the farming practices that actually improve farms' capacity to adapt to water scarcity without jeopardizing farmer livelihoods? And second, can policies support an agroecological transition towards these practices that does not allow their cooptation towards an industrial agriculture–and conversely, what policies are leading our country towards input-intensive industrialized systems even in the face of changing climates? These questions play out in many ways across different agricultural landscapes, and I do not begin to tackle them in their entirety. Instead this dissertation explores both of these questions in two distinct systems: large-scale corn-based rotations in the US Midwest, and tomato dry farming in small-scale, diversified operations on the northern edge of California's Central Coast region.

In my attempts to answer these questions, I have tried to use the tools at my disposal to center farmers and their experience, wisdom, and intimate knowledge of the lands they work. From participatory research, to farmer interviews, to simply trying to understand farmers as complex actors in complex systems, my work has led me to see farmers as adept scientists, and I hope to honor and complement their skills with a few of my own. Given farmers' limited access to time and resources, I have used mapping, lab analyses, field data collection, and statistics to help farmers answer the questions they find most pressing and garner the policy support needed to let diversified farming systems thrive.

I begin in my first chapter, *Biophysical and policy factors predict simplified crop rotations in the US Midwest*, by asking what policy and environmental factors push farmers towards diversifying vs. simplifying their crop rotations in the US Midwest. After the 2012 drought, there is more reason than ever to shift this historically homogenized, highly input intensive agricultural region towards more complex rotations, which promote soil health[24–27] and stabilize yields in times of environmental stress including drought[28–30]. However, while soil health benefits give farmers every reason to explore complex rotations, there has been a continued trend towards rotation simplification in the region over the past century. I therefore explored how policy was reshaping this system, asking how top-down policy pressures combine with biophysical conditions to create fine-scale simplification patterns that threaten the quality and long-term productivity of the United States' most fertile soils. Given the availability of public, spatially explicit data, I developed a novel indicator of crop rotational complexity and applied it to 1.5 million fields across the US Midwest, using bootstrapped linear mixed models to regress field-level rotational complexity against biophysical (land capability, precipitation) and policy-driven (distance to the nearest biofuel plant and grain elevator) factors.

The second and third chapters explore water resiliency in California, using tomato dry farming in the Central Coast region as a case study. Dry farming–a management system that relies on diversified farming practices (cover cropping, compost application, organic management, etc.) to build soil water holding capacity and fertility–allows farmers to grow crops with little to no irrigation and has quickly garnered interest from farmers and policymakers as an alternative to the irrigation-intensive farming that is nearly ubiquitous in the rest of the state. While dry farming is an ancient practice with rich histories in many regions, perhaps most notably the Hopi people in Northeast Arizona[31], vegetable dry farming emerged more recently in California, with growers first marketing dry farm tomatoes as such in the Central Coast region in the early 1980's. In a lineage that likely traces back to Italian and Spanish growers[32], dry farming on the Central Coast relies on winter rains to store water in soils that plants can then access throughout California's rain-free summers, allowing farmers to grow produce with little to no external water inputs. While this system holds great interest and promise for farmers in California, no peer-reviewed research has been published to date on vegetable dry farming in the state.

In my second chapter, *Deep nutrients and fungal communities support tomato fruit yield and quality in dry farm management systems*, I collaborated with farmers to identify and answer key management questions in the dry farm community. This participatory-based process allowed me to build relationships with farmers and begin to coalesce a community of practice that farmers were excited to connect to. As advocacy groups begin to shine a light on dry farming as a potential key to California's water resilient future[33–36], it felt crucial to engage with the farmers who champion this system to collectively come to a deeper understanding of how dry farming functions and the farming practices that can best support its success.

Growers were primarily concerned with fruit yield and quality, with fruit quality being of particular interest due to the quality-based price premiums that farmers rely on when growing in a region with some of the highest agricultural land values in the nation. Managing soils to promote quality and yields presents a unique challenge in dry farm systems, as the surface soils that farmers typically target for fertility management in irrigated systems dry down quickly to a point where roots will likely have difficulty accessing nutrients and water.

As deficit irrigation and drought change microbial community composition in agricultural and natural systems[37–39], farmers were also interested in how dry farm management might shift fungal communities, and if that in turn would improve tomato harvest outcomes. Beyond general shifts in fungal communities, farmers were specifically curious about arbuscular mycorrhizal fungi (AMF) inoculants, which are increasingly available from commercial sellers. Recent research has shown that AMF can help plants tolerate water stress[40–42], and that inoculation can improve harvest outcomes in some agricultural systems[43–45]. Farmers therefore wanted to test commercial AMF inoculants' potential benefits in the dry farm context.

After a collaborative process, we arrived at three questions that farmers wanted to prioritize for immediate research:

1. Which depths of nutrients (and which nutrients) are most influential in determining fruit yield and quality in dry farm tomato systems?
2. Are fungal inoculants that are known to decrease plant water stress effective in this system? And more broadly,
3. How can farmers best support high-functioning soil fungal communities to improve harvest outcomes?

I collected soil and root samples on participating farms throughout the 2021 growing season, as well as weekly harvest and fruit quality data, to answer these questions.

Finally, in my third chapter, *Vegetable dry farming as an agroecological model for California's drought resilient future: Farmers' perspectives and experiences*, I interviewed all of the farmers involved in my second chapter, along with several others, to better understand how this agroecological system might serve as a model for a transition to low-water agriculture in California. In a system that seems to be on the cusp of a strong push for wider adoption, I wanted to understand how farmers view what makes the system successful, and how policy might build on farmers' collective wisdom to better support dry farming as an opportunity for an agroecological transition to low-water farming in California. I focused my interview synthesis on two main questions. First, what business and land stewardship practices characterize successful tomato dry farming on California's Central Coast? And second, what is the potential for dry farming to expand beyond its current adoption while maintaining its identity as a diversified practice that benefits small-scale operations?

In many ways, my dissertation work can be boiled down to my attempts to answer three questions:

1. How does policy go wrong, leading farms towards simplification and industrialized growing practices when there is an increasingly urgent need to diversify farming systems?
2. How do these diversified systems function ecologically, and what management practices might enhance their performance, particularly in the face of water scarcity? And,
3. How could policy go right, supporting agroecological transitions as climate shocks open opportunities for food systems change?

I leave this dissertation fundamentally convinced that these questions are not the niche specialty of a PhD, but at the heart of and hope for a just and sustainable system of agricultural production in this country. Though my work ultimately tackles only slivers of the answers to these questions, I fill the following pages with a place-based approach, grounded in farmer experience, in the hope that offering concrete examples and directions can advance current and future research collaborations, management exploration, and movement building towards an agroecological future in the United States.

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Chapter 1: Biophysical and policy factors predict simplified crop rotations in the U.S. Midwest[1]

1.1. Abstract

Over 70% of the 62 million ha of cropland in the Midwestern United States is grown in corn-based rotations. These crop rotations are caught in a century-long simplification trend despite robust evidence demonstrating yield and soil benefits from diversified rotations. Our ability to explore and explain this trend will come in part from observing the biophysical and policy influences on farmers' crop choices at one key level of management: the field. Yet field-level crop rotation patterns remain largely unstudied at regional scales and will be essential for understanding how national agricultural policy manifests locally and interacts with biophysical phenomena to erode—or bolster—soil and environmental health, agricultural resilience, and farmers' livelihoods. We developed a novel indicator of crop rotational complexity and applied it to 1.5 million fields across the US Midwest. We used bootstrapped linear mixed models to regress field-level rotational complexity against biophysical (land capability, precipitation) and policy-driven (distance to the nearest biofuel plant and grain elevator) factors. After accounting for spatial autocorrelation, there were statistically clear negative relationships between rotational complexity and biophysical factors (land capability and precipitation during the growing season), indicating decreased rotation in prime growing areas. A positive relationship between rotational complexity and distance to the nearest biofuel plant suggests policy-based, as well as biophysical, constraints on regional rotations. This novel rotational complexity index is a promising tool for future fine-scale rotational analysis and demonstrates that the United States' most fertile soils are the most prone to degradation, with recent policy choices further exacerbating this trend.

1.2. Introduction

Biological simplification has accompanied agricultural intensification across the world, resulting in vast agricultural landscapes dominated by just one or two crop species. The Midwestern US is a prime example[1], where corn currently dominates at unprecedented spatial and temporal scales. An area the size of Norway is planted in corn in the Midwest in any given year[2] with little variation in crop sequence; over half of Midwestern cropland is dedicated to corn-soy rotations and corn monoculture[3]. Directly and indirectly, this agricultural homogeneity causes environmental degradation that harms ecosystem health[4–7] while also contributing to climate change[8] and increasing vulnerability to climate shocks[9].

Agricultural diversification in space and time reverses this trend towards homogeneity with practices like crop rotations that vary which harvested crops are grown in a field from year to year. Crop rotations are a traditional agricultural practice with ample evidence that complex rotations—ones that include more species that turn over frequently—benefit farmers, crops, and ecosystems[10–12]. As one of the principles underlying agricultural soil management, diverse crop

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rotations promote soil properties that provide multiple ecosystem services including boosting soil microbial diversity[13,14], enhancing soil fertility[15,16], improving soil structure[17-20] and reducing pest pressur[7,21]. These soil benefits combine to increase crop yields[17,22–24] and stabilize them in times of environmental stress[25–27]. Crop rotations' environmental and economic benefits typically increase with the complexity of the rotation[11,28,29] (as defined by the number of species in rotations and the frequency of their turnover), while conversely, biophysical aspects like soil structure and microbial populations are degraded as rotations are simplified[12,20,30,31].

Despite its benefits, crop rotational complexity continues its century-long decline in the Midwestern US[32–36]. Corn-soy rotations increasingly dominate over historical crop sequences that included small grains and perennials, with corn monocultures (corn grown every year) also on the rise[1]. This increasing simplification is in part the result of a set of interlocking, long-standing federal policies aimed at maximizing production of a handful of commodity crops that distort farmers' economic incentives.

Regional rotation simplification is clear from analyses of crop frequency[33,34], county-level data[7], and farmer interviews[35]. However, fine-grained patterns that more completely reflect farmers' rotational choices across the region, and how those choices relate to influences from policy and biophysical factors that play out across agricultural landscapes, remain largely unstudied. This knowledge is essential for understanding how national agricultural policy manifests locally and interacts with biophysical phenomena to erode—or bolster—soil and environmental health, agricultural resilience, and farmers' livelihoods.

Biofuel mandates[32,37–39] and concerted efforts to craft industrial livestock systems as end-users of these corn production systems[40,41] make corn lucrative above other commodities, while federal crop insurance programs push farmers to limit the number of crops grown on their farms[42–44]. These policies, along with the current corporate food regime[45], drive pervasive economic incentives to grow corn, and farmers must increasingly choose between growing corn as often as possible to provide a source of government guaranteed income[35], and maximizing soil benefits and annual yields through diversified rotations. These policies both alter agricultural economics at a national level by boosting corn prices and manifest locally in grain elevators and biofuel plants that create pockets of high corn prices with rising demand closer to each facility[37].

Biophysical factors like precipitation and land capability (an area's capacity to grow crops based on soils and geography) that are highly localized and spatially heterogeneous can catalyze or impede this simplification trend. For example, increasing rotational complexity is one strategy that farmers may employ to manage marginal soils or greater probability of drought, while ideal soil and climate conditions allow for rotation simplification to be profitable, at least in the short run[5].

As these top-down and bottom-up forces combine, we ask: how do farmers optimize crop rotational diversity in complex social-ecological landscapes, with top-down policy pressures to simplify intertwined with bottom-up biophysical incentives to diversify? (Figure 1). Because biophysical factors and even policy influences (e.g. high prices near biofuel plants) vary greatly at the field scale at which management decisions occur, an approach is needed to assess patterns of crop rotation that can capture simplification and diversification at this scale. Though remotely sensed data on crop types can now show fine-scale crop sequences, previous approaches to quantifying rotational complexity have relied on classifying rotations based on how often a certain crop appears in a region over a given time period[33,34], aggregating over large areas[7], or examining short (3-4 year) sequences[33,34,46]. To date, methods to capture rotational complexity have therefore been unable to address management decisions at the field scale (in the case of aggregation), and/or lose valuable information about the number of crops present in a sequence and the complexity of their order (in the case of crop frequency and short sequences). At the other end of the spectrum, farmer surveys have impressively detailed the economic and biophysical considerations that go into farmers' rotation decisions[35], yet are limited by the number of farmers they can reach and who chooses to respond.

Here, we explore how aspects of farm landscapes influence field-scale patterns of crop rotational complexity across the Midwestern US. We developed the first field-scale dataset of rotational complexity in corn-based rotations, covering 1.5 million fields in eight states across the Midwest and ranking crop sequences based on their capacity to benefit soils. We examined rotations from 2012-2017 to coincide with the introduction of the Renewable Fuel Standard, or "biofuel mandate," which took full effect in 2012. We then correlated fields' rotational complexity with biophysical (land capability and rainfall during the growing season) and policy outcomes (proximity to biofuel plants and grain elevators) factors, using bootstrapped linear mixed models to account for spatial autocorrelation in the data. By identifying spatially explicit predictors of rotational complexity, we illuminate how top-down policy pressures combine with biophysical conditions to create fine-scale simplification patterns that threaten the quality and long-term productivity of the United States' most fertile soils.

1.3. Methods

We focused our analysis on the eight Midwestern states with the highest corn acreage (Illinois, Indiana, Iowa, Kansas, Minnesota, Missouri, Nebraska, Ohio)[2]. We considered the six-year period from 2012 to 2017, which coincides with the introduction of the Renewable Fuel Standard in 2012. After deriving a novel field-scale rotational complexity index (RCI), we used spatially blocked bootstrapped regression to assess how key landscape factors associated with this indicator. These statistical methods account for overly confident parameter estimates that arise in naive models due to spatial autocorrelation in the data. All analyses were conducted in R[47].

1.3.1. Calculation of rotational complexity index (RCI)

We compiled a dataset that shows the crop sequence (cash crops only; cover crops are not detected by the Cropland Data Layer) on each field in the study area (see 'Datasets' below) and used these sequences as a proxy for crop rotation to derive a novel indicator of rotational complexity that could be applied at the field scale. To date, no metric exists that can supply both the flexibility of quantifying different length rotations that occur in the same time period, and the specificity of operating at the field level.

We adapted the rotational diversity index (d) of previous studies[25,48] that quantifies the diversity of a known rotation as a function of the length of the rotation (l, in years) and the number of crops in the rotation (n):

$$d = \sqrt{nl} \qquad \text{(Equation 1)}$$

to accommodate large-scale, remotely-sensed data (see supplement for further details). Instead of trying to identify common rotations of a known length, we observed a fixed-length sequence (in our case, 6 years) of crops in a given field, and replaced rotation length (*l*) with species turnover from year to year (T_1), and turnover every two years (T_2). For example, in a 6-year crop sequence ABABAB, $T_1 = 5$ and $T_2 = 0$, while for ABCABC, $T_1 = 5$ and $T_2 = 4$. We also added a pseudo-turnover (T_p) equal to the number of times a duplicate perennial appears in a field in two consecutive years (e.g. alfalfa-alfalfa), as perennial crops typically provide soil benefits[49–52] but would otherwise be penalized by the metric for their low turnover. For example, in a 6-year crop sequence APPAAA, where A is an annual crop and P is a perennial, $T_1 = 2$, $T_2 = 3$, and $T_p = 1$ for a total turnover score of 6, whereas if P were an annual the total turnover would be 5. This adjustment makes the turnover term for consecutive perennials equivalent to the turnover if different annuals were grown in each year that the perennial is repeated.

The resulting metric:

$$\text{Rotational Complexity Index (RCI)} = \sqrt{n\frac{T_1+T_2+T_p}{2}} \qquad \text{(Equation 2)}$$

yields a single value that can compare rotational complexity across any crop sequence of a given length and can be applied at fine scales with low computational costs (Figure 2). The metric is able to cut through "messy" data with unusual or unexpected crop rotations to sort sequences in terms of their expected potential to benefit soils (see representative RCI values in Table 2).

1.3.2. Datasets

We identified publicly available datasets with a spatial component that might predict rotational complexity. Biophysical predictors included land capability, and magnitude and variability of precipitation during the growing season; policy predictors included distance from the nearest grain elevator and biofuel plant (Table 1). We then compiled rasters from these datasets (Figure S1).

As done in previous analyses[59–61], we used the National Commodity Crop Productivity Index (NCCPI) as a proxy for inherent land capability. The NCCPI combines soil properties (e.g. cation exchange capacity, bulk density, and slope) to form an index that shows agricultural land capacity, with submodels for corn/soy, cotton, and small grains[62]. In the present analysis, we use the highest NCCPI value out of the three submodels for each pixel.

1.3.2.1. Cropland Data Layer

We used the USDA's Cropland Data Layer (CDL) from 2012-2017 to quantify crop rotational complexity in our focal regions[63]. The CDL uses remote sensing to identify the crop species present in a given year on all US cropland at a 30x30m resolution. We aggregated the CDL to 150x150m with a majority filter to avoid small-scale accuracy errors inherent in the dataset. From these aggregated pixels, we included only "corn-based" rotations, defined as pixels that were categorized as corn in at least one of the six years in the study period, in subsequent analyses (71% of total cropland).

1.3.2.2. Field-level aggregation

We aggregated the above datasets using a remotely sensed dataset of agricultural field boundaries produced by Yan and Roy (2016)[57] to avoid overrepresenting large fields. Each variable was averaged over the field (mode for RCI and state, median for rainfall variance, and mean for all remaining), and a new field size variable was created by summing the pixels in each field. Fields were included if the CDL showed them as being at least 50% corn in one or more of the focal years.

1.3.3. Spatially Blocked Bootstrap Regression

To test for a relationship between RCI and predictive factors, all variables were centered and RCI was regressed against a set of covariate data (Table 1) in a linear mixed model (LMM) including US state as a random effect to account for regional differences (see supplement). We included interactions for which we had a priori hypotheses (see Table 3 for full list of terms included). The model was estimated using the R package `lme4`[64].

Two model assumptions are violated in the above model, requiring updated estimates of the parameters' standard errors. First, because RCI is a derived statistic with an unusual domain, the index is not distributed according to a known distribution family and violates the assumption of normality in the residuals. Second, residuals showed high spatial autocorrelation at multiple scales (Global Moran's I = 0.23, p-value < 1e-15, 20 nearest neighbors weights matrix) and with an unknown structure, necessitating a nonparametric approach. Both violations are likely to shrink standard errors of the estimated parameters, leading to overconfident estimates; to illustrate, in the case of spatial autocorrelation, if the explanatory variables are randomly located in relation to crop rotation, spatial autocorrelation in crop rotation would falsely inflate significance. We used nonparametric spatial block bootstrapping to correct for this overconfidence[65,66]. An algorithm for sparsely distributed spatial data, derived by Lahiri 2018, was implemented in R (see supplement).

Spatial block bootstrapping involves iteratively resampling data in spatial blocks to mimic the generation of autocorrelated data. Choice of block size is nontrivial, and choosing the optimal block is an open question[67], but blocks should be larger than the scale at which autocorrelation operates. Using the R package `gstat`[68,69] to compute a variogram of the residuals generated by the naive LMM, we determined that range (distance at which spatial autocorrelation falls off sufficiently) was 400815m. We used this as the dimension of each (square) spatial block (Figure S2). We repeated this bootstrap with a range of possible spatial block sizes and found that this inference on parameters was robust to the choice of block size (Table S1).

1.4. Results

Complexity of Corn-based Rotations in the Midwestern US: RCI values calculated for corn-based rotations create the first map, to our knowledge, that quantifies field-scale rotational complexity across the Midwestern US (Figure 3).

RCI values from 2012-2017 range from 0-5.2 (median = 2.2), and are positively skewed (Fig 3b). Corn monoculture (i.e. corn every year for the six-year period; RCI = 0) accounts for 4.5% of the study area and 3.3% of fields, suggesting that larger fields are more likely to be managed as monocultures (Table 2). The mode RCI score (2.24) corresponds to a corn-soy rotation and dominates the region, covering over half of the study area. Two thirds of the area with this score was a CSCSCS or SCSCSC sequence, while the remaining third corresponds to other rotations that yield the same RCI (e.g. substituting soy for another crop, or a three-year perennial followed by three years of corn).

1.4.1. Predictors of Rotational Complexity

RCI scores have statistically clear correlations with land capability, mean rainfall, distance to the nearest biofuel plant, and field size, as well as with several interactions between these variables (Table 3; conditional R2 = 0.14). Standard errors from the spatially blocked bootstrap were much larger than uncorrected naive confidence intervals, reflecting that accounting for spatial non-independence is necessary to estimate uncertainty of parameter estimates.

Rotational complexity decreased with NCCPI, a proxy for land capability. We find that land of higher inherent capability (flatter slopes, lower bulk density, etc.) is more likely to be used for lower complexity rotations.

Rotational complexity decreased with average rainfall during the growing season. Fields with ample precipitation during the growing season are more likely to have simplified rotations.

Though the relationship between the proximity of the nearest grain elevator and a field's rotational complexity is not statistically clear (95% CI includes zero), RCI showed a clear increase with distance to the nearest biofuel plant. Fields that are closer to biofuel plants are therefore more likely to have simplified rotations.

Rotational complexity decreased with field size, with larger fields being more likely to have simplified rotations.

Two of the interactions included in the model show statistically clear relationships. There is a positive interaction between land capability and field size, with higher quality land associated with decreasing RCI on small fields and slightly increasing RCI on large fields (Figure 4a). The interaction between land capability and rainfall variance show a negative effect on RCI, with highly variable rainfall accentuating land capability's impact on RCI (Figure 4b).

Interpretations of the relationship that each variable has with rotational complexity are shown in Table 4. Though each change is associated with a small shift in average RCI across the region, these can represent massive shifts in regional land management.

1.5. Discussion

As crop rotations continue to simplify in the Midwestern US despite robust evidence demonstrating yield and soil benefits from diversified rotations, our ability to explain and understand these trends will come in part from observing the biophysical and policy influences on farmers' crop choices at one key scale of management: the field. By developing a novel metric, RCI, that can classify rotational complexity over large areas at the field scale, we open the door to regional analyses that can address the unique landscape conditions that impact farmers' field-level management choices and their subsequent influence on rotational simplification. We find that as farmers are pushed towards simplification by broad federal policies (e.g. the biofuel mandate), physical manifestations of these policies like biofuel plants are correlated with intensified simplification pressures. Similarly, we see that the pressure to build soils and boost crop yields through diversified rotations intensifies in fields with lower land capability, while conversely the negative effects of cropping system simplifications are accentuated on the region's best soils.

1.5.1. Crop rotational complexity in the US Midwest at the field scale

RCI uses the sequence of cash crops on a given field as a proxy for crop rotation, and sorts these sequences into scores based on the sequence's complexity and potential for agro-ecosystem health. Because this metric has not been used in previous analyses, we verified RCI's validity through comparisons to previous estimates of rotational prevalence in the region. For example, two separate surveys of farmers in the Midwestern US showed that between 24% and 46% report growing "diversified rotations"[35,70] which we consider to be an RCI of greater than 2.24 (i.e. corn-soybean). In the present study, 34% of fields had an RCI greater than 2.24. This and further comparisons of RCI to previous work (see supplement) show that RCI is capable of capturing previously-noted trends in the region[3,34,35,63,71].

1.5.2. Influence of landscape factors on crop rotational complexity

The ability to analyze rotations at the field scale across the entire Midwestern US allows us to ask how farmers optimize their rotations in complex economic and biophysical landscapes that include pressures to both simplify and diversify. Several biophysical and policy variables show statistically clear relationships with rotational complexity: high land capability, high rainfall during the growing season, and proximity to biofuel plants are all associated with rotational simplification. Given policy incentives, farmers often find that "corn on corn on dark dirt usually pencil out to be the way to go," with farmers growing corn year after year when high quality soil is available[35]. However, when that proverbial "dark dirt" is not available, calculations are not so simple. If growing conditions are sufficiently poor (low land capability and low rainfall), these intensive corn systems may not be profitable, and farmers will have to rely more heavily on non-corn crops (or else inputs that eat into their profits) to maintain crop health and profitability in their fields.

We see this dynamic at play with land capability in the present analysis. Despite—or rather because of— the fact that more diverse rotations improve soils, the most degrading cropping systems counterintuitively tend to occur on the highest quality land. Highly capable lands can be farmed intensively without dipping into a production "danger zone" in years with weather that is historically typical for the region, creating a pattern of land use that is likely to degrade these high quality lands in the long term and potentially jeopardize future yields, particularly in the face of climate change[25].

Recent analyses show that enhanced drought tolerance and resilience for crops is one of the key benefits of diverse crop rotations[25,27,72]. In the present analysis, mean rainfall during the growing season correlates positively with rotational simplification. Farmers may therefore be employing crop rotation in areas of low rainfall to achieve production levels that will keep a farm solvent, as was seen with rotational complexity increases in Nebraska during a drought period from 1999 to 2007[73]. This trend is further accentuated by the negative interaction between land capability and rainfall variance in our analysis, where higher rainfall variability leads to even more diverse rotations on marginal lands.

Proximity to biofuel plants, the main policy indicator in our model, showed a statistically clear trend towards rotational simplification, likely due to increased economic profits. Local corn prices increase by \$0.06 - \$0.12/bushel in the vicinity of a biofuel plant, amplifying incentives to grow corn more frequently[37]. Wang and Ortiz Bobea[39] were surprised not to find an impact of biofuel plant proximity on county-level frequencies of corn cropping in their own analysis, and the present analysis—done at a field rather than county scale—shows exactly this expected effect: corn-based rotations are simplified when in closer proximity to a biofuel plant.

In the current economic and policy landscape, farmers are pushed to simplify rotations through more frequent corn cropping, especially in proximity to biofuel plants, while marginal soils and low rainfall pull fields towards more diverse rotations.

1.6. Conclusion

1.6.1. Opportunities and Recommendations for Future RCI Use

RCI's ability to classify rotational complexity across large regions at the field scale and with low computational cost opens doors to future analyses that explore the interplay between localized landscape conditions, management choices, and agricultural, environmental, and economic outcomes. We see a strong potential to employ this metric not only in new regions, but in analyses that address how results from field experiments with crop rotation may scale up to regional levels[33].

We also note that the metric should be used with caution. For example, because RCI cannot recognize functional groups in crop sequences (e.g. legumes vs. grains), it cannot capture the added benefits that diverse functional groups often add to a rotation. In addition, though RCI includes a perennial correction that avoids penalizing multiple consecutive years of perennials the metric likely still underestimates the benefits of perennials in rotations. RCI is neutral to the soil benefits of annuals vs. perennials, while in practice the year-round cover and crop species mixes (which are coded as a single crop in the Cropland Data Layer) that often accompany perennials may boost soil benefits beyond those of annuals[74]. Consecutive years of perennials are uncommon in our study area (e.g. less than 5% of studied crop area in Iowa), and we encourage caution before applying the metric to regions with a more substantial perennial presence.

We therefore recommend using RCI in studies that explore a wide range of cropping sequences where large differences in RCI are very likely to be meaningful, rather than as a tool to rank sequences that give similar scores. It is also important to note that, though the index can be applied to data of any sequence length, RCI values from different sequence lengths cannot be compared to each other; a rotation that results in a 2.2 from examining a six-year sequence will not be a 2.2 when examining a five or seven-year sequence.

We also note that in using crop sequence as a proxy for crop rotation, RCI cannot fully capture the cyclical nature of true crop rotations. Because RCI examines a fixed number of years, it may "split up" identical rotations in ways that give slightly different scores (for example, an 'AABB' rotation might appear as either AABBAA (RCI = 2.4) or ABBAAB (RCI = 2.6) in a six-year sequence). As these discrepancies will decrease when longer sequences are considered, we recommend applying RCI to sequences that are as long or longer than the longest expected rotation in the study region.

We hope to see RCI used in future analyses that extend beyond the Midwest; however, regional and historic patterns of crop production likely influence farmers' rotational decisions and may render RCI scores calculated from disparate geographical regions difficult to interpret when called into direct comparison. We therefore see great promise in RCI as a rotational metric, and caution against applications that are overly narrow (e.g. comparing very similar RCI scores) and overly broad (e.g. comparing RCI scores across regions).

1.6.2. Policy Implications

The time period chosen in this study, 2012 - 2017, coincides with the introduction of the Renewable Fuel Standard, or "biofuel mandate," which took full effect in 2012. This policy mandates that 7.5 billion gallons of biofuel be blended with gasoline annually, and caused biofuel plants to open and local corn prices to soar across the Midwestern US[75,76]. Now in 2021, there is significant political pressure both to maintain the biofuel mandate in its current state and to relax the standards, and new exemptions to the mandate have already caused several biofuel plants to close in the region[77,78]. Given the link between biofuel plant proximity and rotational complexity, our analysis suggests that these closures, if continued, would likely be associated with an increase in mean RCI in the Midwestern US. Using our current model, simulations ($n = 100$) of randomly closing 20 of the 198 biofuel plants in the region lead to an increase of 0.003 in average RCI in the region, driven by greater distance to the nearest biofuel plant. In turn, increasing average RCI by 0.003 represents, for instance, the equivalent of 41,000 ha of cropland switching from corn-soy rotations to the most diverse rotation possible (6 different crops grown across 6 years).

Rotational simplification near biofuel plants is a pertinent example of the influence that policy can have on farm management decisions and its landscape repercussions. Biofuel mandates are one of several policies, including crop insurance and research funding priorities[79], that currently maintain the profitability of corn production; however, these policies need not be the ones that define rotational landscapes, and increased funding for policies such as the Conservation Stewardship Program could better align farmers' economic incentives with improved environmental health[80] (Figure 1b).

When strong economic incentives encourage rotational simplification, our analysis suggests that it is more likely to occur on land with favorable biophysical conditions for corn growth. With our current policy structure, the highest quality lands in the Midwestern US therefore become the most prone to degradation through intensive management.

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1.9. Figures

Figure 1. Schematic of diversification vs. simplification drivers. Schematic of diversification vs. simplification drivers in the current policy climate (a), and if policies are reformed to encourage crop system diversification (b). In this study, we ask how farmers optimize crop rotational diversity as top-down policy pressures and bottom-up biophysical limits combine on farm fields in the US Midwest.

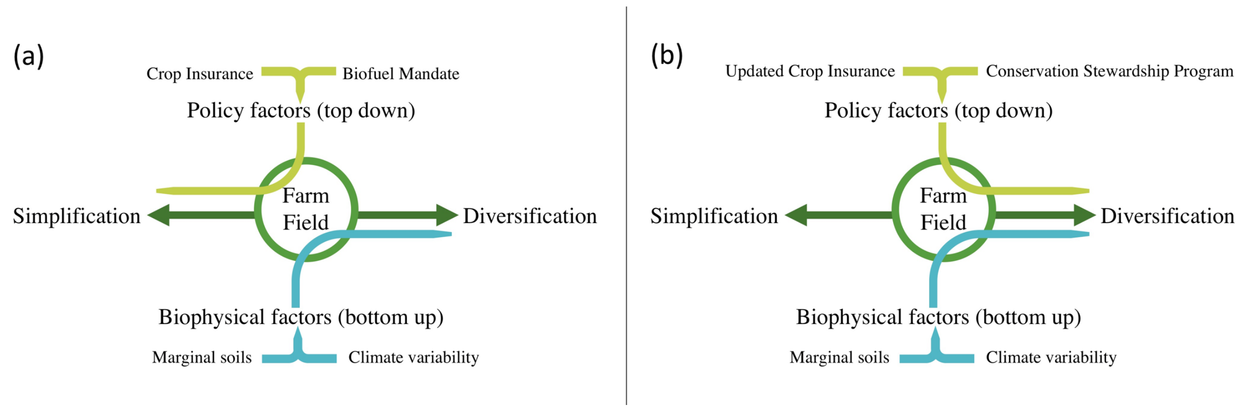


Figure 2. Construction of the Rotational Complexity Index (RCI). Example of a small area out of the eight focal Midwest US states for which a metric of crop rotation complexity (RCI) was calculated. This section of Northwestern Iowa, USA shows six years of crops (a-f), as determined by the Cropland Data Layer, grown in the same area. Each individual pixel sequence is combined into an RCI score (g) using Equation 2. Any pixel that does not include corn in its sequence in any of the six years is not included in the analysis (areas in black). Each pixel represents 2.25 hectares.

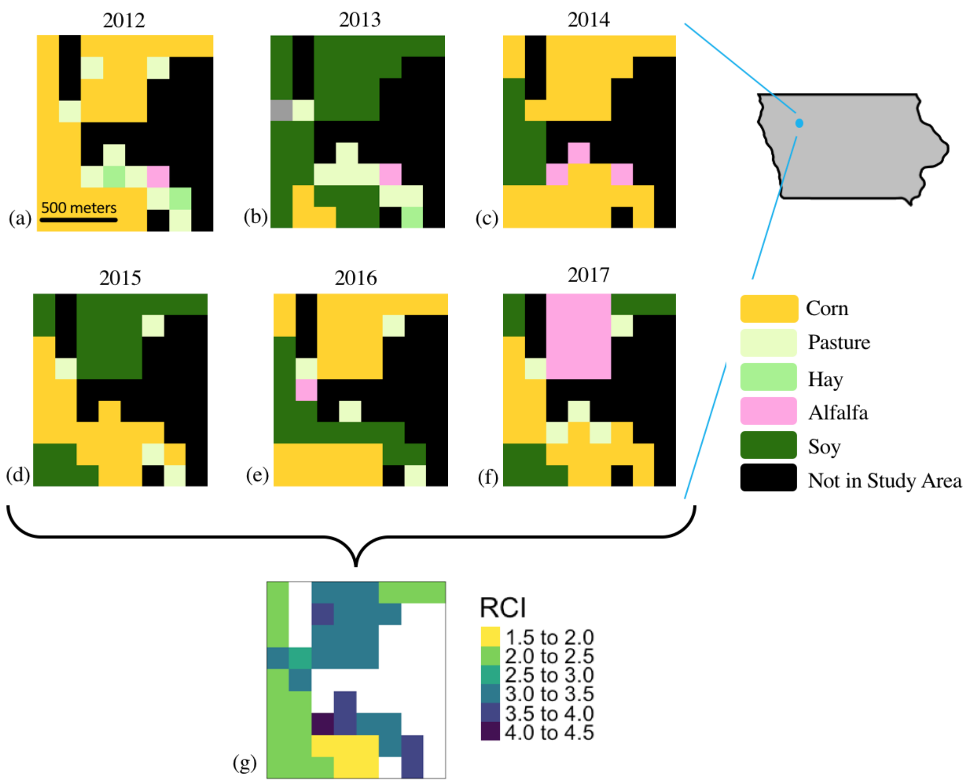
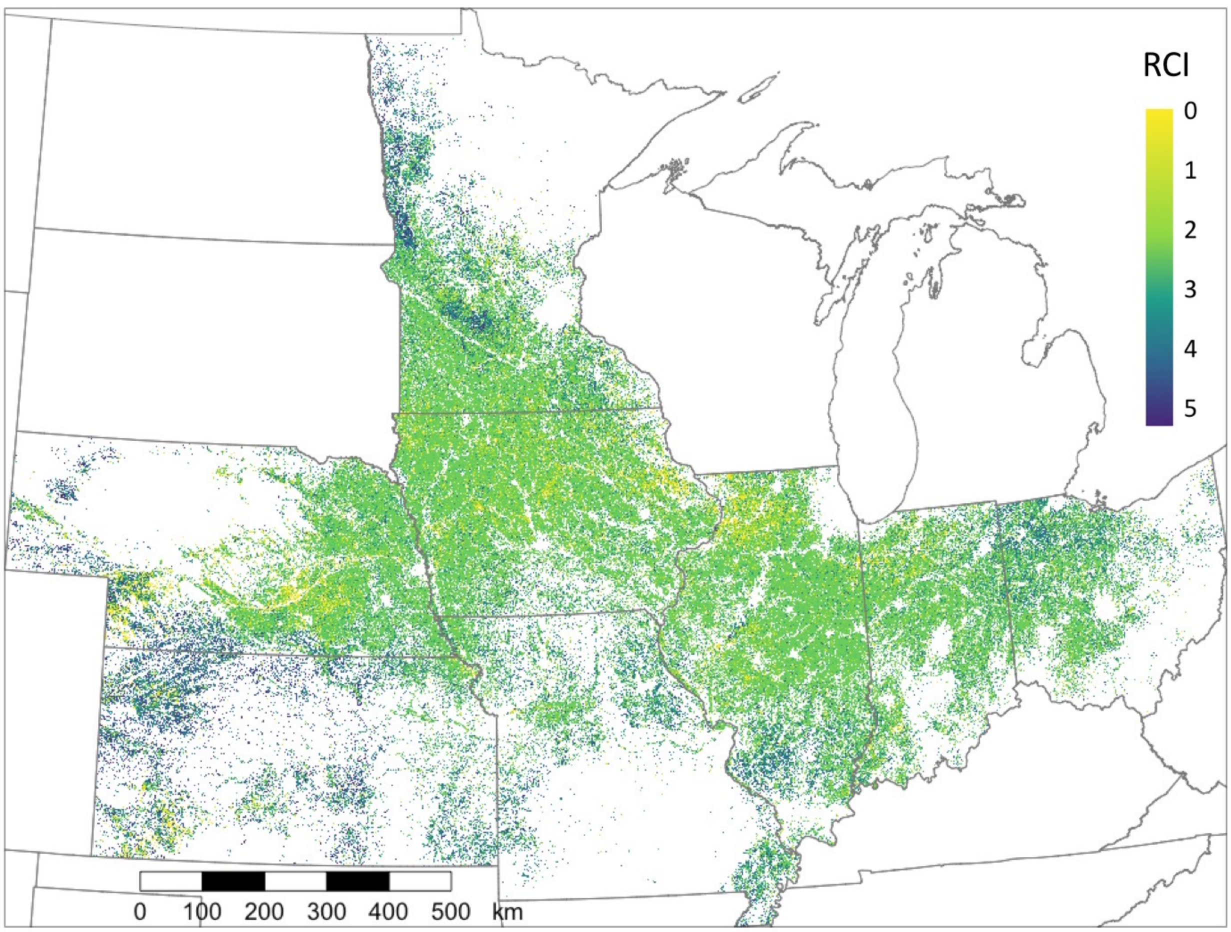


Figure 3. Rotational complexity in the US Midwest.
The six-year crop sequence of each pixel in the eight-state focal region was analyzed to produce an RCI score (a); 0 indicates monoculture corn, 5.2 indicates a different crop grown in each of the six years. Only fields that grew corn in at least one of the six focal years were given a score. The area covered by each RCI score (b) shows a small peak at 0 (corn monoculture), and 2.24 (RCI value corresponding to a corn-soy rotation).

(a)



(b)

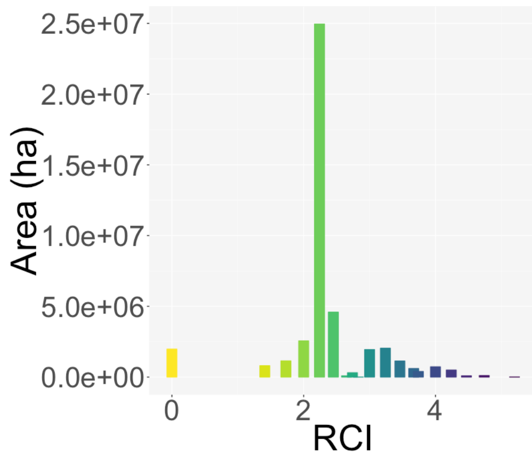
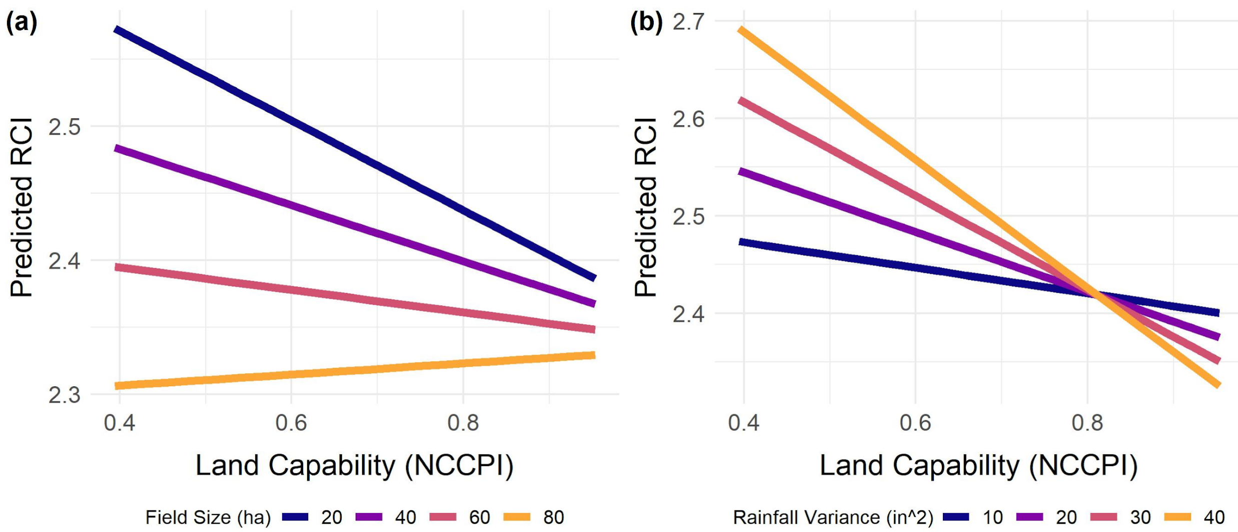


Figure 4. Effects of variable interactions on RCI. The effect of the interaction between field size and land capability (a), and rainfall variance and land capability (b) on predicted RCI while holding all non-interacted variables constant. Focal variables range from two standard deviations below to two standard deviations above their means.



1.10. Tables

Table 1. Datasets used in the analysis.

Variable	Description	Resolution (for rasters)	Source
Land capability (NCCPI)	National Commodity Crop Productivity Index (NCCPI) for corn and soy	30x30m	gSSURGO[53]
Grain elevator distance (km)	Distance to the nearest grain elevator	30x30m	Businesses with SIC code 51530100, 51530102, 51539901, or 51530204 in the 8 focal and 11 surrounding states; data queried in 2019[54]
Biofuel distance (km)	Distance to biofuel production plant	30x30m	Businesses with NAICS code 325193 in focal and surrounding states; data queried in 2019[55]
Mean rainfall (in)	Mean precipitation during the 2012-2017 growing seasons	0.05°	CHIRPS[56]
Rainfall variance (in^2)	Variance in precipitation during the growing season in the 2012-2017 study period	0.05°	CHIRPS[56]
Field size (ha)	Area of field	30x30m	Yan & Roy, 2016[57]
State	US State	NA	U.S. Census Bureau[58]

Table 2. Summary of RCI values and associated attributes. Across the study area there were 19 unique RCI values ranging from corn monoculture (0) to a different crop grown in each of the six years (5.2). Each RCI value (other than zero) can correspond to multiple crop sequences, e.g. CCCCSC, CCSCCC, and CCWCCC would all have an RCI of 1.73. We give an example from the dataset of a sequence that corresponds to each RCI level; however, the options are nearly limitless. In these example rotations, C = corn, S = soy, O = oats, W = wheat, A = alfalfa (perennial), P = pasture (perennial).

RCI	RCI Area (ha)	Percent of Study Area	Percent of Fields	Example Rotation
0.00	1,974,302	4.49%	3.26%	CCCCCC
1.41	802,458	1.83%	1.79%	CCCCCS
1.73	1,142,046	2.60%	2.53%	CCCCSC
2.00	2,554,793	5.82%	5.50%	CCCCAA
2.24	24,951,911	56.80%	53.12%	CSCSCS
2.45	4,589,477	10.45%	10.65%	CSCSSC
2.65	82,270	0.19%	0.26%	CAAACC
2.74	305,785	0.70%	0.92%	CPCSSS
2.83	3,201	0.01%	0.01%	AACAAC
3.00	1,941,698	4.42%	5.75%	CPCSCS
3.24	2,038,480	4.64%	6.25%	SCPCSC
3.46	1,134,947	2.58%	3.30%	CPPSPP
3.67	600,854	1.37%	1.53%	OCSOCS
3.74	394,328	0.90%	1.17%	CPCOCA
4.00	725,024	1.65%	2.15%	APAACS
4.24	494,406	1.13%	1.23%	COSAAC
4.47	83,723	0.19%	0.26%	PCOASA
4.74	104,083	0.24%	0.30%	SPOACS
5.20	6,725	0.02%	0.02%	CSPOAW

Table 3. Regression coefficients. Coefficients from linear mixed models of RCI on various biophysical and social variables, with state as a random effect. Estimates are given from a naïve (non-bootstrapped) model, while confidence intervals are obtained from spatially blocked bootstrap regressions. After running 1000 bootstrapped models, the 2.5 percentile was used as the lower limit of the 95% confidence interval, while the 97.5 percentile was the upper limit. Interactions were chosen conservatively and *a priori* by author expectations about possible important interaction processes. Because variables were unscaled, magnitudes of coefficients are not directly comparable. Coefficients whose 95% confidence interval does not include zero are shown in bold.

Variable	Estimate	95% CI
Intercept	2.47e-02	-4.43e-02 – 6.99e-02
Land capability	**-2.84e-01**	**-5.20e-01 – -6.63e-02**
Grain elevator distance (km)	6.68e-04	-2.21e-03 – 3.63e-03
Biofuel distance (km)	**1.09e-03**	**2.47e-04 – 1.82e-03**
Mean rainfall (in)	**-4.12e-02**	**-5.93e-02 – -1.07e-02**
Mean rainfall squared (in^2)	3.82e-03	-2.54e-03 – 9.08e-03
Rainfall variance (in^2)	2.40e-03	-3.04e-03 – 4.12e-03
Field size (ha)	**-2.70e-03**	**-2.99e-03 – -1.93e-03**
Land capability x Biofuel distance	-2.78e-04	-2.86e-03 – 3.81e-03
Land capability x Grain distance	-3.26e-03	-1.85e-02 – 7.21e-03
Land capability x Mean rainfall	-8.98e-02	-1.73e-01 – 1.02e-01
Land capability x Rainfall variance	**-1.75e-02**	**-2.48e-02 – -4.08e-03**
Land capability x Field size	**6.27e-03**	**1.31e-03 – 7.81e-03**
Biofuel distance x Field size	5.57e-06	-5.67e-06 – 1.28e-05
Grain distance x Field size	-1.31e-05	-4.49e-05 – 2.82e-05
Mean rainfall x Rainfall variance	1.86e-03	-1.43e-04 – 3.87e-03
State random effect (σ^2_{state})	4.52e-02	2.52e-02 – 8.59e-02

Table 4. Interpretations of regression coefficients. Predicted effect on RCI after changing each statistically clear predictor of RCI from its 10th to 90th percentile value in the dataset, while keeping all other variables constant (at their median values). We give context to the resulting changes in RCI by asking what percent of the study area would need to switch from a corn-soy rotation to the most diverse rotation (a different crop grown in each of the six focal years) in order for the predicted RCI change to occur.

Variable	**Change in variable (from 10th to 90th percentile)**	**Resulting predicted effect on RCI**	**Context for change in RCI**
Land capability	0.35	-0.11	An increase of 0.35 in inherent land capability is equivalent to **3.7%** of the study area (1.6 million ha) **switching from growing a different crop in each year to a corn-soy rotation.**
Mean precipitation	5.2 in	-0.21	An increase of 5.2 inches in mean precipitation is equivalent to **7.2%** of the study area (3.2 million ha) **switching from growing a different crop in each year to a corn-soy rotation.**
Biofuel distance	79 km	0.06	An increase of 79 km in distance to the nearest biofuel plant is equivalent to **2.1%** of study area (920,000 ha) **switching from corn-soy rotation to growing a different crop in each year**
Field size	51 ha	-0.12	An increase in field size of 51 ha is associated with the equivalent of **4.1%** of the study area (1.8 million ha) **switching from growing a different crop in each year to a corn-soy rotation.**

1.11. Supplementary information

S1. Methods

S1.1. Construction of Rotational Complexity Index (RCI)

To accommodate the heterogeneity of crop rotations in the region--and even on a single farm--such a metric must be able to classify a sequence of crops in a single field, rather than relying on data aggregated across larger scales. Due to the long duration of some planned crop rotations and the vast number of possible cropping sequences (in our case there are over a trillion possible unique combinations) in the region, this metric also needed to be flexible to encompass rotations of varying and sometimes protracted lengths, and able to distinguish between successions of crops without relying on identifying/classifying individual rotations. In field experiments, rotational studies[1,2] have quantified the diversity of a known rotation with a diversity index (d) that is a function of the length of the rotation (l, in years) and the number of crops in the rotation (n):

$$d = \sqrt{nl} \quad \text{(Equation 1)}$$

In the above metric, higher scores indicate more complex rotations, which should in turn show higher benefits to soils. This diversity index has the crucial benefit of being able to consolidate rotations of varying lengths and crop species into a single number that can be compared across rotations. However, it is not feasible to apply this metric on large-scale remotely-sensed data where there is no known rotation of a set length, crop sequences may be irregular, and pattern recognition is extremely computationally expensive.

We therefore adapted the diversity index to use the six-year crop sequence for a given field to measure the number of crop species and turnover events from year to year, and combine them to calculate a rotational complexity score for the field (Figure 2). We chose a six-year sequence as it is highly unusual for farmers in the Midwest to have a planned rotation that lasts longer than five years[3,4] and it therefore encompasses the full gamut of rotational diversity we might expect to see in the Midwest.

We replaced rotation length (which cannot be determined without classifying each sequence as a known rotation), with crop species turnover between years to capture the additional complexity of longer rotation. We define first order turnover (T_1) as a change in crop type between two adjacent years (e.g. for a 6-year crop sequence ABABAB, $T_1 = 5$), and second order turnover (T_2) as a change in crop type every other year (e.g. for ABABAB, $T_2 = 0$; for ABCABC, $T_2 = 4$), and take their average to make a proxy that is substituted into Equation 1 for rotation length:

$$\sqrt{n \, \frac{T_1 + T_2}{2}} \qquad \text{(Equation 2)}$$

Similar to rotation length, this turnover term increases as rotations become more complex, and maintains a metric where higher scores reflect more complex rotations.

Perennial crops typically improve soils[5–8]; however the naive metric will show low turnovers (and therefore low scores) when perennials repeat from year to year. Because our aim was to construct a metric that reflects the soil benefits provided by more complex rotations, we avoided penalizing repeated instances of perennial plants by including a perennial correction as a pseudo-turnover ($T_{(p)}$) equal to the number of times a duplicate perennial (grass/pasture, alfalfa, other hay/non-alfalfa, vetch, and clover/wildflowers) appears in two consecutive years in a pixel's crop sequence, giving:

$$\text{Rotational Complexity Index (RCI)} = \sqrt{n\frac{T_1+T_2+T_{(p)}}{2}} \qquad \text{(Equation 3)}$$

S1.2. Naive linear mixed model

Prior to formal uncertainty quantification, we obtained estimates using a linear mixed model of the form

$$RCI_i = \beta_0 + X_i^T\beta + \alpha_{state(i)} + \varepsilon_i, \varepsilon_i \sim N(0, \sigma_\epsilon), \alpha_{state} \sim N(0, \sigma_{state}), \sum_{i=1}^{n\ states} \alpha_i = 0$$

to estimate the covariate effect sizes $\beta$and the standard deviation of the state random effect σ_ϵ. A full list of the covariates in *X* can be found in Table 3.

Nonparametric spatial block bootstrap for unevenly distributed data

Uncertainty quantification based on the standard linear mixed model is overly optimistic in this case due to known spatial autocorrelation in the residuals and unmet model assumptions (particularly non-continuity in the response domain). We chose to use a spatial block bootstrap for uncertainty quantification, which resulted in more conservative and appropriate estimates of the distributions of estimated model parameters.

Because our spatial data were unevenly distributed spatially, a parametric spatial bootstrap approach (in which residuals are resampled in a manner preserving their spatial relatedness) was inappropriate. We used a nonparametric spatial block bootstrap method tailored to the case of uneven data distribution (Lahiri 2018). The algorithm used to quantify uncertainty is as follows.

Given a dataset of N data points spanning study area R,

1. Define a spatial block size with dimension *b* and area *b*^2.
2. Denote the minimum set of non-overlapping spatial blocks of area *b*^2 so that the study area *R* is covered by the union of these blocks. Say we have *k* such homogeneous blocks B, uniquely identified by their centers, to cover the study area.
3. For each bootstrap iteration:
    a. Initialize an empty 0-row data frame df to hold new data.
    b. For each block in the *k* disjoint blocks:
        i. Identify a random point *p* within R such that a bounding box with dimension *b* centered on *p* is contained within the union of the blocks.
        ii. Define a bootstrap block B* centered on *p*.
        iii. Extract data that fall inside B* and add them to `df`.

c. Fit the naive LMM on `df` and extract the parameter estimates. (It's almost certain that the number of data points in `bootstrap_sampled_pts`, N*, does not equal N, which is accounted for in the method development.)

The distribution of parameter estimates from the model fits (3c) in each bootstrap approximates the asymptotic distribution of the estimators (Lahiri 2018).

S1.3 Choice of bounding box size

As yet, the optimal choice of bounding box dimension *b* isn't known (Lahiri 2018). As *b* represents a unit of spatial interdependence, we chose *b* conservatively based on an analysis of the scale of spatial autocorrelation. Using the package `gstat`, we fit a spatial variogram of the residuals obtained from the LMM with a Gaussian decay structure (Figure SX). We found the range of the fit variogram to be 400456.1 m, and therefore chose a spatial bounding box of b = 400 km to represent the most conservative size at which all spatial interdependence is captured.

To check for sensitivity of analyses to the size of the bounding box, we ran the complete bootstrap procedure over a range of bounding box dimensions (Table S2).

S2. Comparison between RCI and previous studies

Though there is some error in crop identification associated with the CDL, the overall accuracy (proportion of pixels that were identified correctly) is quite high across the states in our study area (e.g. 86% mean overall accuracy in 2017), suggesting a strong correlation between on-the-ground rotations and the indices in our analysis[9]. Importantly, because of the way the RCI metric functions, the CDL does not need to correctly identify each crop species for RCI scores to be accurate, but rather distinguish if each crop is similar or different from crops grown in previous years. Because corn and soy account for over 86% of cropland in the study area, their correct identification is key to the metric's success, and corn/soy show the highest accuracies (over 90% of pixels labeled as corn/soy are correctly identified and less than 5% of pixels labeled as not corn/soy are misidentified) of any crop type in the studied states[9].

We also find it relevant to compare our results to previous studies. First, we find that an RCI of zero, which corresponds to corn monoculture, accounts for 4.5% of cropland in the study area over the six year period from 2012-2017, while previous estimates in the region give the prevalence of four-year monoculture as 7% in 2010[10], and ten-year monoculture as 2% in 2019[11]. Second, previous studies have examined the prevalence of corn-soy rotations in the Midwest, arriving at estimates of 53% of land planted in 3-year corn-soy rotations in 1997 [12], and 72% of cropland in Iowa (4-year rotations, ending in 2016)[13]. Because these estimates come from sequences of shorter duration, they are likely to report higher estimated areas than our six-year sequences. Our analysis across the Midwest shows that 37% of the study area was in exactly a CSCSCS or SCSCSC sequence, while 57% of the study area (cropland that grew corn in at least one of the six focal years) had an RCI of 2.24, the value that corresponds to a corn-soy rotation for a 6-year sequence.

S3. Supplemental Tables and Figures

Figure S1. Input rasters used as regression variables, all gathered from publicly available data. Land capability (A) from the National Commodity Crop Productivity Index ranging from 0-1, or poor to high quality; distance to the nearest biofuel plant (B) from geolocated businesses with NAICS code 325193; distance to nearest grain elevator (C) from geolocated businesses with SIC codes 51530100, 51530102, 51539901, or 51530204; mean rainfall during the growing season (D) from CHIRPS data; and the variance in rainfall during the growing season (E).

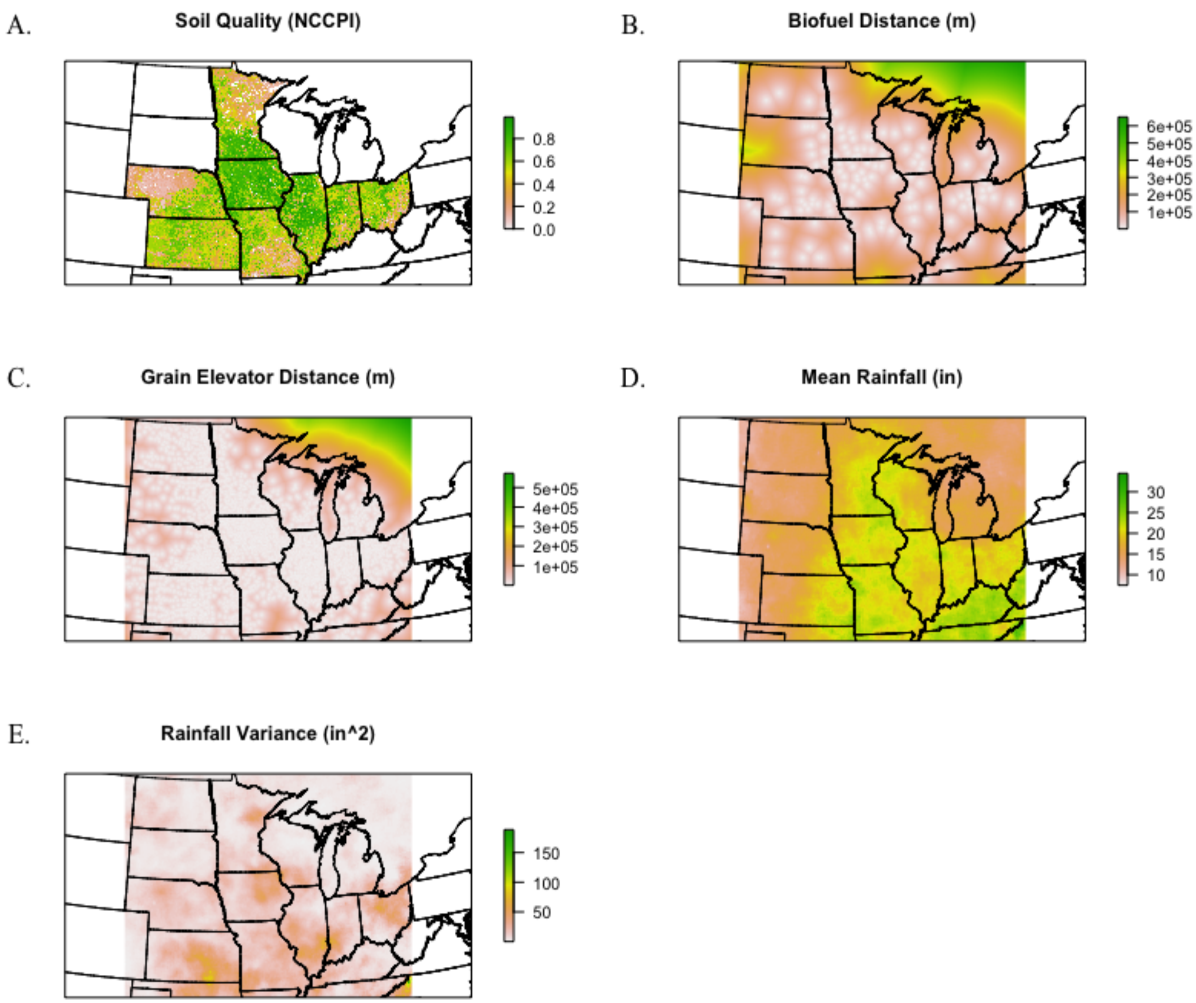


Figure S2. Semivariogram of LMM residuals used to choose the dimension of the spatial bootstrap bounding box.

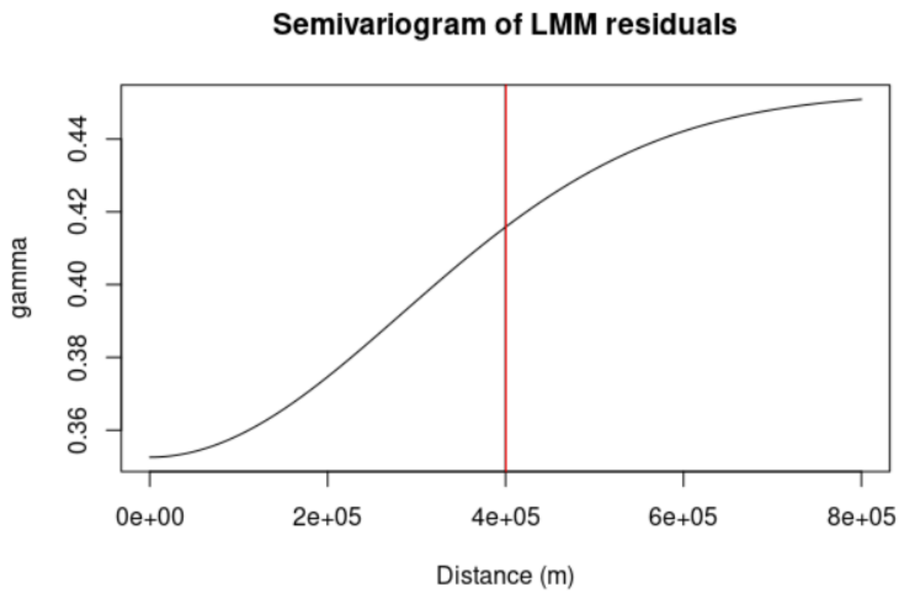


Figure S3. Histograms of bootstrap estimates of each model parameter, 1000 samples per parameter. Vertical red lines indicate 0 on the x-axis.

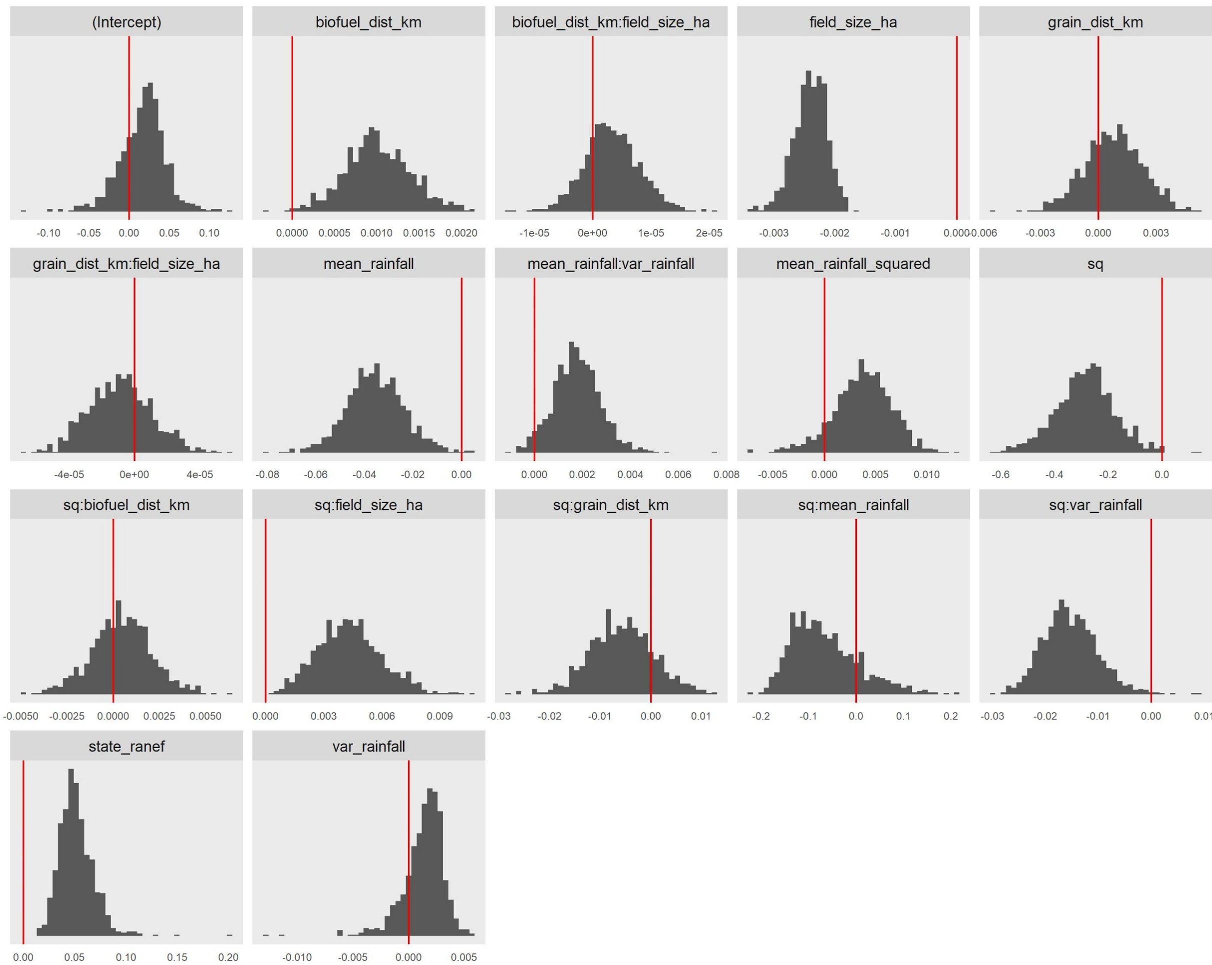


Table S1. A comparison of estimated effects and 95% confidence intervals over a range of bounding box sizes. Bolded cells are estimates whose 95% CIs do not overlap 0. Inference ("significance") is largely stable across bounding box sizes, with some exceptions due to CIs with boundaries close to zero and/or simulation stochasticity. All terms considered significant in the final report (indicated by bold parameter name) were estimated as significant across all bounding box sizes tested.

	Bounding box size					
Parameter	16 km	40 km	120 km	160 km	320 km	640 km
(Intercept)	**0.0243 (0.014, 0.0345)**	**0.0235 (0.00208, 0.0462)**	0.023 (-0.0141, 0.0642)	0.023 (-0.0222, 0.0648)	0.0196 (-0.0356, 0.0671)	0.0046 (-0.127, 0.0487)
Land capability	**-0.284 (-0.333, -0.231)**	**-0.287 (-0.375, -0.197)**	**-0.276 (-0.434, -0.124)**	**-0.275 (-0.452, -0.11)**	**-0.282 (-0.509, -0.0775)**	**-0.325 (-0.552, -0.114)**
Distance to grain elevator	0.000659 (-0.000713, 0.00203)	0.000642 (-0.00153, 0.0027)	0.000749 (-0.00207, 0.00333)	0.000784 (-0.0024, 0.00339)	0.000752 (-0.00242, 0.00337)	-0.000115 (-0.00267, 0.00264)
Distance to biofuel refinery	**0.00108 (0.000872, 0.00129)**	**0.0011 (0.000709, 0.00152)**	**0.00105 (0.000485, 0.00171)**	**0.00104 (0.000345, 0.0018)**	**0.000944 (0.000205, 0.00173)**	**0.000981 (0.000227, 0.0017)**
Mean rainfall	**-0.0413 (-0.046, -0.0362)**	**-0.0409 (-0.0518, -0.0307)**	**-0.0397 (-0.0585, -0.0218)**	**-0.039 (-0.0603, -0.0191)**	**-0.0387 (-0.065, -0.0156)**	**-0.0365 (-0.0673, -0.0117)**
Mean rainfall squared	**0.00388 (0.00212, 0.00564)**	**0.00396 (0.000622, 0.00724)**	0.00393 (-0.00235, 0.0097)	0.00389 (-0.00296, 0.0101)	0.00436 (-0.00253, 0.00985)	0.00381 (-0.0022, 0.0124)
Interannual variance in rainfall	**0.00242 (0.00165, 0.00317)**	**0.00243 (0.00103, 0.00394)**	0.00244 (-5.71e-06, 0.00547)	0.00243 (-0.00015, 0.00552)	0.00193 (-0.00158, 0.00469)	0.00103 (-0.00566, 0.00353)
Field size	**-0.00269 (-0.00283, -0.00255)**	**-0.0027 (-0.00294, -0.00247)**	**-0.00269 (-0.00315, -0.00229)**	**-0.00268 (-0.00324, -0.0022)**	**-0.00248 (-0.00304, -0.002)**	**-0.00219 (-0.00269, -0.00175)**
(Land capability) x (distance to biofuel refinery)	-0.000234 (-0.00159, 0.00112)	-0.000254 (-0.00277, 0.00204)	-0.000229 (-0.0037, 0.00294)	-8.91e-05 (-0.00334, 0.00335)	0.000274 (-0.00317, 0.00341)	0.00115 (-0.00169, 0.00381)
(Land capability) x (distance to grain elevator)	-0.00314 (-0.0104, 0.00366)	-0.00261 (-0.0134, 0.00755)	-0.00263 (-0.0163, 0.0101)	-0.00284 (-0.017, 0.00855)	-0.00363 (-0.0171, 0.00878)	-0.00782 (-0.0233, 0.00389)
(Land capability) x (mean rainfall)	**-0.0915 (-0.12, -0.0623)**	**-0.0884 (-0.139, -0.0357)**	**-0.091 (-0.168, -0.00502)**	-0.0966 (-0.174, 0.00908)	-0.0908 (-0.183, 0.0776)	-0.0109 (-0.132, 0.163)

(Land capability) x (rainfall variance)	**-0.0175 (-0.0207, -0.0138)**	**-0.0174 (-0.0236, -0.0115)**	**-0.0169 (-0.0271, -0.00726)**	**-0.0167 (-0.0272, -0.00687)**	**-0.0154 (-0.0254, -0.00429)**	**-0.0132 (-0.0217, -0.0012)**
(Land capability) x (field size)	**0.00628 (0.0051, 0.00736)**	**0.00634 (0.00443, 0.0083)**	**0.00643 (0.00345, 0.00958)**	**0.00625 (0.00328, 0.0101)**	**0.00479 (0.00159, 0.00869)**	**0.00275 (0.000139, 0.00631)**
(Distance to biofuel refinery) x (distance to grain elevator)	**5.48e-06 (1.86e-06, 9.36e-06)**	5.61e-06 (-5.31e-07, 1.09e-05)	4.5e-06 (-4.17e-06, 1.36e-05)	4.08e-06 (-5.11e-06, 1.42e-05)	3.86e-06 (-4.81e-06, 1.5e-05)	2.51e-06 (-5.78e-06, 1.06e-05)
(Distance to grain elevator) x (field size)	-1.37e-05 (-3.92e-05, 1.07e-05)	-1.45e-05 (-5.15e-05, 1.64e-05)	-1.26e-05 (-5.31e-05, 2.48e-05)	-1.08e-05 (-5.3e-05, 2.72e-05)	-7.27e-06 (-4.64e-05, 3.18e-05)	-2.43e-06 (-4.01e-05, 3.96e-05)
(Mean rainfall) x (variance in rainfall)	**0.00185 (0.00141, 0.0023)**	**0.00179 (0.000906, 0.00263)**	**0.00164 (0.000219, 0.00326)**	**0.00163 (0.000117, 0.00316)**	0.00164 (-0.000162, 0.00367)	**0.00186 (0.000109, 0.00444)**

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Chapter 2: Deep nutrients and fungal communities support tomato fruit yield and quality in dry farm management systems.

2.1. Abstract

Changing climates are causing agricultural water shortages at unprecedented scales and magnitudes, especially in regions historically reliant on irrigation. Identifying and understanding systems of farming that allow continuity in farming operations in times of water scarcity is an increasingly urgent need. Vegetable dry farming relies on winter rains stored in soils to reduce irrigation to 0-2 events per season and has become prevalent on California's Central Coast in recent decades. Until now, this system has been unexplored in scientific literature beyond extension publications, despite its promise as a model for low-water agriculture. Dry farm management presents a unique challenge given the low water content in surface soils that restricts nutrient access in the areas farmers usually target for irrigated fertility management. Managing soil nutrients at depth and potentially the microorganisms that provide plant nutrients and alleviate water stress (e.g. arbuscular mycorrhizal fungi, or AMF) could be crucial to dry farm success, and we engaged in a collaborative research design process with six farmers managing seven commercial dry farm tomato fields to identify and answer three key management questions: 1. What are the depths at which nutrients influence harvest outcomes given low water content in surface soils?, 2. Are commercially available AMF inoculants effective at improving harvest outcomes?, and 3. How does the broader fungal community change in dry farm soils, and do those changes map to harvest outcomes? Only soil nitrate and ammonium concentrations below 60cm depth were correlated with tomato yield and fruit quality, while blossom end rot negatively correlated with ammonium at 30-60cm. Nutrients in surface soil were not correlated with yield or quality. We identified a fungal class, Sordariomycetes, as a "signature" fungal group in dry farm soils that distinguished them from irrigated management and correlated with positive quality outcomes, while commercial AMF inoculation showed little benefit. These findings can inform management practices that optimize fruit yield and quality, and can guide farmers and policy makers alike in efforts to minimize agricultural water use.

2.2. Introduction

As rainfall becomes more variable with changing climates, farmers around the world are contending with droughts that are increasing in both intensity and duration[1–4]. For many farmers, restricted water use has become a constant and looming threat, forcing the agricultural sector to confront a key question: how can we adapt to water scarcity without jeopardizing farmer livelihoods?

This question is particularly salient for California's agricultural system, which has become increasingly fragile in recent decades due to its dependence on a shifting and shrinking water supply[5,6]. Changing climates have caused droughts that not only result in massive financial losses (the 2015 drought cost California agriculture $2.7 billion[7]), but also raise major concerns for farmers' ability to maintain continuity in their farming operations[8,9]. Because California's waters are over-allocated even in years of typical rainfall, the Sustainable Groundwater Management Act, which requires sustainable groundwater use by 2040, implies that irrigation will need to be discontinued on hundreds of thousands of cropland acres[10,11].

In this backdrop, dry farming, a practice in which farmers grow crops with little to no irrigation, has quickly garnered interest from farmers and policy-makers around the state. While dry farming is an ancient practice with rich histories in many regions, perhaps most notably the Hopi people in Northeast Arizona[12], dry farming emerged more recently in California, with growers first marketing dry farm tomatoes as such in the Central Coast region in the early 1980's. In a lineage that likely traces back to Italian and Spanish growers[13], dry farming on the Central Coast relies on winter rains to store water in soils that plants can then access throughout California's rain-free summers, allowing farmers to grow produce with little to no external water inputs.

As water-awareness gains public attention, dry farming has been increasingly mentioned as an important piece in California's water resiliency puzzle[14–16], however, while some extension articles exist[17–19], no peer-reviewed research has been published to date on vegetable dry farming in California. We therefore assembled a group of six dry farming operations on the Central Coast to collaboratively identify and answer key management questions in the dry farm community. Growers identified three main management questions that would benefit from further research: 1. Which depths of nutrients (and which nutrients) are most influential in determining fruit yield and quality? 2. Are AMF inoculants effective in this low-water system, and more broadly, 3. How can farmers best support high-functioning soil fungal communities to improve harvest outcomes?

Growers were primarily concerned with fruit yield and quality, with blossom end rot prevention and overall fruit quality being of particular interest due to the water stress and high market value inherent to this system. Managing for yields and quality present a unique challenge in dry farm systems, as the surface soils that farmers typically target for fertility management in irrigated systems dry down quickly to a point where roots will likely have difficulty accessing nutrients and water. Because plants are likely to invest heavily in deeper roots as compared to irrigated crops, we hypothesized that nutrients deeper in the soil profile would be more instrumental in determining fruit yields and quality.

As deficit irrigation and drought change microbial community composition in other agricultural and natural systems[20–22], we hypothesized that dry farm management would cause shifts in fungal communities in response to dry farm management, which could in turn improve tomato harvest outcomes. Beyond general shifts in fungal communities, farmers were specifically interested in arbuscular mycorrhizal fungi (AMF) inoculants, which are increasingly available from commercial sellers. Recent research has shown that AMF can help plants tolerate water stress[23–25], and we therefore hypothesized that commercial AMF inoculants might be beneficial[26–28]

We organized a season-long field experiment from early spring to late fall of 2021 to answer these questions, sampling soils and collecting harvest data from plots on seven dry farm tomato fields (all on the six farms involved in research design) on the Central Coast. Each farmer managed the fields exactly as they normally would, with AMF inoculation being the only experimental manipulation. We sampled soils for nutrients (nitrate, ammonium, and phosphate) and water content at four depths down to one meter throughout the growing season to determine which nutrient depths influenced harvest outcomes. We also took DNA samples from soils and roots in surface and subsurface dry farm soils, as well as nearby irrigated and non-cultivated soils, sequencing the ITS2 region to analyze the fungal community to verify inoculation establishment and more broadly characterize soil fungal communities to see how fungal communities changed under dry farm management (as compared to irrigated and non-cultivated soils) and determine whether these changes or the introduction of an inoculant influenced harvest outcomes. We then used Bayesian generalized linear mixed models to estimate the effects of nutrient depths and fungal community metrics on yield and fruit quality data from 10-20 weekly harvests on each field. Our results highlight a tension between managing nutrients for fruit yield and quality, while fungal community metrics show promise for increasing fruit quality.

2.3. Methods

2.3.1. Field sites.

The experiment was conducted on seven certified organic dry farm tomato fields in Santa Cruz and San Mateo counties in California during the 2021 growing season. Five blocks (10 total experimental plots) were established on each field over the course of a full growing season (see 'Experimental design' below), for a total of 70 experimental plots. These fields are managed by six farms; one farm contributed two fields at two separate sites. Each farmer continued to manage their field for the duration of the experiment according to their typical practices. Each dry farm crop was preceded by a crop in the winter prior to the experiment, either in the form of a cover crop (6 fields), or continuous winter production (1 field). All fields were disked (~15cm) prior to planting, and two fields additionally ripped down to 60-90cm. Each field's plant and bed spacing, plant date, and tomato variety are listed in Table 1, along with amendments added to the soil. Fields also varied in their rotational history (Table 2). The mapped soil series, measured texture, and soil pH are listed in Table 3.

From March 2 (first transplant) to October 27 (last harvest) there were 15 rain events greater than 1 mm recorded at the De Laveaga CIMIS weather station (centrally located between all farms), none of which occurred between the months of May and October (Table S1). Monthly weather data is summarized in Table 4.

2.3.2. Experimental design and inoculation.

A nested experimental design was used to account for management and biophysical differences across fields. Ten plots were established at each field site (70 plots total) within three days of tomato transplant. Each plot contained 12 plants, and plots were divided across two beds with a buffer row between (Figure 1). Plots were randomly selected to be inoculated in the first experimental row and then paired with a counterpart in the second experimental row that received the opposite inoculation condition to achieve a randomized complete block design with five blocks per field. Here we refer to a pair of inoculated and control plots as a block. There were three non-inoculated buffer plants between each plot and at least twenty buffer plants at the start and end of each experimental row.

A commercial AMF inoculant (Valent MycoApply Ultrafine Endo; a four species mix of *Glomus intraradices*, *Glomus mosseae*, *Glomus aggregatum*, and *Glomus etunicatum*) was used to inoculate transplants. This inoculum has been shown to impact crop physiology and improve plant water status in various field and greenhouse applications[29–32]. Each of the 12 plants in plots in the inoculation condition received 0.2 g of inoculum, which was mixed with 40 mL of water and then poured at the base of the plant within three days of transplanting, as per manufacturer instructions.

2.3.3. Fruit harvests and quality.

Harvests began when farmers indicated that they were beginning to harvest the portion of their field that included the experimental plots. Each field was harvested once per week from its start date to its end date, with the exception of Farm 5, which was harvested twice per week, in accordance with farmer desires. All red tomatoes were harvested from each plot and sorted into marketable, blossom end rot, sunburnt, or "other unmarketable" fruits and then weighed. Harvests stopped when there were no remaining tomatoes in the field or when farmers decided to terminate the field.

Fruit size and quality were assessed on the third, sixth, and ninth week of harvest at a given field. Ten representative marketable tomatoes were taken from each plot, weighed, dried at 70 degrees C and then weighed again to establish the percent dry weight (PDW). PDW was used as a proxy for fruit quality, with fruits with a lower water content (higher PDW) increasing fruit quality up to a certain point. Extension research has linked dry farm fruit quality with lower fruit water content, as opposed to specific compounds that are elevated in dry farm tomatoes[33,34], and we expect PDW to correlate highly with the concentration of flavors previously found to create dry farm fruits' superior quality. After eliciting quality categorization from farmers in the study, we determined that fruit quality increases up to a PDW of 8%, peaks between 8 and 12%, and falls above 12%.

2.3.4. Soil water, nutrients, and texture.

Soil samples were taken three times over the course of the field season: once at transplant (within three days after plant date), once mid-season (9 weeks after transplant), and once during harvest (18 weeks after transplant). Each time samples were taken from four depths (0-15cm, 15-30cm, 30-60cm, 60-100cm) at each plot. Samples were homogenized and a subsample was immediately put on ice for transport to the lab. Each sample was then divided into fresh soil (N analyses), dried at 60 degrees C (Olsen P, texture), and dried at 105 degrees C (gravimetric water content).

Ammonium and nitrate levels were measured after using 2M KCl to extract samples from transplant (all depths), midseason (0-15cm and 30-60cm), and harvest (0-15cm and 30-60cm) samples using colorimetry[35,36]. As soil pH was close to neutral, Olsen P[37] was used to measure plant-available phosphate on samples from transplant (all depths) and midseason (0-15cm and 30-60cm). Gravimetric water content was assessed for all samples. Samples from transplant were composited by depth at each field, and texture was assessed using a modified pipette method[38].

At transplant, a soil core was taken with a bucket auger down to one meter from a central plot in each field and used to calculate bulk density at each depth increment. We then took a weighted average of GWC at each plot to calculate available water using bulk density and a pedotransfer function based on soil texture[39] (see Table 3).

Potentially leachable soil nitrate levels were calculated for each field using nitrate concentrations from the top 15cm at the harvest sampling event, which occurred within the first three weeks of harvest. Though the plants continued to grow for the duration of the harvest, it is unlikely that nitrate from the top 15cm were used due to the soil's low water content, and no precipitation or irrigation occurred for the duration of harvest. Bulk density in the top 15cm was assumed to be 1.2 g soil/cm3 as experimental bulk density was measured with 1m of soil and likely overestimated the bulk density at the surface of the soil.

2.3.5. Soil and root sampling for DNA extractions.

Soil subsamples taken from 0-15cm and 30-60cm at midseason were set aside for DNA analysis. In addition to the experimental plots, samples were also taken from both depths at the nearest irrigated crop production areas and non-cultivated soils, such as hedgerows, field sides, etc. (3 sites at least 2m apart for each).

Gloves were worn while taking these samples and the auger was cleaned thoroughly with a wire brush between each sample. Roots were also collected from one plant per plot and were dug out using a trowel from the top 15 cm of soil. These samples (soil and roots) were stored on-site in an ice-filled cooler and transferred to a -80 degree C freezer immediately upon returning to the lab (within ten hours). Roots were later washed in PBS Buffer/Tween20 and ground using liquid N.

2.3.6. DNA extractions, quantification, and sequencing.

Root DNA was extracted using a NucleoSpin Plant II kit (Macherey-Nagel). Soil DNA was extracted using a DNeasy PowerSoil Pro Kit (Qiagen). Two technical replicates were extracted for each sample for a total of 0.5g of soil and 0.2g of roots. The technical replicates were combined using an equal mass of DNA from each replicate prior to library prep. All samples were sent to the University of Minnesota Genomics Center for sequencing using ITS2 primers.

2.3.7. Primer selection.

The ITS2 rRNA region (5.8-Fun/ITS4-Fun) was selected for amplification and fungal community analysis. This region has been successfully utilized in recent AMF community studies[40,41]. Though AMF-specific primers exist (e.g. SSU, LSU), we chose the more general ITS2 fungal primers for several key reasons. First, in the field, SSU primers (e.g. Wanda-AML2) detect more taxa in non-Glomeraceae families but give lower resolution in the Glomeraceae family[42,43]. Because the four species in our inoculant are in the Glomeraceae family and this family is dominant in agricultural systems and clay soils[44–46], we prioritized species resolution in Glomeraceae over other families. More broadly, the higher variability in the ITS2 region can lead to more unassigned taxa, but does not run as much of a risk (compared to the SSU or LSU regions) that distinct taxa will be lumped together[40,47,48].

Third, and of particular importance in our root samples, these primers are better able to select for fungal over plant material than other ITS primer options[49]. Finally, ITS2 allowed us to also examine the broader fungal community in our samples, whereas SSU and LSU options are AMF-specific and cannot be used to characterize other fungi.

2.3.8. Bioinformatics.

Qiime2 was used for all bioinformatics[50]. Reads without a primer were discarded, and primer/adapter sequences were trimmed off reads using cutadapt. Samples were denoised with DADA2, and taxonomy was assigned using the UNITE version 9 dynamic classifier for all eukaryotes[51]. Taxa outside of the fungal kingdom were removed from all samples and SRS normalization was used to reduce each sample to 7190 reads. 7190 was chosen as a cutoff due to a natural break where no samples fell between 4000 and 7190 reads. Because depths below 4000 retained less than 90% of sample richness, 7190 was chosen, retaining over 95% of richness. The 22 samples out of 301 samples that fell below this cutoff were discarded. These samples included all 5 blanks, 3 samples from field 1A (all 30-60cm), 4 samples from field 1B (all 30-60cm), 2 samples from field 2 (one 0-15cm and one 30-60cm), 4 samples from field 3 (one 0-15cm and three 30-60cm), and 4 samples from field 4 (one 0-15cm and three 30-60cm).

2.3.9. Statistical analyses.

All analyses were done using R Statistical Software (v4.1.2)[52]. Bayesian mixed models were estimated using the R package `brms`[53]. Permutational multivariate analyses of variance (PERMANOVA) were done with the `vegan` package[54] using Bray distances and 9999 permutations. Differential expression analyses were done with the `MicrobiotaProcess` package[55].

2.3.9.1. Variable reduction.

Due to the large number of potential covariates (nutrients and water at four depths for each of three sampling events, 48 total variables) and high collinearity in each category (see Figure S1), variables were grouped by type and depth (nutrients at 0-15cm, 15-30cm, 30-60cm, 60-100cm; water at all depths; texture at all depths) and summarized by their principal components (PCs) for initial modeling. The variables within each group are listed in Table S2. Enough principal components were included to account for at least 55% of the variance in the data.

2.3.9.2. Model selection.

We modeled all yield and fruit quality data (percent dry weight and blossom end rot) with Bayesian generalized mixed effect models. Due to zero-inflated data, we used hurdle models for yields and blossom end rot (BER), while percent dry weight (PDW) was always non-zero and therefore did not require a hurdle. To pick a model family, we modeled the non-zero data from each outcome variable with gaussian, lognormal, and gamma families, using Bayesian leave-one out estimates of the expected log pointwise predictive densities to compare model fits. Gamma models showed the best fit for each outcome variable and were therefore used for all linear models.

2.3.9.3. Model structure.

In addition to the variables of interest, each model had a random effect of field and block within field. Yields were modeled using the total marketable fruit weight harvested from each plot at each harvest point, while BER was modeled using the proportion of fruits that were classified as non-marketable due to BER from each plot at each harvest point. Yield models and BER models treated weekly harvests as repeated measures, adding random effects of plot within block and harvest number. For hurdle models, random effects were treated as correlated between the conditional and hurdle portions of the model.

Because PDW was measured at three time points, the initial PDW model treated the timepoints as a repeated measure and added a random effect of plot within block. However, given the nonlinear relationship between PDW and fruit quality described by farmers, further models used only PDW at the 6th harvest when fruit quality was at its peak and therefore did not include any repeated measures.

2.3.9.4. Variable selection.

The initial model for each outcome variable included plant spacing and PC1 for soil texture (both field-level effects), along with PC1 for GWC and PCs 1 and 2 for nutrients at all four depths (all plot-level effects), as well as the interaction between texture and GWC. In this initial model, only one depth showed a statistically clear relationship with each outcome variable (marketable yield, proportion BER, and PDW).

To improve model interpretability, we then replaced the two PC's from the depth of interest with the scaled transplant values of nitrate, ammonium and phosphate at that depth, also adding the ratio of nitrate to ammonium and an ammonium-squared term to allow for nonlinearities in outcome response to nitrogen levels. Because all nutrient variables (both the remaining PC's and raw values from the depth of interest) had variance inflation factors over 5 in this model (calculated by running the hurdle gamma model mixed effect model with the `glmmTMB` package[56] and checking variance inflation on this model with the `performance` package), we dropped nutrient PC's for each depth that was not of interest, leaving only the transplant nutrient values at the depth of interest in the model. All nutrient VIF values were below 5 in the resulting model. Reported models were run using unscaled nutrient values for ease of interpretation.

Transplant nutrient levels were used rather than midseason/harvest both because they are the most relevant to farmer management and because their interpretation is more clear than later timepoints, when low levels can either indicate lower initial nutrient levels, or that plants have more thoroughly depleted those nutrients.

2.3.9.5. Adding fungal community correlates to yield and fruit quality models.

Two fungal community descriptors were calculated for each soil depth and root fungal community: the Shannon index and the count of OTUs in the class Sordariomycetes, which was identified as an indicator of dry farm soils (see Results). Counts were scaled, and both community descriptors were added to the final model described in the "Variable selection" section to determine the impact of fungal community structure while controlling for water, nutrients, and texture. Because the metrics between roots and the two depths of soil fungal communities were highly correlated, three separate models were run: one with both fungal community metrics from 0-15cm, one with metrics from 30-60 cm, and one with root community metrics.

2.3.9.6. Priors.

Weakly informative gaussian priors (mean = 0) were chosen for each fixed effect such that, for 90% of the distribution of potential coefficients, a change from the minimum to the maximum value observed for the variable of interest would correspond to a change in the outcome variable no larger than its full observed range. In other words, priors were specified such that 10% of the distribution of potential coefficients would lead to larger changes in the outcome variable than what we observed in our dataset. Priors for random effects were student t distributions (df = 3, mu = 0, sigma = 2.5), as designated by `brms` package defaults.

For the hurdle portion of the model, when included, priors were set such that 90% of coefficients in the distribution (gaussian mean = 0 for fixed effects, student t for random effects) would lead to a difference in log odds of a non-zero outcome less than or equal to 4.

2.4. Results

2.4.1. Harvests.

Fruit harvests lasted 10-20 weeks and tended to peak 3-5 weeks after the first harvest (Figure 2A). These peaks coincided with when fruit quality was at its highest, as identified by farmers in the study and measured by fruit percent dry mass (optimal range is 8-12% dry mass by weight; Figure beat B). The cumulative marketable harvest for an individual field ranged from 6.5 - 88.5 T/ha, or 1.5 - 4.5 kg/plant, with a mean of 34 T/ha and 2.6 kg/plant. Over the course of the season, on average 4.7% (sd = 11%) of the fruits harvested from each experimental plot were unmarketable due to blossom end rot (Table 5).

2.4.1.1. Model results.

After preliminary modeling with principal components (see Methods and Supplement), we determined that nutrients at 60-100cm had a statistically meaningful influence on yields and PDW, while nutrients at 30-60cm showed an influence on BER. We then regressed inoculation and nutrient levels from these depths of interest against each harvest outcome variable–yields, proportion BER and percent dry weight–while controlling for other soil and field characteristics (GWC, plant spacing, and texture), as well as random effects; see Table 6 and "model structure" above.

We also added two fungal metrics (Shannon diversity and Sordariomycetes counts, each at 0-15cm, 30-60cm, and in roots) to each model (see 'fungal community' below). Sordariomycetes counts at 30-60cm, a signature of dry farmed soils, showed a clear relationship with fruit quality, after controlling for all variables in Table 6 (see Table 7). Full results for each model can be found in the supplement.

Where indicated, significant and positive coefficients in the hurdle portions of models signify that the outcome is more likely to be zero. Specifically, BER was less likely to occur in plots with higher ammonium levels (in the regression with proportion of fruits with blossom end rot), and Sordariomycetes counts were associated with plots where no marketable tomatoes were harvested on a given day (in the marketable yield regression).

2.4.1.2. Yields.

Squared transplant ammonium concentrations at 60-100cm showed a clear negative relationship with yields (95% CI = [-0.24, -0.06]), while nitrate concentrations at 60-100cm showed a significant positive relationship (95% CI = [0.03, 0.20]). The hurdle term on Sordariomycetes counts indicates that yields on a given harvest day are more likely to be zero in plots with higher Sordariomycetes counts (95% CI = [0.35, 3.01]); however, given the low incidence of plots with zero yield (<2%), this result is unlikely to influence cumulative yields for a field.

Given the signs of the water and texture principal components, the positive water by texture interaction indicates that combined high soil GWC and low clay content are associated with increased yields (or low soil water and high clay content, which is exceedingly unlikely given the study system). Or, put another way, lower clay content can be beneficial when soil water levels are high enough.

2.4.1.3. Blossom end rot.

Squared ammonium concentrations at 30-60cm were associated with a decreased likelihood of BER being present in a plot (95% CI = [0.14, 0.85]). No fungal metrics showed a clear relationship with BER.

2.4.1.4. Fruit percent dry weight.

Fruit percent dry weight (PDW), a proxy for fruit quality, increased from the first harvest to the ninth harvest (95% CI = [0.01, 0.13]; Figure 2B). Due to the non-linear relationship between PDW and fruit quality (quality increases up to ~10%, while beyond ~12%, quality decreases with increasing PDW), only PDW data from the 6th harvest was considered in further models, when farmers reported the highest fruit quality and no field averaged above 12%. Squared ammonium concentrations at 60-100cm showed a clear positive relationship with PDW (95% CI = [0.01, 0.07]). In a separate model where scaled marketable yield at 6th harvest was added as a covariate (along with the covariates listed in Table 6), it showed a clear negative correlation with fruit quality (95% CI = [-0.12, -0.01]). The Sordariomycetes count at 30-60cm was positively associated with higher fruit quality (95% CI = [0, 0.06]).

2.4.1.5. Effect of inoculation.

Inoculation was associated with lower fruit quality (95% CI = [-0.09, 0.00]), with inoculated plots showing decreased fruit percent dry weight at the sixth harvest. Inoculation did not have a statistically clear relationship with yield or blossom end rot.

A power analysis conducted before the study using variances from data collected the previous summer suggests that our experimental design could detect an inoculation effect size of ~15% of a measured value (e.g. yield) with a power of 0.8 (see supplement for details). We therefore conclude that, given our null results, it is improbable that inoculation changed yields by more than +/-15%, and the small confidence intervals centered on zero for inoculation coefficients in yield models suggest that the true effect was likely less than that if present at all.

2.4.2. Nitrogen management.

Ammonium concentrations showed a nonlinear relationship with yields in our models, with yields peaking at roughly 1 ug ammonium-N/g soil, especially when high levels of nitrate were present. Nitrate was associated with increasing yields across all ammonium levels. See Figure S2 in supplement for further details.

Though these models indicate that yields are highest at the highest observed nitrate concentrations in the study, it is important to caution against nitrate maximization. Nitrate entering groundwater at a rate of 35 kg/ha/yr is the threshold at which concerns begin to develop for groundwater contamination[57]. At the harvest sampling, three of the seven fields had nitrate levels in the top 15cm of the soil alone that were above this threshold (Figure S3).

2.4.3. Fungal community.

After using scaling with ranked subsampling[58] to reduce the number of counts in each sample to 7190, we found 13,586 fungal taxa across all samples. Of these, 725 were classified as AMF (in the phylum Glomeromycota). Field was the primary force behind community composition in soils and roots (R^2 of field was 0.12 in PERMANOVA of soil fungal communities dissimilarities with main effects of field, GWC, depth, and texture, while next largest R^2 was 0.02 for texture), as is visually apparent in principal coordinates analysis (Figure 3). Field was therefore used as strata in all further PERMANOVAs. Phylum level relative abundance is shown for each field in Figure 4.

2.4.3.1. AMF and inoculation.

Of the AMF taxa that were identified to the species level in soils and roots, none was a species present in the inoculum. After removing samples that did not contain any AMF taxa, PERMANOVAs using Bray distances showed a statistically clear difference between community composition in inoculation vs. control roots ($p < 0.05$, 9999 permutations) but not bulk soils ($p = 0.99$) when stratifying by field and controlling for water, nutrients, and texture. No AMF taxa were significantly enriched in the inoculation or control condition. Taken together, these AMF community results suggest that the inoculum (or the medium in which it was delivered) shifted the root fungal community at transplant and did not persist in bulk soils for the 9 weeks before DNA samples were taken.

2.4.3.2. Non-cultivated, dry farm, and irrigated soils.

A PERMANOVA using Bray distances showed statistically clear differences in fungal community composition in irrigated, dry farm, and non-cultivated bulk soils as well as communities at 0-15cm and 30-60cm ($p < 0.0001$ for both, 9999 permutations) when stratifying by field and controlling for water, texture and their interaction, which also significantly differentiated between communities ($p < 0.0001$, 0.004, and 0.003 respectively, 9999 permutations). Though dry farm, non-cultivated and irrigated soils each had (or in the case of irrigated soils, nearly had) more unique taxa than taxa shared with another location, dry farm and non-cultivated soils each had nearly twice as many unique taxa as taxa shared with a single other location, while irrigated soils had more taxa shared with dry farm soils than unique taxa (Figure 5).

Abundance analysis showed that there were 466 taxa that significantly discriminated (were enriched or depleted) between the three soil locations. We then set the LDA threshold to 3.75 to highlight only the most stark differences, resulting in 13 discriminative taxa (Figure 6). All of the taxa identified as being enriched in dry farm soils were sub-taxa of Sordariomycetes, a fungal class that is highly variable in terms of morphology and function. We therefore identified Sordariomycetes as a dry farm indicator taxa, or a sort of dry farm "signature". We included the Sordariomycetes count in models as an indication of how much the soil had shifted towards a dry farm-influenced community (see below).

AMF taxa were notably absent as discriminative taxa and PERMANOVA did not show a difference in AMF community composition between the two depths, suggesting that AMF are not limited in their dispersal down to 60cm[59].

2.4.3.3. Sordariomycetes.

After identifying Sordariomycetes as an indicator taxa for dry farming, we further explored whether multiple years of dry farming enhance soils' dry farm signature by comparing fields that had not received external water inputs (4 fields, one dry farmed, three fallow in the previous summer season) for multiple years and those which had received regular external water inputs the summer prior to the study. The extent to which Sordariomycetes were enhanced was measured by the difference between counts in dry farm and irrigated soils in the study year (Figure 7A). We found that fields that had not received regular external water inputs the previous year showed a significantly higher difference in Sordariomycetes counts between dry farm and irrigated soils (Figure 7B), indicating that multiple years without irrigation enhance a soil's dry farm signature.

2.5. Discussion

On-farm research across seven commercially managed dry farm fields allowed us to observe tomato, nutrient and soil fungal community dynamics in situ, opening a window into how dry farm systems function on working farms. Given the long-term specialized management that farmers have tailored to their dry farm practice and fields, this on-farm approach facilitated results that reflect this management paradigm across the region and are therefore broadly applicable to dry farm management choices and outcomes on the Central Coast of California.

2.5.1. Yields.

Marketable yields per plot (and per plant) surprisingly did not correlate with plant spacing, which runs counter to current common wisdom in extension publications[18]. Because spacing ranged from 15-48 inches (38-122 cm) between plants (plant density ranged from 2700 - 21000 plants/ha; see bed spacing listed in Table 1), relatively consistent yields on a per-plant basis (1.5-5.3 kg/plant) contributed to a wide range in yields on a per-area basis (6-89 T/ha).

As there are very few irrigated tomatoes in the Central Coast region due to its cool, moist climate, it is difficult to compare dry farm yields to what might be found in an irrigated system in the same region. However, in 2015 (the most recent year for which data are available), the statewide average fresh market tomato harvest was 39 T/ha, a number that is surprisingly on par with the average dry farm yield in this study (34 T/ha, see Table 5). Because there is a clear tradeoff between yield and fruit quality–the highest yielding fields also had the lowest fruit quality, and increasing ammonium concentrations improve fruit quality while lowering yields–it may be difficult to increase yields above the state average while still charging consumers a premium for dry farm quality. Growers can currently charge roughly double the price per kg for dry farm-quality compared to irrigated tomatoes; therefore, short of doubling yields, current dry farmers may be reluctant to shift management to maximize yield over quality. However, these high yields do open the possibility that dry farm management could expand to industrial-scale markets that do not rely on consumer trust in high quality produce, competing instead with irrigated production if larger scale farmers adopt dry farm practices while choosing to intentionally manage for yields over quality.

2.5.2. Soil nutrients.

Only soil nutrients at 30-60cm depth showed correlations with BER, while marketable yields and fruit percent dry weight were only influenced by nutrients below 60cm. Specifically, ammonium concentrations were associated with increased fruit quality (as measured by percent dry weight) but decreased yields and incidence of blossom end rot, while nitrate was associated with increased yields.

Because soils dry down quickly in dry farm fields–available water content on average decreased by 65% in the top 30cm from transplant to midseason, while decreasing by only 16% below 60cm (see Figure S4)–plants likely devote rooting efforts to exploring deeper soils that are not too dry for efficient nutrient acquisition. Farmers also make an effort to plant transplants as deeply as possible, quickly delivering roots to depths below 30 cm. Though tomatoes root adventitiously from their stems and can therefore send out roots at shallower depths, rapidly drying surface soils likely limit nutrient uptake by adventitious roots, directing resources instead towards deeper rooting.

The importance of soil nutrients at transplant at 30-60cm in predicting BER incidence, as compared to 60-100cm for yields/quality, suggests that calcium uptake (which is implicated in BER development[60]) occurs at an earlier stage of plant development when a higher proportion of roots were likely present at 30-60cm (and soils were wet enough for roots to extract nutrients; soils at 30-60cm on average had 4 cm of plant available water at the midseason sample, which roughly coincided with flowering/fruit set, while they had only 2 cm of water at first harvest). Roots likely concentrated more heavily in deeper soils during fruit set and development, causing only nutrients below 60cm to show a relationship with fruit yields and PDW.

Our results also show a surprising relationship between transplant ammonium levels and fruit yields/quality. Though ammonium levels are quite low below 30cm (<5 ug N/g soil in all but one field), their negative association with yields suggests that either these low ammonium concentrations were still able to inhibit calcium/water uptake and further stress plants, as seen in studies with higher ammonium concentrations[61,62], or that higher transplant ammonium levels were indicative of other soil circumstances that negatively impacted yields. One possibility is that wetter (but not waterlogged) transplant soils led to higher rates of nitrification, causing decreased ammonium levels and also higher yields due to increased water availability. While GWC was included in our models and was not significant, ammonium concentrations could in some ways be a better indicator of water availability than GWC if they more fully reflect the conditions (e.g. soil texture, organic matter content, aggregate stability) that lead to nitrification. Transplant ammonium also showed a significant positive correlation with clay content ($p < 0.03$; expected given that clays increase CEC and SOM tends to be higher in clays, leading to more microbial activity). It is possible that, within the range of textures seen in this study, plots with higher clay content at depth inhibited plants' ability to root deeply or led to decreased plant available water. This possibility is supported by the water x texture interaction that links plots with low clay and high GWC to increased yields. We note that the plots with the highest ammonium levels were all from one field (Field 5), which exerted a strong influence on results; however, excluding Field 5 from analyses does not change the direction of nutrient coefficients, or the depth at which nutrients show a significant relationship with these outcomes. Additional research is needed to understand the unexpected relationship between ammonium concentration and harvest outcomes found here.

Because nitrate levels correlate positively with yields and do not show a statistically clear relationship with BER or fruit quality, it may be tempting to conclude that farmers should increase nitrate availability in dry farm soils. However, risk of nitrate leaching must be taken into account, especially in this agricultural region that suffers from severe nitrate pollution of groundwater[63,64]. Three of the seven fields in our study had nitrate levels at harvest—in just the top 15cm—above the threshold (35 kg N/ ha) considered likely to cause groundwater contamination if that nitrate were to fully leach out of the rooting zone when it mobilizes in the first large rain event of the fall/winter wet season. These levels would likely be further accentuated by the Birch effect as soils are rewetted[65]. Because this first rain event typically occurs after plants are terminated, or is the terminating event itself, these systems may be particularly prone to nitrate loss when living roots are not present in the soil to recapture it. Though careful cover crop management, which is practiced by all of the farms in this study, can likely attenuate leaching, decisions to fertilize should be made with caution.

Taken together, these results highlight two core challenges for dry farmers. First, there is a tension between fruit quality and yields, with conditions that lead to high yields decreasing fruit quality and vice versa. Second, it is difficult to manage soil fertility deep in the soil profile, especially when nutrients are prone to leaching.

2.5.3. Fungal communities.

2.5.3.1. Inoculation.

While a commercial AMF inoculant applied at tomato transplant changed AMF community composition in roots, it did not provide any benefit to yield outcomes, if anything lowering fruit quality. Diversified farm management (cover cropping[66–68], crop rotation[69,70], etc.) likely made AMF communities in these soils more diverse with higher spore counts than would be seen in more industrialized systems. Altering the AMF community through inoculation may have disrupted (in the case of fruit quality) or simply not altered functions that the endogenous community was as well or better-equipped to provide[71–74]. This result has been seen repeatedly in field research, where commercial inoculants often fail to impact agriculturally relevant outcomes[75,76], or local AMF communities outperform exogenous ones[77–79]. It is also possible that, while the inoculum established enough to shift the AMF community and lower fruit quality, inocula generally will not have a large influence on dry farm tomatoes given that they are applied to surface soils while plants focus on deeper rooting, or that the specific species in the inoculant we used were not well-suited to this system[80].

From a conceptual standpoint, there has been considerable debate in recent decades over how to best maintain agricultural productivity while also achieving systems that can maintain long-term productivity through resilience to environmental stress[81,82]. These conversations often pivot around the idea of replacing industrial input-intensive agricultural practices with ecologically-based, knowledge-intensive systems[83]. These ecologically-based systems are typically depicted as relying on on-farm biological diversity as a mechanism for increasing crops' resilience to environmental conditions, whereas industrial systems are maintained with off-farm inputs.

Even as biological diversification enters the agricultural ethos, there continues to be a pull towards achieving these biological outcomes through off-farm inputs. We typically think of chemicals (e.g. pesticides) and energy (e.g. fossil fuels) as the off-farm additions to conventional systems; however, products that mimic the biological effects of diversification practices (e.g. natural enemies to suppress pest populations) can similarly be introduced from external sources rather than fostered on the farm[84–86].

AMF inoculation is a prime example of how biological outcomes might be realized via external inputs. While AMF inoculation has indeed shown some benefit in more industrially managed systems[87–90], in the present study we observe that in a more diversified system, augmenting a field's endogenous AMF community does not improve plant outcomes. Rather than replacing one external input (in this case irrigation water) with another (AMF inocula), we find that farmers who already practice diversified management will likely have better luck pairing local climatic conditions with locally-adapted microbial communities.

2.5.3.2. Soil location and management.

More broadly, the full fungal community in dry farm, irrigated, and non-cultivated soils were distinct, indicating different selective pressures in each soil condition. Irrigation seems to be a filter on agricultural soils, resulting in a smaller community that overlaps substantially with dry farm soils. Given that in this study only tomatoes were present in dry farm soils, while crops on irrigated soils varied from field to field, we likely overestimate the diversity of irrigated soils relative to dry farm, making this community shrinkage in irrigated soils even more pronounced. While fungal community responses to drought vary widely in the literature[21,22,91], there is precedent for deficit irrigation shifting bacterial communities in processing tomato fields[20], and natural experiments with drought conditions have led to increased fungal diversity in cotton rotations[92]. This lower fungal diversity in irrigated systems may be driven by lower soil temperatures that are less conducive to fungal growth[92], or directly linked to changes in fungal competition induced by water stress[91] that enhance diversity in dry farm systems.

On the other hand, agricultural soils (dry farm) and non-cultivated soils seem to be distinct communities with roughly equal magnitudes of taxa numbers despite high levels of disturbance that might act as a narrowing selective pressure. Dry farm fungal diversity may be caused by external inputs (e.g. compost, crop residue) that introduce non-endogenous taxa to cultivated soils.

Dry farm soils were not only distinct from the other soil locations, but consistently enriched in taxa in the class Sordariomycetes. These indicator taxa formed a dry farm "signature" that was not only present in dry farm soils, but increased in magnitude in soils that had gone multiple years without external water inputs. This signature showed positive associations with fruit quality outcomes, which is of particular importance to farmers in this quality-driven system. Sordariomycetes were also associated with an increased likelihood that a plot would not have any marketable tomatoes on a given harvest day; however, as this was a rare occurrence that happened almost exclusively in the first/last weeks of harvest when yields were low for all plots, we do not expect that farmers will see an association between Sordariomycetes and yield declines. If anything, farmers may notice a slight truncation of harvest season duration in fields that have been dry farmed for several years. Sordariomycetes themselves may not be causing these outcomes, but rather point to the fact that soil microbial communities–possibly including bacteria and other microorganisms in addition to fungi–are consistently adapting to dry farm management. Sordariomycetes enrichment may indicate other community shifts that are ultimately the cause for enhanced fruit quality.

It is also possible that Sordariomycetes themselves are improving dry farm outcomes. Endophytes in the Hypocreales class, which was enriched in dry farm fields, are known to increase drought resistance and decrease pest pressure in their hosts[93], though none of the specific species known to exhibit this behavior (e.g. Trichoderma[94]) were enriched in dry farm soils. On the other hand, Nectriaceae, the family that contains the Fusarium genus, was found to be enriched, though similarly no known pathogenic species were enriched in dry farm soils.

2.5.4. Caveats and limitations.

Our study explored dry farm management practices and their influence on soil nutrient and fungal community dynamics in 7 fields throughout the Central Coast region of California, allowing us to explore patterns across a wide range of management styles, soil types, and climatic conditions. Though we were able to sample from a large swath of contexts in which tomatoes are dry farmed, we are also aware that conditions will vary year to year, especially as climates change and farmers can no longer rely on "typical" weather conditions in the region. While we are confident in the patterns we observed and the recommendations below, we also encourage further study across multiple years to better understand the full scope of the decision space in which dry farm growers are acting.

2.5.5. Management and policy implications.

Given the scope of our current findings, we outline several management and policy implications for dry farmers and dry farming. Though we aim these implications towards the context of dry farm tomatoes in coastal California, we expect that they are likely to generalize to other dry farm crops grown in other regions with Mediterranean climates.

First, given the expense and possibility that it is detrimental to fruit quality, we do not advise AMF inoculation for dry farm tomato growers. Second, we note the importance of nutrients below 60cm and the complexities of subsurface fertility management, and we recommend experimentation with organic amendments and deeply rooted cover crops that may be able to deliver nutrient sources that persist at depth, as well as planning several seasons in advance to build nutrients deeper in the soil profile.

Finally, given our finding that dry farm soils develop a fungal signature that increases over time and its association with improved fruit quality, we encourage farmers to experiment with rotations that include only dry farm crops (e.g. winter squash, dry beans, potatoes) and even consider setting aside a field to be dry farmed in perpetuity. However, fully dry farmed rotations currently do not exist, likely due to a lack of commercially viable options for crops to include in a dry farm rotation.

In order to experiment with potential dry farm rotations, as well as cover crops that can best scavenge excess nitrates and soil management regimes that can increase soil fertility at depth, farmers must be given both research support and a safety net for their own on-farm experimentation. Funding to mitigate the inherent risk in farmers' management explorations will be key in further developing high-functioning dry farm management systems. Expanding land access to farmers who are committed to exploring dry farm management can additionally benefit these explorations.

2.6. Conclusion

Dry farm tomato systems on the Central Coast point to key management principles that can both help current growers flourish and provide guidance for how irrigation can be dramatically decreased in a variety of contexts without harming farmer livelihoods. In these systems, managing nutrients at depth–at least below 30cm and ideally below 60cm–is necessary to influence outcomes in fields where surface soils dry down quickly after transplant. Fostering locally-adapted soil microbial communities that are primed for water scarcity can improve fruit quality. Farmers can otherwise manage nutrients to maximize either yields or quality, giving latitude to match local field conditions to desired markets.

As water scarcity intensifies in California agriculture and around the globe, dry farm management systems are positioned to play an important role in water conservation. Understanding and implementing dry farm best management practices will not only benefit fields under strict dry farm management, but will provide an increasingly robust and adaptable example for how farms can continue to function and thrive while drastically reducing water inputs.

2.7. Acknowledgements

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2.9. Figures

Figure 1. Sample experimental layout for one field. Seven total fields were included in the study.

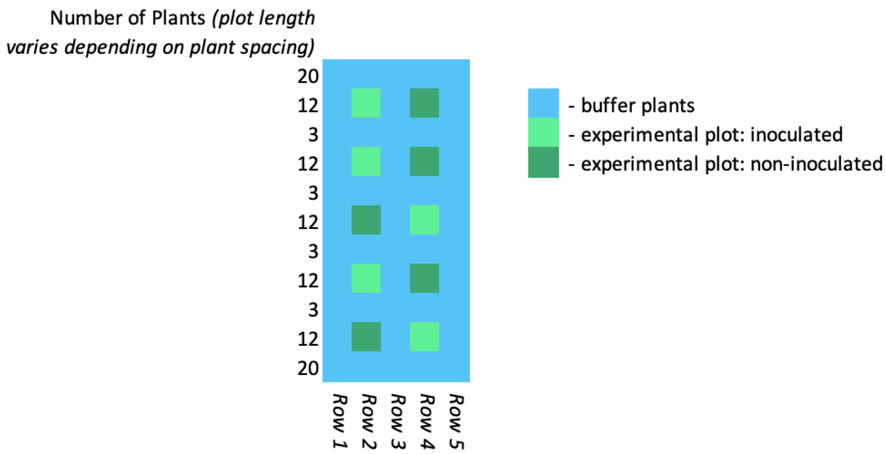
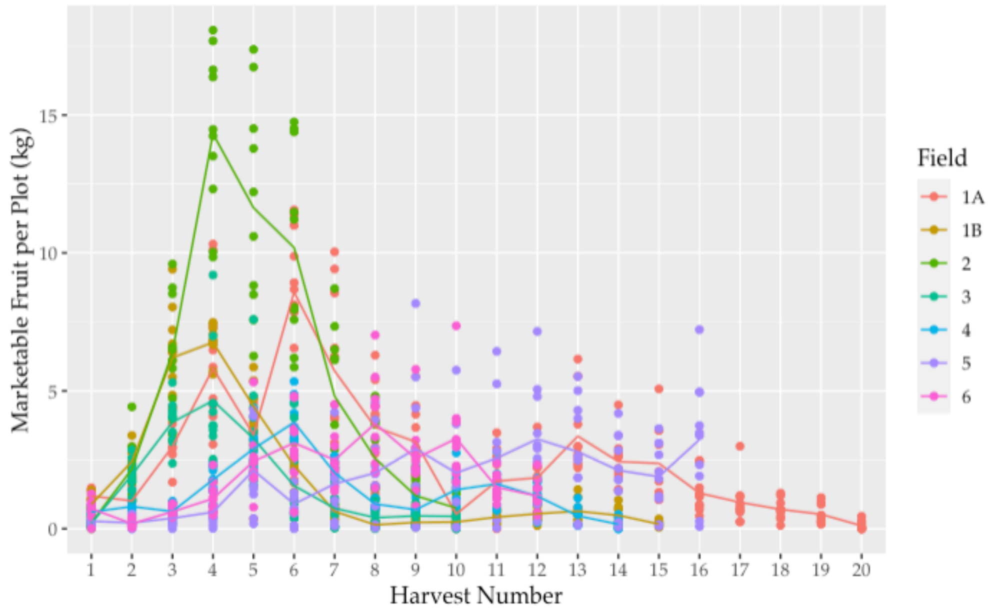
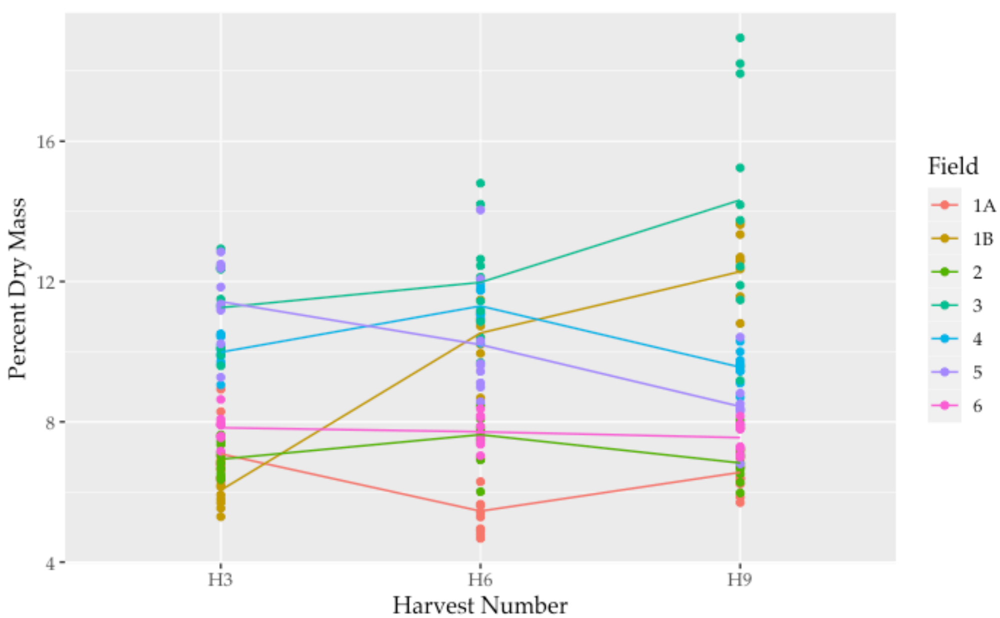


Figure 2. Harvest outcomes. Marketable fruit yield (kg per experimental plot) in weekly harvests are shown in (A). Tomato fruit quality in each experimental plot as measured by percent fruit dry matter (g dry mass/g fresh fruit) are shown in (B).

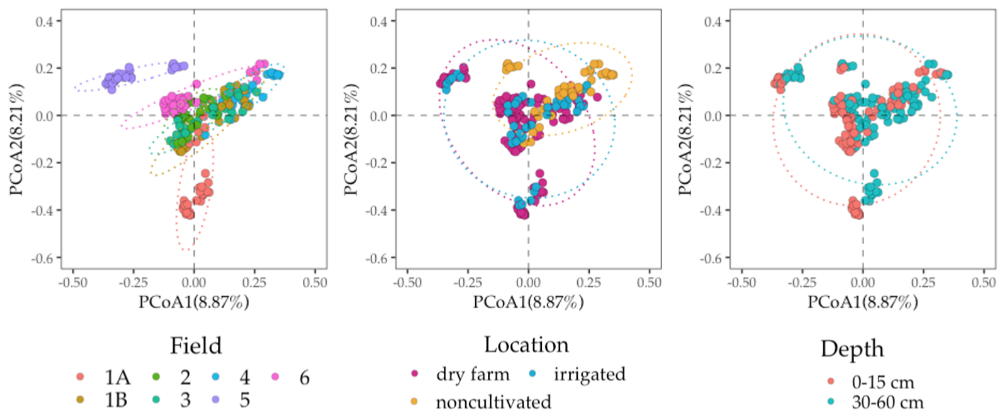


A.

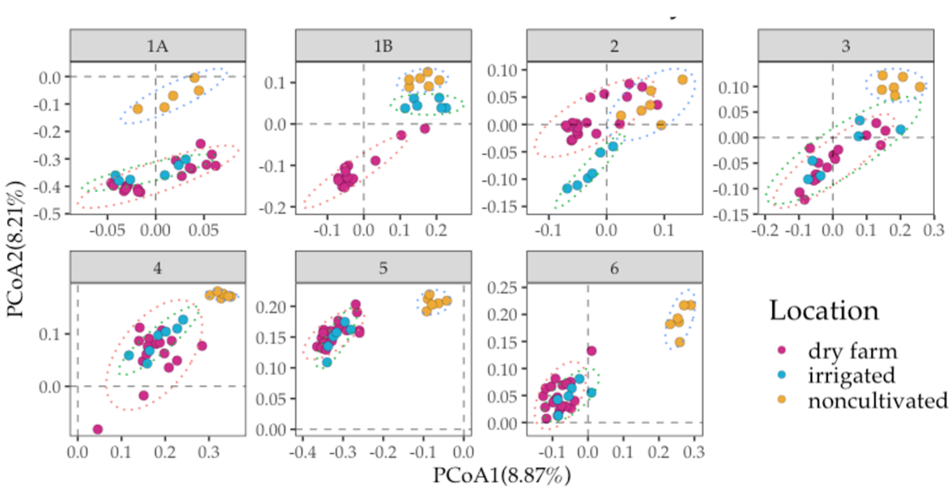


B.

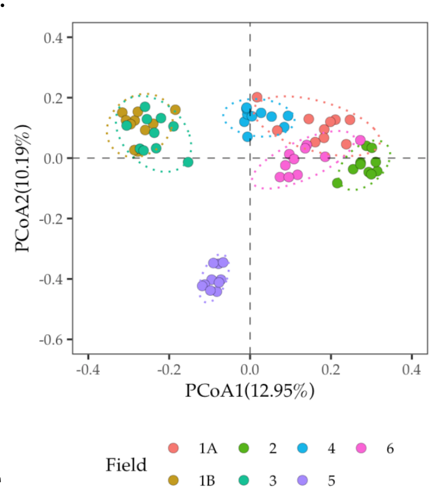
Figure 3. Principal coordinate analyses of bulk soil and root communities. The same PCoA is shown for each panel in (A), which represents the fungal community in each bulk soil sample that was collected as a single point, positioned by its similarity to the fungal community in other samples. Each sample is colored by a different attribute in the three panels: field, location, and depth. Each field is shown separately in (B), and colored by sample location. Root fungal communities are shown in (C).



A.



B.



C.

Figure 4. Relative abundance of phyla in each field for bulk soil (A) and roots (B). Note the low relative abundance of Glomeromycota (the phylum containing AMF) in both bulk soils and roots.

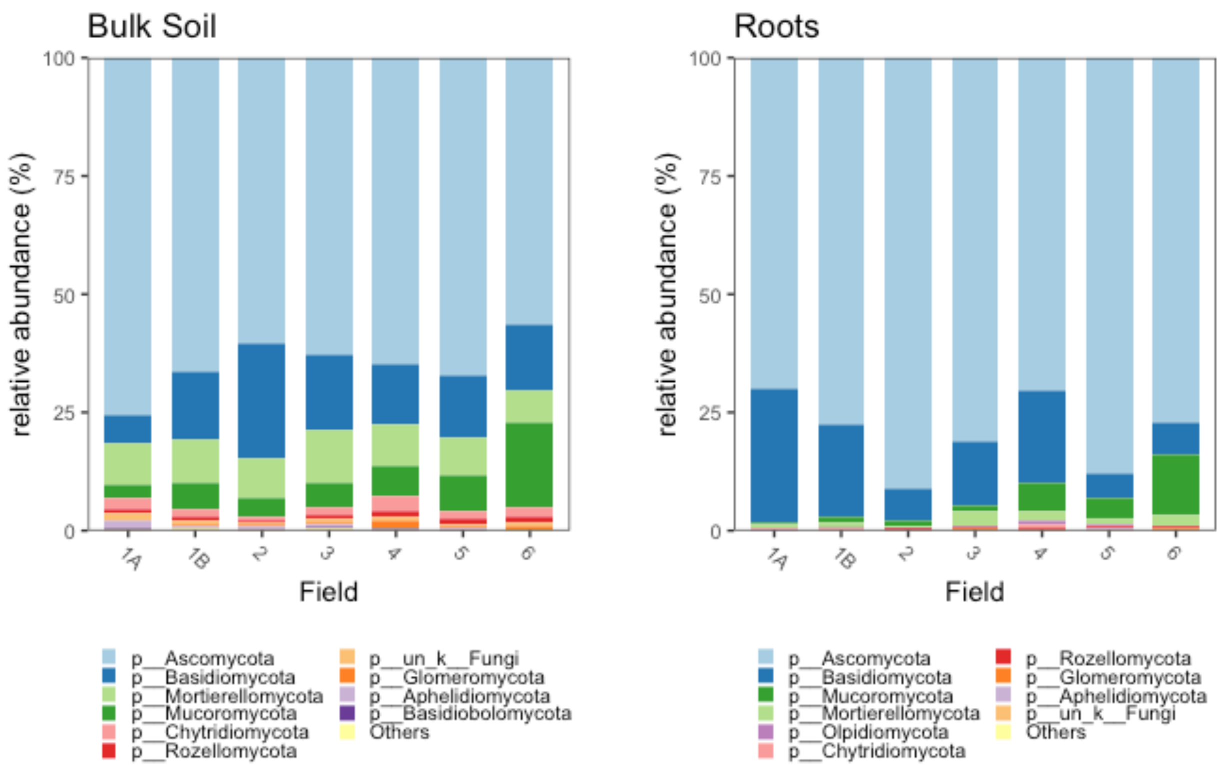


Figure 5. Venn Diagram depicting the number of distinct OTUs shared between each soil location for all bulk soil samples.

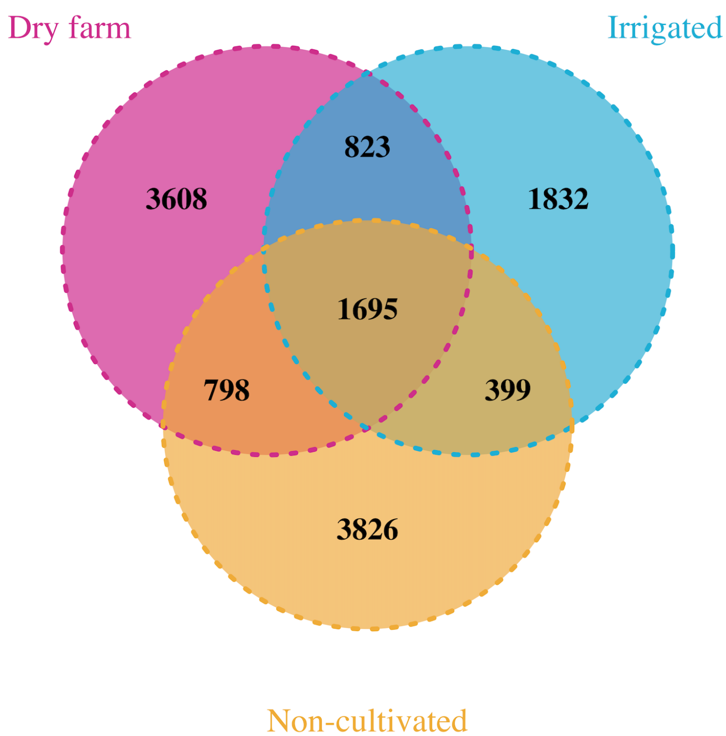


Figure 6. Taxa found to be significantly enriched in either dry farm, irrigated, or non-cultivated bulk soil through differential expression analysis. Of the 466 significantly discriminative taxa, only those where the log of the linear discriminant analysis score was greater than 3.75 are shown. Lefthand panel shows relative abundance of the taxa for each soil location, while righthand panel shows the magnitude of the difference between soil locations. Taxonomic level is denoted by the letter in front of the name. See Table 7 for yield outcomes associated with changes in Sordariomycetes relative abundance.

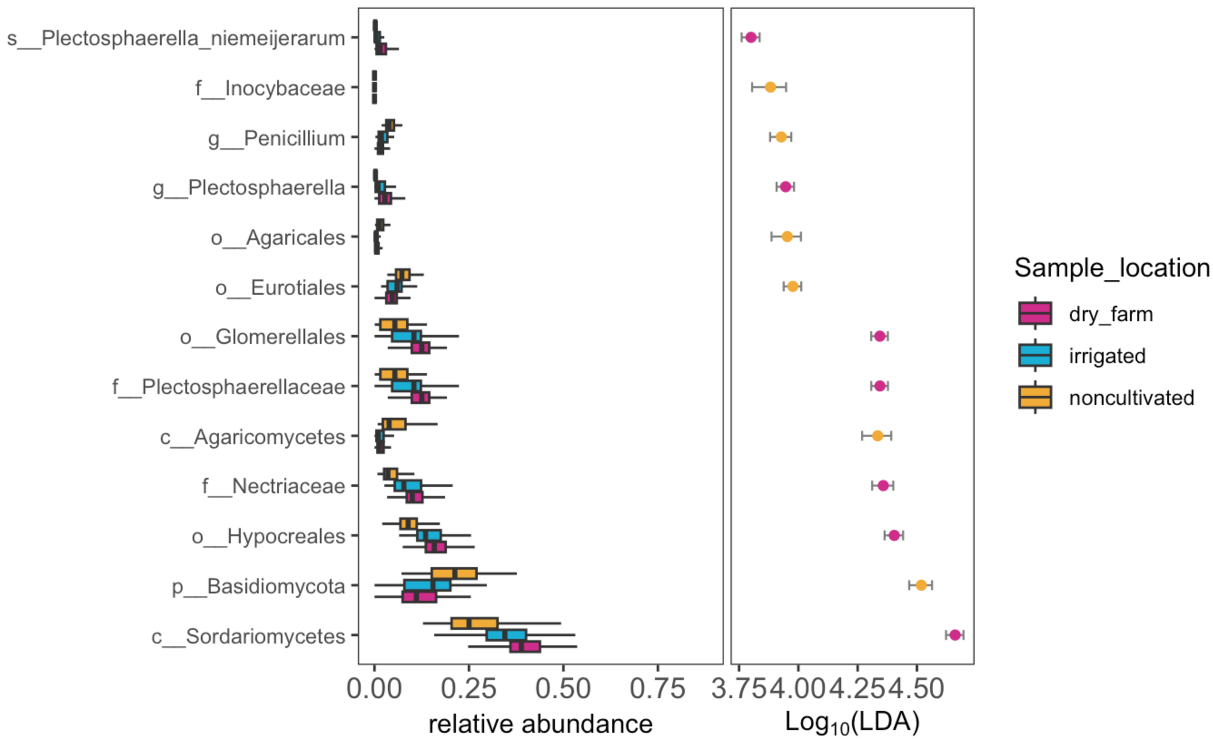
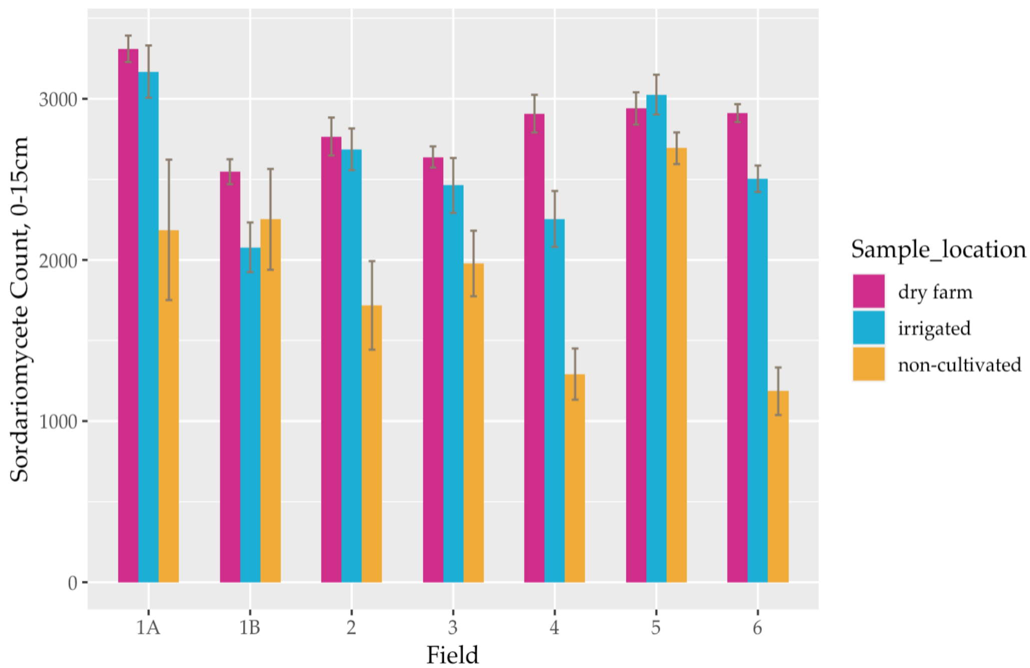
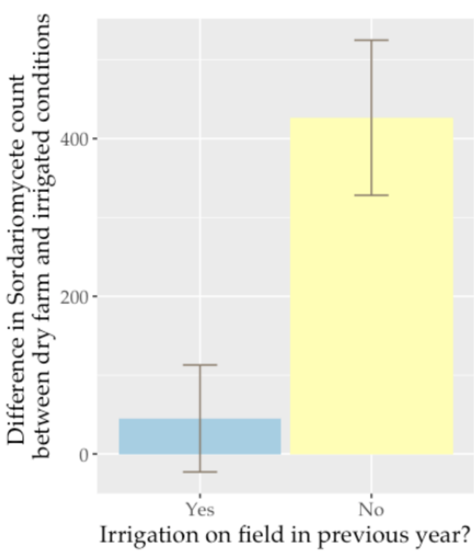


Figure 7. Sordariomyecetes counts in dry farm, irrigated, and non-cultivated soils on each field. For (B) there were 3 fields that received external water inputs in the previous year and 4 that did not.



A.



B.

2.10. Tables

Table 1. Field and planting characteristics on all farms. Where application rates are not listed, they were not known by the farmer.

Field	Plant Spacing (in)	Bed Spacing, center to center (in)	Plant date	Soil amendments
Farm 1A	15	50	3/2	Compost every other year (not applied in study year)
Farm 1B	15	50	3/25	Compost every other year (not applied in study year)
Farm 2	18	80	3/29	Compost (10-15 T/ac) Gypsum (2 T/ac) Feather meal 8-5-5- fertilizer
Farm 3	24	96	4/8	Compost (15 T/ac) Pelletized 8-5-1- fertilizer (.4 T/ac)
Farm 4	18	62	4/10	Pelletized 4-3-3- fertilizer
Farm 5	48	120	4/25	Compost (2 T/ac) Bone meal
Farm 6	21	72	5/17	Compost (5-10 T/ac) Pelletized 8-4-1 fertilizer (40 lb N/ac) Gypsum

Table 2. Crop rotation on each field.

Field	Summer crop 2 years prior	Summer crop 1 year prior	Field cover winter prior	Tomato variety	Crop planned for following year
Farm 1A	brassicas	eggplant	Cover crop (bell beans, vetch, peas, rye)	Early Girl	strawberry/sungolds
Farm 1B	tomato	tomato	Cover crop (bell beans, vetch, peas, rye)	Early Girl	tomato
Farm 2	strawberry	brassicas	Fall cover crop (buckwheat) / Winter crop (broccoli)	Early Girl	leeks/lettuce/beans/ summer squash
Farm 3	tomato	fallow	Cover crop (bell beans, vetch, peas, oats)	Early Girl	fallow
Farm 4	fallow	fallow	Cover crop (grass)	Early Girl	tomato
Farm 5	fallow	Mixed brassicas	Cover crop (peas, vetch, fava, rye)	New Girl	potato
Farm 6	Winter squash	fallow	Cover crop (legume mix)	Dirty Girl	onion

Table 3. Soil characteristics from each field. Soil series taken from the Web Soil Survey, soil texture and pH measured experimentally (see methods). Available water calculated using pedotransfer function from Román Dobarco et al., 2019, with analytical error calculated via running the same pedotransfer function using lower and upper 95% confidence limits for all model parameters.

Field	Soil series	Soil texture (0-30cm)	Soil pH in $CaCl_2$ at surface (0-15cm)	Available water in top meter of soil at transplant (cm)
Farm 1A	Elder	Sandy loam	6.9	22 ± 1.8
Farm 1B	Elkhorn	Sandy clay loam	6.7	22 ± 2.1
Farm 2	Elder	Clay loam	6.4	22 ± 1.9
Farm 3	Elkhorn	Sandy clay loam	7.0	19 ± 2.0
Farm 4	Aptos	Sandy clay loam	6.9	18 ± 2.1
Farm 5	Lockwood	Clay loam	6.1	21 ± 2.0
Farm 6	Elkhorn	Loam	6.5	11 ± 1.9

Table 4. Monthly weather totals for duration of experiment (first transplant to last harvest). Data taken from De Laveaga CIMIS weather station (centrally located between all farms).

Month	Total Precip (mm)	Total ETo (mm)	Avg Max Air Temp (C)
March	70	102	16.7
April	7	117	18.3
May	2	146	20.7
June	3	152	23.6
July	1	134	21.5
August	2	119	22.4
September	1	104	23
October	142	81	21.9

Table 5. Tomato yields and fruit quality for each field over the course of the 2021 growing season. Fruit percent dry weight is used as a proxy for fruit quality (optimal range 8% - 12%), and is shown at the 6th harvest when qualities tend to be at their peak.

Field	Cumulative marketable yield (T/ha)	Percent total harvest impacted by BER	Fruit percent dry weight at 6th harvest
Farm 1A	88.5	0.2	5.5
Farm 1B	45.6	1.3	10.5
Farm 2	48.6	4.9	7.6
Farm 3	9.8	15.3	12
Farm 4	22.0	18.6	11.3
Farm 5	6.5	3.3	10.2
Farm 6	19.6	0.1	7.7

Table 6. Variables in bold show a statistically clear relationship with the outcome variable. Depth of interest was identified as the only depth where nutrient principal components showed a significant correlation with the outcome variable in initial modeling. Hurdle coefficients are only shown when significant; full model results, including hurdle estimates and random effects, can be found in the supplement.

Outcome variable	Depth of interest	Fixed effect	Estimate	95% CI lower bound	95% CI upper bound
Marketable Yield	60 - 100 cm	Inoculation	-0.05	-0.20	0.09
		Plant spacing	0.10	-0.10	0.34
		Texture (PC1)	0.01	-0.91	0.89
		GWC (PC1)	0.11	-.03	0.25
		Texture x GWC	**0.05**	**0.00**	**0.11**
		Ammonium, 60-100cm	-0.07	-0.69	0.52
		Ammonium^2	**-0.15**	**-0.24**	**-0.06**
		Nitrate, 60-100cm	**0.11**	**0.03**	**0.20**
		Phosphate, 60-100cm	0.00	-0.02	0.01
		Nitrate to Ammonium ratio	-0.03	-0.02	0.01
Proportion of fruits with blossom end rot	30 - 60 cm	Inoculation	0.17	-0.14	0.49
		Plant spacing	0.01	-0.22	0.23
		Texture (PC1)	-0.15	-0.96	0.74
		GWC (PC1)	0.13	-0.11	0.39
		Texture x GWC	-0.04	-0.14	0.06
		Ammonium, 30-60cm	0.68	-0.64	1.93
		Ammonium^2	-0.07	-.035	0.21
		Nitrate, 30-60cm	-0.04	-0.22	0.14
		Phosphate, 30-60cm	0.00	-0.03	0.02
		Nitrate to Ammonium ratio	0.02	-0.11	0.15
		Hurdle Ammonium^2, 30-60cm	**0.50**	**0.14**	**0.85**
Fruit percent dry weight	60 - 100 cm	**Inoculation**	**-0.05**	**-0.09**	**0.00**
		Plant spacing	-0.01	-0.10	0.06
		Texture (PC1)	0.02	-0.32	0.37
		GWC (PC1)	-0.03	-0.07	0.01
		Texture x GWC	-0.01	-0.03	0.01
		Ammonium, 60-100cm	-0.10	-0.29	0.10
		Ammonium^2	**0.04**	**0.01**	**0.07**
		Nitrate, 60-100cm	-0.01	-0.03	0.02
		Phosphate, 60-100cm	0.00	-0.01	0.00
		Nitrate to Ammonium ratio	0.00	-0.02	0.01

Table 7. Fungal community metrics with a statistically clear relationship with the outcome variable when controlling for all fixed effects listed in Table 6 and random effects as described in "model structure" above. Due to high correlations between fungal metrics across community locations (soil at 0-15 and 30-60cm, and roots), separate regressions were run for each community. Sordariomycetes counts were scaled before being included in the regression.

Outcome variable	Fungal community metric	Estimate	95% CI lower bound	95% CI upper bound
Marketable Yield	Hurdle Sordariomycetes count, 0-15cm	1.57	0.35	3.01
Proportion of fruits with blossom end rot	n/a			
Fruit percent dry weight	Sordariomycetes count, 30-60cm	0.03	0.00	0.06

2.11. Supplementary information

Full model results

Marketable Yield (initial model with principal components to identify depth of interest)

```
Group-Level Effects: 
~Field_short (Number of levels: 7) 
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.48      0.41     0.02     1.54 1.00      581     1268
sd(hu_Intercept)                1.24      1.20     0.05     4.58 1.00     1398     1398
cor(Intercept,hu_Intercept)    -0.10      0.56    -0.96     0.93 1.00     3033     1921

~Field_short:block (Number of levels: 35) 
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.15      0.09     0.01     0.33 1.00      327      718
sd(hu_Intercept)                1.10      0.77     0.04     2.95 1.00      738     1204
cor(Intercept,hu_Intercept)     0.04      0.55    -0.91     0.95 1.00     1310     1551

~Field_short:block:Plot (Number of levels: 70) 
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.28      0.06     0.15     0.41 1.01      496     1261
sd(hu_Intercept)                1.60      0.78     0.17     3.37 1.00      800      650
cor(Intercept,hu_Intercept)    -0.58      0.31    -0.98     0.18 1.00     1064     1388

~harvest_number (Number of levels: 20) 
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.83      0.15     0.59     1.17 1.00      968     1494
sd(hu_Intercept)                1.65      0.46     0.93     2.68 1.00     2465     2614
cor(Intercept,hu_Intercept)    -0.76      0.19    -0.99    -0.30 1.00     1285     1246

Population-Level Effects: 
                       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                  0.35      1.25    -2.74     2.48 1.00     1185     1298
hu_Intercept              -8.13      7.09   -22.54     5.85 1.00     1568     1379
Inoc_longinoculated       -0.10      0.09    -0.28     0.08 1.00     2415     2564
plant_spacing              0.01      0.06    -0.09     0.14 1.00     1213     1265
tex_PC1                    0.27      0.19    -0.11     0.66 1.00     1687     1465
water_PC1                 -0.03      0.09    -0.20     0.15 1.00     1545     1556
nutA_PC1                  -0.03      0.07    -0.18     0.11 1.00     2043     1614
nutA_PC2                   0.06      0.09    -0.11     0.24 1.00     1461     1931
nutB_PC1                   0.04      0.06    -0.07     0.16 1.00     1952     1968
nutB_PC2                  -0.02      0.15    -0.30     0.28 1.00     2420     2240
nutC_PC1                  -0.09      0.09    -0.26     0.08 1.00     2103     2214
nutC_PC2                   0.12      0.08    -0.03     0.27 1.00     1979     2032
nutD_PC1                  -0.02      0.07    -0.16     0.12 1.00     2429     2436
nutD_PC2                  -0.64      0.13    -0.90    -0.40 1.00     1633     1804
tex_PC1:water_PC1          0.04      0.03    -0.02     0.11 1.00     1305     1686
hu_Inoc_longinoculated     0.83      0.94    -0.93     2.82 1.00     2651     1837
hu_plant_spacing           0.07      0.34    -0.63     0.74 1.00     1646     1561
hu_tex_PC1                -0.35      0.99    -2.41     1.55 1.00     2037     2024
hu_water_PC1              -0.02      0.65    -1.30     1.30 1.00     1891     1986
hu_nutA_PC1               -0.32      0.73    -1.77     1.11 1.00     2074     2163
hu_nutA_PC2                0.33      0.90    -1.57     2.08 1.00     2427     2090
hu_nutB_PC1               -0.85      0.96    -2.98     0.77 1.00     2911     2084
hu_nutB_PC2                1.73      1.57    -1.37     4.87 1.00     2215     1716
hu_nutC_PC1               -0.93      1.05    -3.13     0.98 1.00     2516     2319
hu_nutC_PC2               -0.16      0.91    -1.82     1.81 1.00     2321     2179
hu_nutD_PC1               -0.27      0.90    -2.11     1.48 1.00     2524     2106
hu_nutD_PC2                0.18      1.15    -2.01     2.48 1.00     2723     2306
hu_tex_PC1:water_PC1       0.07      0.25    -0.44     0.55 1.00     1759     1636

Family Specific Parameters: 
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape     1.38      0.06     1.26     1.50 1.00     4228     1954
```

Marketable Yield (final model, nutrients at 60-100cm)

```
Group-Level Effects:
~Field_short (Number of levels: 7)
                             Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                    1.40      0.66     0.53     3.05 1.00     1183     1090
sd(hu_Intercept)                 0.88      0.81     0.03     3.00 1.00     1753     1578
cor(Intercept,hu_Intercept)     -0.02      0.59    -0.95     0.95 1.00     2483     1832

~Field_short:block (Number of levels: 35)
                             Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                    0.08      0.06     0.00     0.21 1.00      689     1252
sd(hu_Intercept)                 0.91      0.62     0.04     2.33 1.00      813     1525
cor(Intercept,hu_Intercept)     -0.02      0.56    -0.95     0.92 1.00     1260     1465

~Field_short:block:Plot (Number of levels: 70)
                             Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                    0.18      0.06     0.04     0.30 1.00      421      303
sd(hu_Intercept)                 1.45      0.60     0.37     2.74 1.00      754     1022
cor(Intercept,hu_Intercept)     -0.62      0.33    -0.98     0.23 1.00      737      616

~harvest_number (Number of levels: 20)
                             Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                    0.84      0.16     0.58     1.19 1.00      556     1008
sd(hu_Intercept)                 1.66      0.47     0.91     2.71 1.00     1569     1892
cor(Intercept,hu_Intercept)     -0.76      0.19    -0.99    -0.28 1.00     1395     1429

Population-Level Effects:
                           Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                     -1.66      2.50    -6.94     3.19 1.00      880      993
hu_Intercept                  -7.99      4.87   -17.53     2.07 1.00     1540     1589
Inoc_longinoculated           -0.05      0.08    -0.20     0.09 1.00     2025     1856
plant_spacing                  0.10      0.11    -0.10     0.34 1.00      881     1046
tex_PC1                        0.01      0.43    -0.91     0.89 1.00      860     1132
water_PC1                      0.11      0.07    -0.03     0.25 1.00     2183     2048
nh4_TD                        -0.07      0.31    -0.69     0.52 1.00     1470     1833
nh4_sq                        -0.15      0.05    -0.24    -0.06 1.00     1658     2012
no3_TD                         0.11      0.04     0.03     0.20 1.00     1586     1869
T_OP_D                        -0.00      0.01    -0.02     0.01 1.00     2260     1613
nitrate_to_ammonium_TD        -0.03      0.02    -0.08     0.01 1.00     1516     1825
tex_PC1:water_PC1              0.05      0.03     0.00     0.11 1.00     1930     2226
hu_Inoc_longinoculated         0.97      0.80    -0.51     2.67 1.00     2639     1522
hu_plant_spacing               0.14      0.23    -0.33     0.61 1.00     1377     1641
hu_tex_PC1                    -0.89      0.73    -2.39     0.51 1.00     1692     1881
hu_water_PC1                  -0.26      0.51    -1.34     0.71 1.00     2011     1921
hu_nh4_TD                      0.53      2.78    -4.85     6.13 1.00     1850     2285
hu_nh4_sq                     -0.81      0.94    -2.97     0.60 1.00     1773     1503
hu_no3_TD                     -0.21      0.48    -1.15     0.74 1.00     1587     1843
hu_T_OP_D                     -0.03      0.05    -0.13     0.07 1.00     1831     1987
hu_nitrate_to_ammonium_TD      0.07      0.26    -0.52     0.54 1.00     1623     1507
hu_tex_PC1:water_PC1          -0.04      0.20    -0.44     0.34 1.00     1475     1298

Family Specific Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape     1.37      0.06     1.26     1.49 1.00     3155     1945
```

Marketable Yield (fungal metrics - 0-15cm)

```
Group-Level Effects:
~Field_short (Number of levels: 7)
                             Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                    1.35      0.66     0.54     3.04 1.00     1004     1663
sd(hu_Intercept)                 1.00      1.01     0.04     3.56 1.00      718      875
cor(Intercept,hu_Intercept)     -0.13      0.57    -0.96     0.91 1.00     1882     1681

~Field_short:block (Number of levels: 35)
                             Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
```

```
sd(Intercept)                     0.09      0.06     0.01     0.22 1.00      604     1407
sd(hu_Intercept)                  0.97      0.67     0.06     2.58 1.00      640     1011
cor(Intercept,hu_Intercept)      -0.13      0.58    -0.97     0.92 1.00      794     1679

~Field_short:block:Plot (Number of levels: 67)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                     0.21      0.07     0.07     0.33 1.00      664      891
sd(hu_Intercept)                  1.22      0.63     0.10     2.61 1.01      617      732
cor(Intercept,hu_Intercept)      -0.62      0.36    -0.99     0.39 1.00      907      999

~harvest_number (Number of levels: 20)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                     0.82      0.15     0.57     1.16 1.00      738     1599
sd(hu_Intercept)                  1.65      0.45     0.90     2.70 1.00     1830     2056
cor(Intercept,hu_Intercept)      -0.77      0.18    -0.99    -0.32 1.00      895      632

Population-Level Effects:
                          Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                    -1.01      2.58    -6.60     3.95 1.00     1005     1114
hu_Intercept                -12.50     11.51   -35.24    10.24 1.00     1989     1657
Inoc_longinoculated          -0.04      0.09    -0.21     0.13 1.00     2070     2358
plant_spacing                 0.10      0.10    -0.09     0.33 1.00      904      949
tex_PC1                       0.02      0.44    -0.93     0.84 1.00      902     1106
water_PC1                     0.11      0.08    -0.05     0.26 1.00     2153     2006
nh4_TD                       -0.09      0.35    -0.79     0.57 1.00     1152     1610
nh4_TD_sq                    -0.15      0.05    -0.25    -0.04 1.00     1469     1598
no3_TD                        0.12      0.05     0.02     0.21 1.00      993     1234
T_OP_D                       -0.00      0.01    -0.02     0.02 1.00     1566     1722
nitrate_to_ammonium_TD       -0.03      0.02    -0.08     0.01 1.00      943     1429
sor.count.A.scaled           -0.01      0.06    -0.12     0.10 1.00     1878     1605
shannon.A                    -0.15      0.26    -0.66     0.37 1.00     2139     2196
tex_PC1:water_PC1             0.05      0.03    -0.00     0.11 1.00     1393     1583
hu_Inoc_longinoculated        1.22      0.84    -0.39     2.95 1.00     2120     1968
hu_plant_spacing              0.20      0.28    -0.36     0.73 1.01     1025      795
hu_tex_PC1                   -0.94      0.72    -2.48     0.42 1.00     1348     1325
hu_water_PC1                 -0.31      0.50    -1.37     0.62 1.00     1364     1017
hu_nh4_TD                     0.12      2.46    -4.69     4.93 1.00     2181     1898
hu_nh4_TD_sq                 -1.10      0.97    -3.22     0.48 1.00     1586     1728
hu_no3_TD                     0.13      0.52    -0.87     1.18 1.00     1366     1439
hu_T_OP_D                    -0.06      0.05    -0.17     0.04 1.00     1502     1569
hu_nitrate_to_ammonium_TD    -0.08      0.28    -0.67     0.43 1.00     1374     1420
hu_sor.count.A.scaled         1.57      0.67     0.35     3.01 1.00     1905     1613
hu_shannon.A                  0.90      2.14    -3.43     5.18 1.00     2981     2288
hu_tex_PC1:water_PC1         -0.03      0.21    -0.44     0.39 1.01     1148     1143

Family Specific Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape     1.37      0.06     1.25     1.50 1.00     3451     2371
```

Marketable Yield (fungal metrics - 30-60cm)

```
Group-Level Effects:
~Field_short (Number of levels: 7)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                     1.31      0.67     0.43     3.05 1.00      857     1081
sd(hu_Intercept)                  0.87      0.80     0.03     2.98 1.00     1645     1520
cor(Intercept,hu_Intercept)      -0.02      0.58    -0.96     0.94 1.00     3232     1715

~Field_short:block (Number of levels: 34)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                     0.12      0.08     0.01     0.29 1.00      635     1459
sd(hu_Intercept)                  0.70      0.56     0.03     2.11 1.00     1379     1748
cor(Intercept,hu_Intercept)      -0.10      0.56    -0.96     0.94 1.00     1986     2046

~Field_short:block:Plot (Number of levels: 57)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
```

```
sd(Intercept)                    0.22      0.07     0.08     0.37 1.00      604      941
sd(hu_Intercept)                 1.42      0.62     0.36     2.81 1.00     1221     1109
cor(Intercept,hu_Intercept)     -0.61      0.33    -0.99     0.25 1.00     1143     1000

~harvest_number (Number of levels: 20)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                    0.78      0.15     0.53     1.11 1.00      773     1311
sd(hu_Intercept)                 1.60      0.50     0.78     2.71 1.00     1922     1613
cor(Intercept,hu_Intercept)     -0.72      0.21    -0.98    -0.20 1.00     1528     1675

Population-Level Effects:
                          Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                    -0.94      2.56    -6.08     4.24 1.00      681      554
hu_Intercept                 -7.53      5.56   -18.74     3.13 1.00     2105     2086
Inoc_longinoculated          -0.13      0.10    -0.33     0.06 1.00     2328     1929
plant_spacing                 0.08      0.11    -0.14     0.32 1.00      693      521
tex_PC1                       0.09      0.47    -0.85     1.02 1.00      703      569
water_PC1                     0.14      0.10    -0.05     0.33 1.00     1740     1743
nh4_TD                       -0.29      0.41    -1.10     0.50 1.00     1345     1777
nh4_TD_sq                    -0.11      0.06    -0.22     0.00 1.00     1556     1915
no3_TD                        0.11      0.06     0.00     0.22 1.00     1351     1967
T_OP_D                       -0.00      0.01    -0.02     0.02 1.00     2082     1957
nitrate_to_ammonium_TD       -0.04      0.03    -0.09     0.01 1.00     1347     1838
sor.count.C.scaled           -0.06      0.06    -0.19     0.06 1.00     2544     2345
shannon.C                    -0.01      0.07    -0.16     0.13 1.00     2340     2018
tex_PC1:water_PC1             0.04      0.03    -0.02     0.11 1.00     1740     2513
hu_Inoc_longinoculated        1.41      0.99    -0.40     3.47 1.00     3101     2351
hu_plant_spacing              0.01      0.26    -0.49     0.51 1.00     1777     1832
hu_tex_PC1                   -1.15      0.79    -2.79     0.33 1.00     1810     1839
hu_water_PC1                 -0.13      0.63    -1.42     1.09 1.00     1927     2010
hu_nh4_TD                    -0.83      2.53    -5.79     4.04 1.00     2572     2582
hu_nh4_TD_sq                 -0.39      0.80    -2.26     0.88 1.00     1901     1829
hu_no3_TD                    -0.45      0.58    -1.65     0.70 1.00     1789     1617
hu_T_OP_D                    -0.06      0.06    -0.17     0.05 1.00     1571     1598
hu_nitrate_to_ammonium_TD     0.16      0.29    -0.44     0.72 1.00     1935     2008
hu_sor.count.C.scaled        -1.09      0.64    -2.44     0.03 1.00     2065     1917
hu_shannon.C                  0.65      0.78    -0.78     2.26 1.00     2481     2176
hu_tex_PC1:water_PC1         -0.23      0.25    -0.72     0.27 1.00     1451     1704

Family Specific Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape     1.37      0.07     1.24     1.50 1.00     4510     2081
```

Marketable Yield (fungal metrics - roots)

```
Group-Level Effects:
~Field_short (Number of levels: 7)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                    1.34      0.65     0.50     3.03 1.00      884     1318
sd(hu_Intercept)                 0.84      0.77     0.03     2.73 1.00     1887     1750
cor(Intercept,hu_Intercept)     -0.09      0.58    -0.96     0.94 1.00     2823     1762

~Field_short:block (Number of levels: 35)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                    0.08      0.06     0.00     0.22 1.00      828     1231
sd(hu_Intercept)                 0.79      0.61     0.04     2.25 1.00     1322     1990
cor(Intercept,hu_Intercept)     -0.02      0.56    -0.93     0.94 1.00     1707     1711

~Field_short:block:Plot (Number of levels: 70)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                    0.20      0.06     0.08     0.32 1.00      747     1212
sd(hu_Intercept)                 1.41      0.59     0.43     2.75 1.00     1227     1405
cor(Intercept,hu_Intercept)     -0.70      0.26    -0.99    -0.02 1.00     1386     2000

~harvest_number (Number of levels: 20)
```

```
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.83      0.15     0.59     1.18 1.00      725     1415
sd(hu_Intercept)                1.69      0.48     0.91     2.77 1.00     2365     2014
cor(Intercept,hu_Intercept)    -0.76      0.19    -0.99    -0.26 1.00     1620     1868

Population-Level Effects:
                          Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                    -1.38      2.39    -6.45     3.24 1.00     1102     1335
hu_Intercept                 -3.92      5.29   -13.62     6.62 1.00     1933     1971
Inoc_longinoculated          -0.05      0.08    -0.22     0.11 1.00     2249     2224
plant_spacing                 0.10      0.10    -0.10     0.32 1.00      987     1263
tex_PC1                       0.03      0.43    -0.82     0.90 1.00     1165     1228
water_PC1                     0.10      0.08    -0.06     0.25 1.00     1864     1445
nh4_TD                       -0.08      0.31    -0.69     0.52 1.00     1606     1842
nh4_TD_sq                    -0.15      0.05    -0.24    -0.06 1.00     2159     1999
no3_TD                        0.12      0.05     0.03     0.21 1.00     1330     1994
T_OP_D                       -0.00      0.01    -0.02     0.01 1.00     2175     1712
nitrate_to_ammonium_TD       -0.03      0.02    -0.08     0.01 1.00     1255     1557
sor.count.R.scaled            0.01      0.05    -0.09     0.10 1.00     2708     2270
shannon.R                    -0.07      0.11    -0.28     0.13 1.00     2461     2143
tex_PC1:water_PC1             0.06      0.03     0.00     0.11 1.00     1597     2133
hu_Inoc_longinoculated        0.93      0.81    -0.63     2.57 1.00     3493     2270
hu_plant_spacing              0.12      0.24    -0.34     0.60 1.00     1682     1679
hu_tex_PC1                   -1.14      0.71    -2.60     0.19 1.00     1953     1778
hu_water_PC1                 -0.29      0.52    -1.32     0.72 1.00     2353     1849
hu_nh4_TD                     0.54      2.34    -3.96     5.22 1.00     2954     2447
hu_nh4_TD_sq                 -0.66      0.80    -2.59     0.56 1.00     2226     1947
hu_no3_TD                    -0.22      0.47    -1.18     0.72 1.00     2187     2038
hu_T_OP_D                    -0.05      0.05    -0.15     0.05 1.00     1763     1759
hu_nitrate_to_ammonium_TD     0.10      0.26    -0.46     0.57 1.00     1913     1685
hu_sor.count.R.scaled         0.74      0.49    -0.21     1.75 1.00     2658     2198
hu_shannon.R                 -1.28      1.03    -3.43     0.66 1.00     2440     2202
hu_tex_PC1:water_PC1         -0.11      0.20    -0.51     0.28 1.00     1550     1698

Family Specific Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape     1.37      0.06     1.26     1.49 1.00     3924     2306
```

Blossom End Rot (initial model with principal components to identify depth of interest)

```
Group-Level Effects:
~Field_short (Number of levels: 7)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   1.06      0.50     0.36     2.24 1.00      760     1044
sd(hu_Intercept)                1.98      0.67     1.02     3.66 1.00     1579     1833
cor(Intercept,hu_Intercept)    -0.69      0.30    -0.99     0.12 1.00     1397     1714

~Field_short:block (Number of levels: 35)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.16      0.11     0.01     0.41 1.00      849     1366
sd(hu_Intercept)                0.26      0.18     0.01     0.66 1.00      938     1335
cor(Intercept,hu_Intercept)    -0.19      0.56    -0.98     0.89 1.00     1070     1737

~Field_short:block:Plot (Number of levels: 70)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.33      0.12     0.10     0.55 1.01      596      740
sd(hu_Intercept)                0.46      0.19     0.06     0.82 1.00      499      414
cor(Intercept,hu_Intercept)    -0.40      0.41    -0.97     0.62 1.00      695      764

~harvest_number (Number of levels: 20)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.67      0.19     0.36     1.12 1.00     1023     1110
sd(hu_Intercept)                1.10      0.26     0.69     1.68 1.00     1399     1981
cor(Intercept,hu_Intercept)    -0.52      0.25    -0.86     0.07 1.00      718      871

Population-Level Effects:
```

```
                       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                 -1.54      1.99    -5.53     2.39 1.00      902     1291
hu_Intercept               1.60      3.68    -6.29     8.38 1.00     1329     1561
Inoc_longinoculated        0.20      0.15    -0.09     0.50 1.00     1775     1824
plant_spacing             -0.08      0.09    -0.26     0.11 1.00      915     1296
tex_PC1                   -0.31      0.33    -0.97     0.38 1.00     1085     1420
water_PC1                  0.04      0.13    -0.21     0.29 1.00     1861     1957
nutA_PC1                   0.06      0.12    -0.18     0.29 1.00     1422     1532
nutA_PC2                   0.15      0.13    -0.10     0.39 1.00     1570     1953
nutB_PC1                  -0.03      0.15    -0.33     0.27 1.00     2135     1992
nutB_PC2                  -0.09      0.21    -0.48     0.36 1.00     1564     1724
nutC_PC1                   0.15      0.17    -0.19     0.49 1.00     1319     2069
nutC_PC2                  -0.31      0.17    -0.65     0.04 1.00     1487     1689
nutD_PC1                  -0.04      0.12    -0.26     0.19 1.00     2271     1943
nutD_PC2                   0.34      0.22    -0.07     0.79 1.00     1165     1384
tex_PC1:water_PC1         -0.09      0.05    -0.18     0.00 1.00     1345     1453
hu_Inoc_longinoculated     0.20      0.24    -0.24     0.69 1.00     2793     2044
hu_plant_spacing          -0.04      0.17    -0.36     0.31 1.00     1335     1732
hu_tex_PC1                -0.63      0.63    -1.93     0.55 1.00     1372     1602
hu_water_PC1              -0.07      0.20    -0.46     0.33 1.00     2352     1848
hu_nutA_PC1                0.12      0.20    -0.27     0.51 1.00     1856     1996
hu_nutA_PC2               -0.07      0.21    -0.49     0.35 1.00     2121     2247
hu_nutB_PC1               -0.07      0.18    -0.40     0.31 1.00     2471     1816
hu_nutB_PC2                0.27      0.36    -0.42     0.98 1.00     2116     2067
hu_nutC_PC1               -0.02      0.26    -0.54     0.52 1.00     1630     1992
hu_nutC_PC2               -0.48      0.23    -0.96    -0.05 1.00     2495     2103
hu_nutD_PC1               -0.04      0.18    -0.42     0.32 1.00     2483     1811
hu_nutD_PC2                0.61      0.35    -0.10     1.33 1.00     1745     1703
hu_tex_PC1:water_PC1      -0.04      0.08    -0.19     0.11 1.00     1524     1993

Family Specific Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape     1.72      0.15     1.45     2.02 1.00     2305     2088
```

Blossom End Rot (final model, nutrients at 30-60cm)

```
Group-Level Effects:
~Field_short (Number of levels: 7)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   1.27      0.56     0.52     2.71 1.00     1406     1556
sd(hu_Intercept)                2.08      0.66     1.12     3.69 1.00     2079     1843
cor(Intercept,hu_Intercept)    -0.64      0.29    -0.98     0.08 1.00     1749     1750

~Field_short:block (Number of levels: 35)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.13      0.10     0.01     0.37 1.00      994     1377
sd(hu_Intercept)                0.28      0.17     0.02     0.64 1.00     1223     1657
cor(Intercept,hu_Intercept)    -0.15      0.57    -0.96     0.91 1.00     1229     1813

~Field_short:block:Plot (Number of levels: 70)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.37      0.12     0.15     0.60 1.00      653     1141
sd(hu_Intercept)                0.25      0.16     0.01     0.60 1.00      970     1373
cor(Intercept,hu_Intercept)    -0.20      0.52    -0.95     0.87 1.00     1936     1777

~harvest_number (Number of levels: 20)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.62      0.19     0.32     1.07 1.00      787     1133
sd(hu_Intercept)                1.07      0.25     0.67     1.66 1.00     1798     1850
cor(Intercept,hu_Intercept)    -0.51      0.25    -0.87     0.07 1.00     1176     1483

Population-Level Effects:
                          Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                    -3.66      2.49    -8.85     1.31 1.00     1182     1474
hu_Intercept                  5.34      3.90    -2.14    13.25 1.00     1436     1790
Inoc_longinoculated           0.17      0.16    -0.14     0.49 1.00     2579     2050
plant_spacing                 0.01      0.11    -0.22     0.23 1.00     1207     1255
```

```
tex_PC1                      -0.15      0.43    -0.96     0.74 1.00     1328     1090
water_PC1                     0.13      0.13    -0.11     0.39 1.00     2043     2238
nh4_TC                        0.68      0.65    -0.64     1.93 1.00     1578     1812
nh4_TC_sq                    -0.07      0.14    -0.35     0.21 1.00     1611     2026
no3_TC                       -0.04      0.09    -0.22     0.14 1.00     1933     1778
T_OP_C                       -0.00      0.01    -0.03     0.02 1.00     1578     1696
nitrate_to_ammonium_TC        0.02      0.06    -0.11     0.15 1.00     1807     2003
tex_PC1:water_PC1            -0.04      0.05    -0.14     0.06 1.00     2231     1845
hu_Inoc_longinoculated        0.24      0.21    -0.16     0.65 1.00     4185     2403
hu_plant_spacing             -0.17      0.18    -0.53     0.17 1.00     1475     1681
hu_tex_PC1                   -0.33      0.69    -1.72     1.01 1.00     1368     1378
hu_water_PC1                 -0.30      0.20    -0.69     0.10 1.00     2532     2326
hu_nh4_TC                    -1.43      0.81    -3.01     0.16 1.00     1925     2041
hu_nh4_TC_sq                  0.50      0.18     0.14     0.85 1.00     1964     2066
hu_no3_TC                     0.10      0.08    -0.04     0.27 1.00     2245     2022
hu_T_OP_C                    -0.02      0.02    -0.05     0.01 1.00     2919     2316
hu_nitrate_to_ammonium_TC    -0.07      0.07    -0.21     0.07 1.00     2015     2083
hu_tex_PC1:water_PC1         -0.11      0.07    -0.26     0.03 1.00     3042     2460

Family Specific Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape     1.70      0.15     1.42     2.00 1.00     2076     2034
```

Blossom End Rot (fungal metrics - 0-15cm)

```
Group-Level Effects:
~Field_short (Number of levels: 7)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   1.26      0.56     0.51     2.69 1.00     1689     2032
sd(hu_Intercept)                1.98      0.66     1.05     3.60 1.00     2289     2153
cor(Intercept,hu_Intercept)    -0.64      0.30    -0.99     0.13 1.00     1658     1492

~Field_short:block (Number of levels: 35)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.17      0.12     0.01     0.43 1.00      809     1402
sd(hu_Intercept)                0.29      0.18     0.01     0.68 1.00      822      954
cor(Intercept,hu_Intercept)    -0.24      0.55    -0.98     0.89 1.00     1100     1547

~Field_short:block:Plot (Number of levels: 67)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.33      0.13     0.09     0.58 1.01      644      664
sd(hu_Intercept)                0.27      0.17     0.01     0.65 1.00      822     1538
cor(Intercept,hu_Intercept)    -0.06      0.52    -0.92     0.91 1.00     1386     1761

~harvest_number (Number of levels: 20)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.62      0.19     0.32     1.06 1.00     1075     1765
sd(hu_Intercept)                1.06      0.25     0.66     1.66 1.00     1707     2077
cor(Intercept,hu_Intercept)    -0.48      0.27    -0.88     0.15 1.00      820     1382

Population-Level Effects:
                          Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                    -5.67      2.95   -11.36     0.16 1.00     1625     2264
hu_Intercept                 10.38      5.20     0.05    20.54 1.00     2094     1873
Inoc_longinoculated           0.24      0.16    -0.09     0.57 1.00     2713     1974
plant_spacing                -0.00      0.11    -0.21     0.21 1.00     1157     1417
tex_PC1                      -0.20      0.41    -1.00     0.60 1.00     1260     1353
water_PC1                     0.12      0.13    -0.15     0.38 1.00     2206     2180
nh4_TC                        0.93      0.67    -0.37     2.25 1.00     1690     2067
nh4_TC_sq                    -0.11      0.14    -0.38     0.17 1.00     1674     2015
no3_TC                       -0.03      0.09    -0.21     0.16 1.00     1880     2078
T_OP_C                       -0.00      0.01    -0.02     0.02 1.00     1869     1890
nitrate_to_ammonium_TC        0.01      0.07    -0.12     0.14 1.00     1886     2342
sor.count.A.scaled           -0.02      0.11    -0.22     0.19 1.00     2262     2075
shannon.A                     0.44      0.39    -0.35     1.17 1.00     3610     2586
tex_PC1:water_PC1            -0.05      0.05    -0.15     0.05 1.00     2222     2072
hu_Inoc_longinoculated        0.29      0.24    -0.18     0.75 1.00     3843     2414
```

```
hu_plant_spacing            -0.17      0.16    -0.50     0.15 1.00     1402     1766
hu_tex_PC1                  -0.23      0.62    -1.51     0.99 1.00     1424     1765
hu_water_PC1                -0.22      0.21    -0.61     0.19 1.00     2767     2424
hu_nh4_TC                   -1.42      0.84    -3.09     0.18 1.00     2013     2079
hu_nh4_TC_sq                 0.49      0.19     0.13     0.86 1.00     2138     2231
hu_no3_TC                    0.08      0.08    -0.06     0.26 1.00     1949     2294
hu_T_OP_C                   -0.01      0.02    -0.04     0.02 1.00     2674     2005
hu_nitrate_to_ammonium_TC   -0.05      0.07    -0.20     0.10 1.00     1978     2054
hu_sor.count.A.scaled       -0.06      0.16    -0.37     0.26 1.00     2680     2180
hu_shannon.A                -1.19      0.83    -2.88     0.43 1.00     3459     2058
hu_tex_PC1:water_PC1        -0.11      0.07    -0.26     0.03 1.00     2299     2132

Family Specific Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape     1.71      0.15     1.43     2.02 1.00     2232     2089
```

Blossom End Rot (fungal metrics - 30-60cm)

```
Group-Level Effects:
~Field_short (Number of levels: 7)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.97      0.63     0.05     2.48 1.00      643      516
sd(hu_Intercept)                1.70      0.65     0.66     3.28 1.00     1922     1617
cor(Intercept,hu_Intercept)    -0.50      0.43    -0.99     0.60 1.00     1037     1172

~Field_short:block (Number of levels: 34)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.19      0.14     0.01     0.53 1.00      983     1481
sd(hu_Intercept)                0.29      0.19     0.02     0.72 1.00     1201     1960
cor(Intercept,hu_Intercept)    -0.20      0.58    -0.97     0.91 1.00     1184     1741

~Field_short:block:Plot (Number of levels: 57)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.55      0.15     0.28     0.86 1.00      642     1261
sd(hu_Intercept)                0.40      0.21     0.03     0.85 1.00      790     1398
cor(Intercept,hu_Intercept)    -0.51      0.41    -0.99     0.61 1.00     1586     1691

~harvest_number (Number of levels: 20)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.60      0.20     0.28     1.05 1.00      889     1525
sd(hu_Intercept)                1.12      0.26     0.71     1.74 1.00     1752     2522
cor(Intercept,hu_Intercept)    -0.43      0.28    -0.84     0.21 1.01     1180     1843

Population-Level Effects:
                          Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                   -3.95      2.40    -8.93     0.45 1.00     1540     1981
hu_Intercept                 3.40      3.53    -3.38    10.93 1.00     2389     2077
Inoc_longinoculated          0.19      0.23    -0.26     0.65 1.00     2695     2336
plant_spacing                0.03      0.10    -0.17     0.24 1.00     2649     2094
tex_PC1                     -0.37      0.40    -1.09     0.52 1.00     1434     1972
water_PC1                   -0.10      0.22    -0.51     0.32 1.00      983     1438
nh4_TC                       0.94      0.95    -0.98     2.77 1.00     1224     1743
nh4_TC_sq                   -0.10      0.19    -0.46     0.29 1.00     1054     1641
no3_TC                      -0.04      0.13    -0.30     0.22 1.00     1926     2048
T_OP_C                      -0.01      0.02    -0.04     0.02 1.00      858     1334
nitrate_to_ammonium_TC       0.01      0.10    -0.18     0.19 1.00     1424     1235
sor.count.C.scaled          -0.03      0.13    -0.28     0.22 1.00     1987     1816
shannon.C                   -0.04      0.14    -0.33     0.23 1.00     2344     2074
tex_PC1:water_PC1           -0.00      0.07    -0.14     0.13 1.00     2504     2132
hu_Inoc_longinoculated       0.42      0.27    -0.09     1.00 1.00     3892     2368
hu_plant_spacing            -0.22      0.15    -0.54     0.07 1.00     2280     2130
hu_tex_PC1                  -0.12      0.58    -1.36     0.96 1.00     1865     1992
hu_water_PC1                -0.01      0.30    -0.55     0.62 1.00     1849     1474
hu_nh4_TC                   -0.38      1.05    -2.39     1.73 1.00     1846     1906
hu_nh4_TC_sq                 0.31      0.22    -0.13     0.74 1.00     1780     2016
hu_no3_TC                    0.04      0.10    -0.14     0.25 1.00     2629     2175
hu_T_OP_C                   -0.01      0.02    -0.04     0.03 1.00     1911     2192
```

```
hu_nitrate_to_ammonium_TC     0.04      0.09    -0.15     0.22 1.00     2443     2600
hu_sor.count.C.scaled         0.12      0.16    -0.19     0.44 1.00     2841     2391
hu_shannon.C                  0.32      0.19    -0.04     0.70 1.00     2959     2243
hu_tex_PC1:water_PC1         -0.17      0.09    -0.34    -0.01 1.00     2756     2393

Family Specific Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape     1.79      0.18     1.46     2.16 1.00     1790     2295
```

Blossom End Rot (fungal metrics - roots)

```
Group-Level Effects:
~Field_short (Number of levels: 7)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   1.29      0.57     0.47     2.68 1.00     1233     1210
sd(hu_Intercept)                2.09      0.67     1.12     3.77 1.00     2103     2106
cor(Intercept,hu_Intercept)    -0.64      0.30    -0.98     0.12 1.00     1669     1693

~Field_short:block (Number of levels: 35)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.14      0.11     0.01     0.41 1.00      895     1315
sd(hu_Intercept)                0.24      0.17     0.01     0.61 1.00      922     1843
cor(Intercept,hu_Intercept)    -0.10      0.56    -0.96     0.92 1.00     1717     1791

~Field_short:block:Plot (Number of levels: 70)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.39      0.12     0.14     0.63 1.01      499      654
sd(hu_Intercept)                0.27      0.17     0.01     0.63 1.00      840     1294
cor(Intercept,hu_Intercept)    -0.18      0.51    -0.96     0.87 1.00     1371     1677

~harvest_number (Number of levels: 20)
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)                   0.62      0.19     0.33     1.07 1.00      935     1835
sd(hu_Intercept)                1.09      0.26     0.67     1.70 1.00     1652     2173
cor(Intercept,hu_Intercept)    -0.50      0.26    -0.87     0.11 1.00      837     1578

Population-Level Effects:
                          Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                    -3.84      2.56    -8.92     1.49 1.00     1159     1567
hu_Intercept                  5.81      3.89    -1.50    13.74 1.00     1208     1609
Inoc_longinoculated           0.19      0.16    -0.14     0.50 1.00     2184     2258
plant_spacing                -0.01      0.11    -0.24     0.22 1.00     1152     1429
tex_PC1                      -0.17      0.42    -0.96     0.69 1.00     1290     1534
water_PC1                     0.14      0.14    -0.14     0.40 1.00     1376     1834
nh4_TC                        0.70      0.68    -0.64     2.00 1.00     1481     1578
nh4_TC_sq                    -0.07      0.15    -0.34     0.23 1.00     1411     1618
no3_TC                       -0.03      0.10    -0.22     0.16 1.00     1803     2109
T_OP_C                       -0.00      0.01    -0.03     0.02 1.00     1429     1816
nitrate_to_ammonium_TC        0.02      0.07    -0.12     0.15 1.00     1699     2052
sor.count.R.scaled            0.07      0.10    -0.15     0.26 1.00     2064     2047
shannon.R                     0.12      0.19    -0.26     0.49 1.00     3026     2363
tex_PC1:water_PC1            -0.05      0.05    -0.15     0.05 1.00     1965     2025
hu_Inoc_longinoculated        0.22      0.21    -0.18     0.66 1.00     3997     2548
hu_plant_spacing             -0.15      0.17    -0.49     0.18 1.00     1242     1639
hu_tex_PC1                   -0.29      0.64    -1.58     0.98 1.00     1444     1754
hu_water_PC1                 -0.31      0.20    -0.69     0.09 1.00     2917     2186
hu_nh4_TC                    -1.38      0.81    -2.93     0.24 1.00     1597     1712
hu_nh4_TC_sq                  0.48      0.18     0.12     0.83 1.00     1489     1833
hu_no3_TC                     0.10      0.08    -0.04     0.27 1.00     2067     1853
hu_T_OP_C                    -0.02      0.02    -0.05     0.01 1.00     2860     2279
hu_nitrate_to_ammonium_TC    -0.07      0.07    -0.21     0.07 1.00     2171     1931
hu_sor.count.R.scaled        -0.12      0.14    -0.39     0.14 1.00     4102     1964
hu_shannon.R                 -0.30      0.29    -0.87     0.27 1.00     4218     2041
hu_tex_PC1:water_PC1         -0.09      0.07    -0.23     0.06 1.00     2001     2361

Family Specific Parameters:
```

```
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape     1.71      0.15     1.44     2.03 1.00     1768     1716
```

Fruit Quality (initial model with principal components to identify depth of interest)

```
Group-Level Effects:
~Field_short (Number of levels: 7)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.31      0.21     0.05     0.83 1.00      516      512

~Field_short:block (Number of levels: 35)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.02      0.01     0.00     0.06 1.00     1294     1059

~Field_short:block:Plot (Number of levels: 69)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.02      0.01     0.00     0.05 1.00     1247     1163

Population-Level Effects:
                    Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept               1.95      0.62     0.83     3.37 1.01      888      981
harvest_codeH6          0.05      0.03    -0.01     0.11 1.00     2982     2603
harvest_codeH9          0.07      0.03     0.01     0.13 1.00     3071     2496
Inoc_longinoculated    -0.00      0.03    -0.05     0.05 1.00     3645     2225
plant_spacing           0.01      0.03    -0.05     0.05 1.00      914      916
tex_PC1                -0.04      0.11    -0.25     0.18 1.01      847      731
water_PC1              -0.01      0.02    -0.05     0.04 1.00     1658     1886
nutA_PC1               -0.03      0.02    -0.07     0.02 1.00     1958     2222
nutA_PC2               -0.00      0.02    -0.05     0.05 1.00     2181     2005
nutB_PC1               -0.00      0.01    -0.03     0.03 1.00     3088     2246
nutB_PC2                0.03      0.05    -0.06     0.12 1.00     1524     1923
nutC_PC1                0.02      0.03    -0.03     0.08 1.00     1295     1691
nutC_PC2                0.01      0.02    -0.04     0.05 1.00     1389     1749
nutD_PC1                0.02      0.02    -0.02     0.06 1.00     1920     1894
nutD_PC2                0.11      0.04     0.03     0.19 1.00     1518     1265
tex_PC1:water_PC1      -0.01      0.01    -0.03     0.01 1.00     1474     2002

Family Specific Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape    34.55      3.62    27.81    41.91 1.00     3679     2134
```

Fruit Quality (final model, nutrients at 60-100cm)

```
Group-Level Effects:
~Field_short (Number of levels: 7)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.52      0.30     0.20     1.26 1.00     1678     2180

~Field_short:block (Number of levels: 35)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.03      0.02     0.00     0.07 1.00     1310     2476

Population-Level Effects:
                       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                  2.60      0.92     0.73     4.51 1.00     1697     1909
Inoc_longinoculated       -0.05      0.02    -0.09     0.00 1.00     5279     3809
plant_spacing             -0.01      0.04    -0.10     0.06 1.00     1587     2153
tex_PC1                    0.02      0.17    -0.32     0.37 1.00     1643     2183
water_PC1                 -0.03      0.02    -0.07     0.01 1.00     2890     3474
nh4_TD                    -0.10      0.10    -0.29     0.10 1.00     2447     3271
nh4_TD_sq                  0.04      0.01     0.01     0.07 1.00     2774     3683
no3_TD                    -0.01      0.01    -0.03     0.02 1.00     3300     3329
T_OP_D                    -0.00      0.00    -0.01     0.00 1.00     4907     3912
nitrate_to_ammonium_TD    -0.00      0.01    -0.02     0.01 1.00     2943     3091
tex_PC1:water_PC1         -0.01      0.01    -0.03     0.01 1.00     4913     3844
```

```
Family Specific Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape   121.32     26.41    77.12   180.58 1.00     2322     3022
```

Fruit Quality (fungal metrics - 0-15cm)

```
Group-Level Effects:
~Field_short (Number of levels: 7)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.52      0.32     0.19     1.43 1.00      630      585

~Field_short:block (Number of levels: 35)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.03      0.02     0.00     0.08 1.00      728     1093

Population-Level Effects:
                       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                  2.35      1.04     0.18     4.46 1.00      618      564
Inoc_longinoculated       -0.06      0.03    -0.11    -0.00 1.00     3378     2324
plant_spacing             -0.01      0.04    -0.10     0.07 1.00      570      493
tex_PC1                    0.01      0.18    -0.37     0.38 1.00      576      465
water_PC1                 -0.03      0.02    -0.08     0.02 1.00     3392     2345
nh4_TD                    -0.10      0.11    -0.32     0.11 1.00     1586     1837
nh4_TD_sq                  0.04      0.02     0.01     0.07 1.00     2104     1952
no3_TD                    -0.01      0.01    -0.04     0.02 1.00     1917     2115
T_OP_D                    -0.00      0.00    -0.01     0.00 1.00     2140     2228
nitrate_to_ammonium_TD    -0.00      0.01    -0.02     0.01 1.00     1593     2013
sor.count.A.scaled        -0.00      0.02    -0.04     0.03 1.00     3298     2310
shannon.A                  0.06      0.09    -0.11     0.24 1.00     3731     2134
tex_PC1:water_PC1         -0.01      0.01    -0.03     0.01 1.00     2856     2064

Family Specific Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape   116.83     27.75    71.29   177.99 1.00     1334     1962
```

Fruit Quality (fungal metrics - 30-60cm)

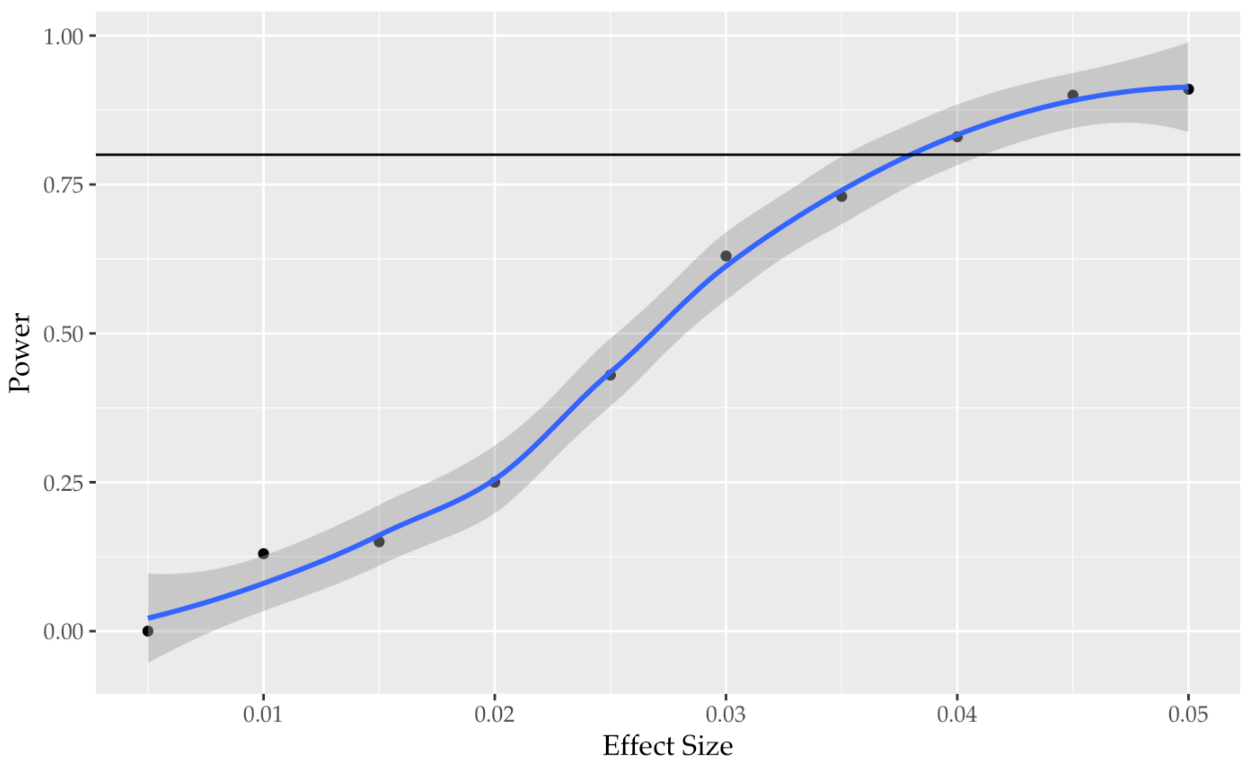
```
Group-Level Effects:
~Field_short (Number of levels: 7)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.57      0.33     0.21     1.50 1.01      644     1153

~Field_short:block (Number of levels: 34)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.02      0.02     0.00     0.06 1.00     1166      838

Population-Level Effects:
                       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                  2.67      0.93     0.81     4.65 1.00      847      992
Inoc_longinoculated       -0.02      0.03    -0.08     0.04 1.00     2625     2296
plant_spacing             -0.02      0.04    -0.11     0.06 1.00      887      922
tex_PC1                    0.02      0.18    -0.35     0.40 1.00      858     1047
water_PC1                 -0.03      0.03    -0.09     0.02 1.00     2312     1988
nh4_TD                    -0.00      0.11    -0.22     0.21 1.00     1134     1501
nh4_TD_sq                  0.03      0.02    -0.00     0.06 1.00     1362     1795
no3_TD                    -0.01      0.02    -0.04     0.02 1.00     1472     1873
T_OP_D                    -0.00      0.00    -0.01     0.00 1.00     3416     2274
nitrate_to_ammonium_TD     0.00      0.01    -0.01     0.02 1.00     1317     1551
sor.count.C.scaled         0.03      0.02    -0.00     0.06 1.00     2867     2453
shannon.C                  0.01      0.02    -0.03     0.05 1.00     3495     2364
tex_PC1:water_PC1         -0.01      0.01    -0.03     0.01 1.00     2702     2038

Family Specific Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape   119.43     27.93    71.19   178.15 1.00     2217     2030
```

Fruit Quality (fungal metrics - roots)

```
Group-Level Effects:
~Field_short (Number of levels: 7)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.52      0.29     0.20     1.27 1.01      693     1050

~Field_short:block (Number of levels: 35)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.03      0.02     0.00     0.07 1.00      815     1151

Population-Level Effects:
                       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                  2.57      0.95     0.59     4.50 1.00      915     1064
Inoc_longinoculated       -0.05      0.02    -0.09     0.00 1.00     3707     2013
plant_spacing             -0.01      0.04    -0.10     0.07 1.00      963     1143
tex_PC1                   -0.00      0.17    -0.38     0.35 1.00     1002     1189
water_PC1                 -0.03      0.02    -0.07     0.02 1.00     3750     2402
nh4_TD                    -0.10      0.10    -0.30     0.10 1.00     2046     2057
nh4_TD_sq                  0.04      0.01     0.01     0.07 1.00     2613     2344
no3_TD                    -0.01      0.01    -0.03     0.02 1.00     2615     2415
T_OP_D                    -0.00      0.00    -0.01     0.00 1.00     3217     2637
nitrate_to_ammonium_TD    -0.00      0.01    -0.02     0.01 1.00     2160     2223
sor.count.R.scaled         0.01      0.02    -0.02     0.04 1.00     4684     2282
shannon.R                 -0.01      0.03    -0.07     0.06 1.00     5135     2122
tex_PC1:water_PC1         -0.01      0.01    -0.03     0.01 1.00     4021     1894

Family Specific Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape   118.83     26.62    73.45   180.04 1.00     1675     1930
```

Power Analysis

A power analysis conducted before the study using variances from data collected the previous summer suggests that our experimental design could detect an inoculation effect size of ~15% of a measured value (e.g. yield) with a power of 0.8. In this analysis we used the model structure described in the 'Model structure' section in the methods to run a regression in glmmTMB that gave the variance for all random effects in the model (field, block, harvest, and residual). We then used these variance to generate simulated datasets with a specified effect size for inoculation. We picked 20 potential effect sizes, and generated 30 datasets for each. We then fit a model to the generated data and, for each effect size, determined what proportion of the p values for inoculation were below 0.05 (i.e. power). We plotted effect size against power to determine what effect size could be detected with a power of 0.8 (Figure below).



Power for simulated data with a set effect size given variances from field data. Black line shows a power of 0.80.

This effect size (0.037 kg) was 16% of mean daily plot yields (0.23 kg).

Figure S1. Correlation matrix of variables included in variable reduction. For variable names, T, M, and H refer to timing of sample event (Transplant, Midseason, Harvest), and A, B, C, D refers to depth of sample (A = 0-15cm, B = 15-30cm, C = 30-60cm, D = 60-100cm). OP = Olsen P, gwc = gravimetric water content.

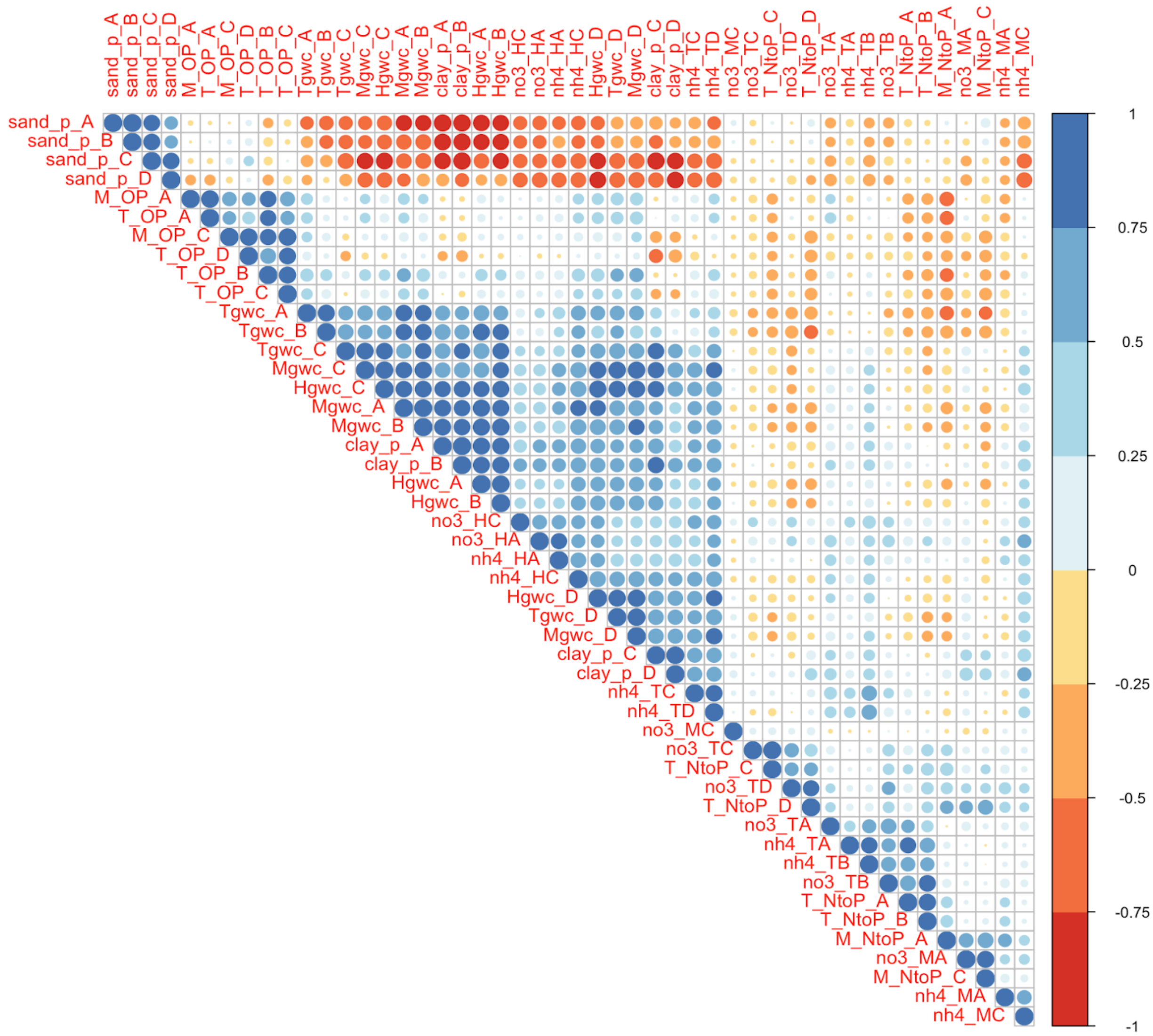
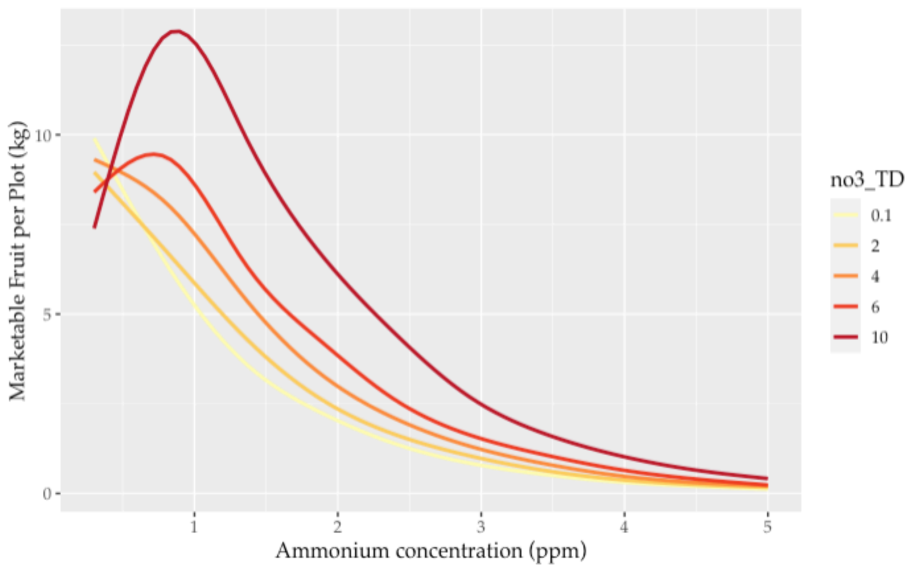
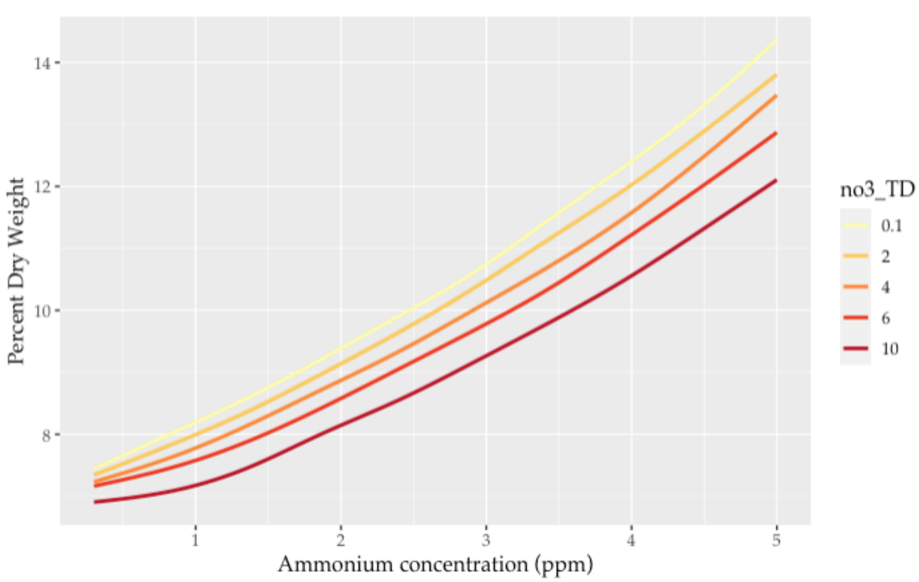


Figure S2. Predicted response to increasing ammonium levels at 60-100cm for five different levels of nitrate, using the models shown in Table zeta. Each panel depicts the mean posterior distribution (200 draws) for a given plot (in this case plot 24) across levels of ammonium and nitrate that correspond to the minimum and maximum observed values across all plots in the study, and using the true values of all other variables for the chosen plot. Though the values predicted for the outcome variable will change depending on which plot is chosen, the shape of the relationship between nitrate/ammonium and that outcome will remain the same. It is therefore important to note that in some plots, as ammonium increases PDW will exceed the 12% threshold beyond which fruit quality begins to decrease.



A.



B.

Figure S3. Nitrate levels in top 15cm of soil for each field at harvest. Black line indicates the threshold for nitrate contamination in groundwater.

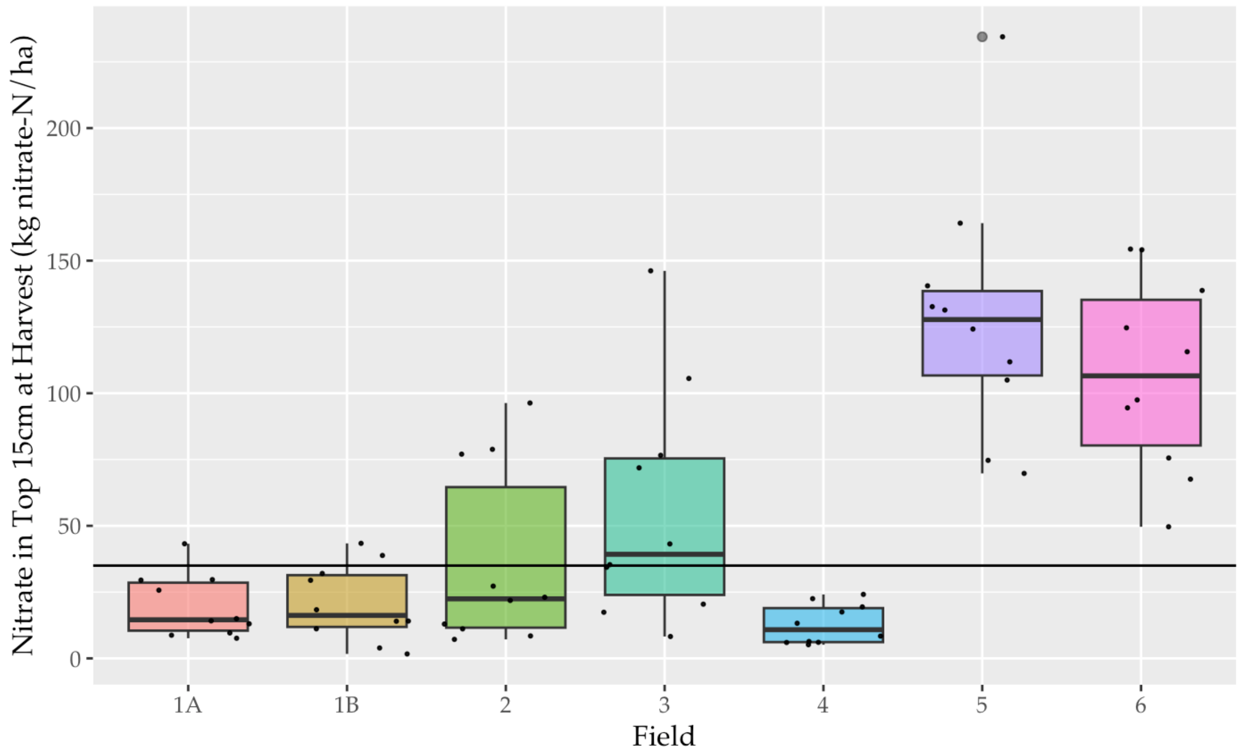


Figure S4. Available water content in top 30cm and 70-100cm of soil at transplant, midseason and harvest. AWC values for 60-100cm were scaled by 0.75 to estimate AWC at 70-100cm in order to easily compare them to the top 30cm of the soil. Negative values indicate that water level is below permanent wilting point.

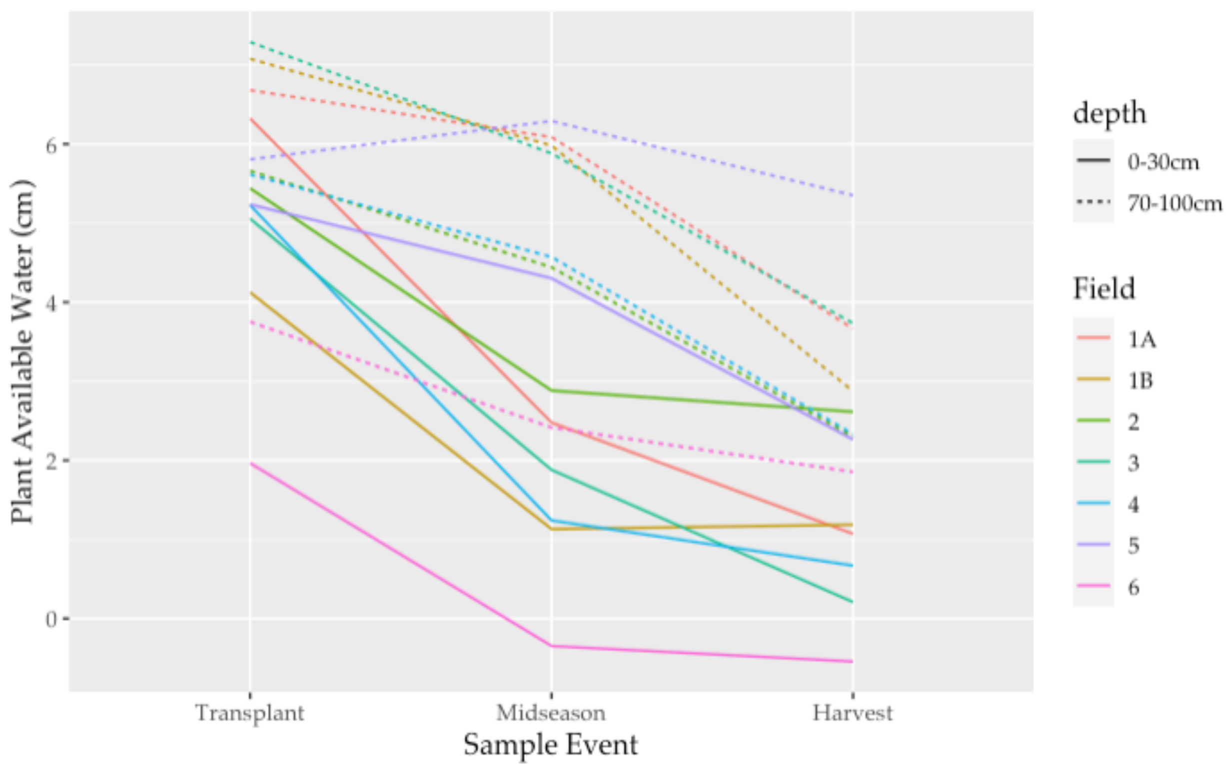


Table S1. All precipitation events above 1mm that occurred from first transplant to last harvest. Data taken from De Laveaga CIMIS weather station (centrally located between all farms).

Date	Precip (mm)
3/5/21	2.9
3/9/21	4.8
3/10/21	9.2
3/11/21	12.1
3/14/21	13.3
3/18/21	25.6
4/25/21	4.4
4/26/21	2.3
10/17/21	1.2
10/20/21	9.2
10/21/21	2.7
10/22/21	16.7
10/23/21	4.3
10/24/21	83.2
10/25/21	24

Table S2. All variables included in variable reduction and number of principal components retained for each. Enough principal components were included to account for at least 55% of the variance in the data.

Group	Variables	Number PCs retained
Nutrients, 0-15cm	Nitrate, Transplant Nitrate, Midseason Nitrate, Harvest Ammonium, Transplant Ammonium, Midseason Ammonium, Harvest Phosphate, Transplant Phosphate, Midseason N:P, Transplant N:P, Midseason	2
Nutrients, 15-30cm	Nitrate, Transplant Ammonium, Transplant Phosphate, Transplant N:P, Transplant	2
Nutrients, 30-60cm	Nitrate, Transplant Nitrate, Midseason Nitrate, Harvest Ammonium, Transplant Ammonium, Midseason Ammonium, Harvest Phosphate, Transplant Phosphate, Midseason N:P, Transplant N:P, Midseason	2
Nutrients, 60-100cm	Nitrate, Transplant Ammonium, Transplant Phosphate, Transplant N:P, Transplant	2
Water	GWC, 0-15cm, Transplant GWC, 0-15cm, Midseason	1

	GWC, 0-15cm, Harvest GWC, 15-30cm, Transplant GWC, 15-30cm, Midseason GWC, 15-30cm, Harvest GWC, 30-60cm, Transplant GWC, 30-60cm, Midseason GWC, 30-60cm, Harvest GWC, 60-100cm, Transplant GWC, 60-100cm, Midseason GWC, 60-100cm, Harvest	
Texture	Percent Clay, 0-15cm Percent Clay, 15-30cm Percent Clay, 30-60cm Percent Clay, 60-100cm Percent Sand, 0-15cm Percent Sand, 15-30cm Percent Sand, 30-60cm Percent Sand, 60-100cm	1

Chapter 3: Vegetable dry farming as an agroecological model for California's drought resilient future: Farmers' perspectives and experiences

3.1. Abstract

Small, diversified farms on California's Central Coast have been dry farming for decades, a practice that allows farmers to grow tomatoes and other vegetables with little to no irrigation in summers without rainfall, relying instead on water stored in soils from winter rains. Though dry farming was originally developed in this region to allow farmers to grow crops on land that had no water access, it has thrived from consumer demand for dry farmed tomatoes. Superior flavors have enticed customers, allowing farmers to charge a premium for dry farm tomatoes and develop markets for this regional specialty. Tomato dry farming in the region has been notably devoid of involvement from academic researchers and extension agents; however, policy groups and the general public have shown growing interest in dry farming in recent years as water shortages in California force a reckoning with the precarity of the state's agricultural water supply. Amidst growing urgency to develop low-water agricultural systems in the state, we interviewed ten Central Coast dry farmers, representing over half of the commercial dry farm operations in the region where the practice was developed, to collaboratively answer two central research questions: 1. What business and land stewardship practices characterize successful tomato dry farming on California's Central Coast? 2. What is the potential for dry farming to expand beyond its current adoption while maintaining its identity as a diversified practice that benefits small-scale operations? We summarize farmers' wisdom into nine themes about current dry farm practice, the potential for expansion, and future opportunities. We also synthesize farmer-stated environmental constraints on where dry farm management may be feasible into a map of areas suitable for dry farming in California. As we consider the process by which dry farming might expand to new areas and new operations, we highlight dry farming's history as an agroecological alternative to industrial farming in the region and the need for careful policy planning to maintain that identity. Because policies that encourage dry farm expansion could change the economic landscape in which dry farming operates, we warn against the possibility that well-intentioned policies will edge small growers out of dry farm markets. At the same time, we emphasize the opportunity for dry farm tomato systems to model an agroecological transition towards water savings in California.

3.2. Introduction

"In California, if you want to farm, sometimes you might not have an option other than dry farming. [With] the increasing drought, how are we still gonna grow food in a drier climate? And whether or not it's even a dry year, I'm thinking about saving water in good and bad years, and building up the market for that."

~Dry farmer on California's Central Coast

A dry farmed Early Girl may well be the best tomato you've ever tasted. Any shopper at a farmer's market on California's Central Coast will confirm the sentiment, and these intensely flavorful, sweet, firm fruits have become a regional specialty sought after by chefs and shoppers in the nearby Bay Area's famous food scene (Bland, 2013; Nast, 2015).

Unlike other forms of dryland farming (e.g. grains), in this region dry farm tomatoes are grown over a summer season where there is a near guarantee of no rainfall. Farmers plant tomatoes into moisture from winter rains, counting on soils to hold on to enough water to support the crops over the course of the entire dry summer and fall. While some farmers irrigate 1-3 times in the first month after transplant, severe water restriction is what gives the fruits their intense flavor, and farmers trade water cuts that lower yields for price premiums that consumers are more than willing to pay for higher quality fruits.

Beyond Bay Area consumer's enthusiasm for high-quality local produce, dry farm tomatoes also trace their origins to a richer food culture of justice-oriented and farmer-centric food distribution in the region (Alkon, 2008; Diekmann et al., 2020; Spencer, 2019). From the Black Panther Party's Free Breakfast Program (Lateef & Androff, 2017) to strong community support for worker-owned and consumer food cooperatives (Lingane, 2015; Sacharoff, 2016), the Bay Area has become a hub of alternative values-based supply chains in a country largely dominated by an industrialized food system (Elias & Marsh, 2020; Kremen et al., 2012). Following this tradition, dry farm tomatoes originally found their footing in the United States in the Central Coast region 30 miles south of the Bay. In the 1970's and 1980's, innovative growers in small-scale cooperatives and teaching farms adapted an Italian and Spanish legacy of vegetable dry farming to the region's Mediterranean climate, maritime influence, and high-clay soils (Simmonds, 2016). While these environmental features were necessary to grow tomatoes under dry farm management, the movement that sparked the reemergence of local farmer's markets in the 1980's also provided the access to direct-to-consumer marketing that small farms needed to win consumer attention and loyalty, allowing farmers to both grow and sell this niche product.

With their origins in local food distribution networks and local adaptations to a unique climate, dry farm tomatoes are now a signature of small, diversified, organic farms on the Central Coast and are a feature of many such operations' business models. To this point, dry farming has largely followed its initial course and is only practiced at a small scale in the region, both in terms of geographic scope, and farm size. Dry farming may therefore be to playing a role in an agroecological transition in the region, buoying small-scale, thought-intensive management styles with access to a steady income source and consumer base.

However, with recent droughts and water shortages in California, dry farming has recently begun to take a more prominent role in social and policy visions for the future of the state's agricultural system. From the Sustainable Groundwater Management Act to emergency orders in drought years, farmers, researchers, policymakers, and the general public have become acutely aware of California's currently unsustainable agricultural water use and the economic ramifications of water shortages (Howitt et al., 2015; Morris & Bucini, 2016). As an option that holds promise for maintaining farmer livelihoods while dramatically cutting water use, journalists and policy groups have touted dry farming as an important system to target for significant expansion (Bland, 2013; CAFF, 2015; DeLonge, 2022; Pottinger & Peterson, 2021; Runwal, 2019; Simmonds, 2016).

Farmers have been considering how to use dry farming to adapt to drier futures for decades, lighting the way for researchers and policymakers' more recent interest. However, up to this point, farmers' thoughts and knowledge about dry farming have not been clearly elicited or formally incorporated into conversations about the future of the practice. Grounding conversations about future expansion of the practice in the knowledge of those who are most intimately familiar with its implementation is essential. At this moment of enthusiasm for dry farming, we look to practitioners to better understand the current state of dry farming on the Central Coast and its potential for expansion across California, along with the benefits and harms that expansion may carry.

We interviewed ten dry farmers, representing over half of the commercial dry farm tomato operations on the Central Coast, in order to collaboratively answer two central research questions. First, what business and land stewardship practices characterize successful tomato dry farming on California's Central Coast? And second, what is the potential for dry farming to expand beyond its current adoption while maintaining its identity as a diversified practice that benefits small-scale operations? The majority of these farmers were part of an ongoing participatory research project in which field data were collected to better understand soil fungal communities and nutrient management in dry farm systems (Chapter 2). These interviews were extensions of conversations and relationships fostered with farmers throughout the research process.

We synthesized farmer insights into nine key themes that broadly describe how dry farming is currently practiced on the Central Coast, its potential to expand in scope (geographies, markets, crops, etc.), and the opportunities that farmers see as particularly provident for the practice. We also used the constraints identified by farmers to map areas most likely to be suitable for future dry farming. At this juncture of a high-functioning, low-water management system and urgent political interest in decreasing agricultural water use–in California and across the globe–we conclude by asking how dry farming can be a model for developing systems that decrease water use, and also how dry farming itself may be scaled out to other small-scale, thought-intensive operations without jeopardizing these same farms' ability to continue profitably growing dry farm produce.

3.3. Methods

3.3.1. Study region.

Interviews were done with farmers who have commercial operations in California's northern Central Coast region (San Mateo and Santa Cruz counties), as well as one farm with operations in Marin and Sonoma counties. Ranges of coastal mountains govern both climate and land use, trapping cool, moist air, and concentrating farming operations in valleys with fertile, alluvial soils. The Central Coast is known for its agricultural production–particularly berries, lettuce, and artichokes–that thrive in its fertile soils and mild climates that allow for year-round cultivation. Agricultural revenue in the region totals over $8 billion annually (CDFA, 2022), making it a larger agricultural producer than most countries. This intensive production has led to both high land values and environmental degradation–largely in the form of water contamination–that shape both farmer decision-making and policy interventions (Dowd et al., 2008; Hall & LeVeen, 1978; Stuart, 2010).

Within this landscape, farms often operate at industrial scales, though many small farms persist. Though cropland is consolidated into fewer, large operations (for example, 20% of farms manage well over 80% of farmland in Santa Cruz County, where the majority of our interviews took place; (USDA NASS, 2017), many smaller farms have found niches selling to local markets.

3.3.2. Interviews.

After building relationships over the course of a year-long participatory field research process with eight tomato dry farmers (representing six growing operations; (Chapter 2), we conducted semi-structured interviews with all farmers involved in that study. We interviewed two additional dry farmers who were not involved in the field project–one whose farm is in Sonoma County (outside the initial study area), and one whose farm could not participate in the field study due to extensive fire damage–for a total of ten farmers representing eight operations. Interviews were done in person (n = 8), over the phone (n = 1), and on Zoom (n = 1) in winter and fall 2022.

Because there is no official record of tomato dry farmers in the Central Coast region, we used a snowball approach to identify farms that might be candidates for inclusion, asking each interviewee what other dry farm operations they knew of in the area. We can identify two dry farm tomato growers in the region who were not interviewed in this study, and we estimate that our interview subjects represented 50-75% of commercial dry farm tomato operations on California's Central Coast.

Interviews lasted 1-2 hours and focused on dry farm management practices, environmental constraints, support, water/land access, and economics (full interview guide in Supplement). Interviews were recorded and transcribed, then analyzed through an interactive process of open, axial, and selective coding (Corbin & Strauss, 1990). Data were grouped into three overarching categories ("Current Practice," "Potential for Expansion," and "Opening Opportunities"), with key themes in each category. Each theme was mentioned in at least half of the interviews.

3.3.3. Suitability.

In order to identify areas that might be suitable for future tomato dry farm management, we used farmer-described constraints to make a suitability map using publicly available datasets. We first compiled the environmental constraints on tomato dry farming described in each interview (Table 2), which fell into three main categories: precipitation, temperature, and soil texture. We limited our analysis to California as the region these farmers are most familiar with to avoid extrapolating constraints beyond the context in which they were given.

We used PRISM 30-year climate normals (1991-2020, 800m resolution) to characterize California's temperature (PRISM Climate Group at Oregon State University, 2022a) and precipitation (PRISM Climate Group at Oregon State University, 2022b). We used the average constraint named by the farmers; however, because these normals are a 30 year average and will stray significantly from these averages in individual years, particularly in the case of precipitation, we expect that we overestimate the extent of suitable areas. As California's temperatures get hotter and precipitation becomes increasingly variable with climate change (Cayan et al., 2008; Pathak et al., 2018), we expect a further systematic overestimation of suitable areas identified based on the past 30 years of weather data.

For the suitability analysis we assigned temperature and soil texture to three categories that were each associated with a score: good (2), tolerable (1), and intolerable (0), while precipitation was divided into ranges that were suitable with no additional irrigation, suitable with additional irrigation, and unsuitable.

For temperature, we considered the average maximum temperature in the three hottest months of the growing season (June, July, August), categorizing them separately with the scores described above (Good: < 86° F, Tolerable: 86 - 95° F, Intolerable: >95° F). We then multiplied these three categorized scores together and took the cube root to get temperature suitability scores for the state, also excluding any areas whose monthly 30-year minimum temperature was above 59° F.

We followed a similar procedure for soil texture, using SSURGO estimates of clay content averaged across soil horizons at a 90m resolution (U.S. Department of Agriculture, Natural Resources Conservation Service, 2008). Because farmers did not give numeric estimates of how much clay was needed in dry farm soils, we made sure our defined 'tolerable' range (5-50% clay) encompassed the full range of clay content observed in participating farms' soils (8-40% clay). To define the 'good' range (10-50%), we excluded the farm with the lowest clay content, which was also the only farm where farmers stated that they could not grow tomatoes of a high enough quality to consistently market them as "dry farm."

We multiplied temperature and soil scores to make a preliminary suitability map. This multiplication reflects the interaction between temperature and soil texture, in which good texture can compensate for higher temperatures by increasing soil water holding capacity, and lower temperatures can lessen the evapotranspirative demand that would be particularly problematic for plants growing in sandier soils with a lower soil water holding capacity. We then separated the dataset into three areas based off of farmers' understandings of where tomato dry farming could occur with no added irrigation (>22" annual rainfall) and where it could occur with supplemental irrigation (14-22"), and excluding areas that would not get enough winter rain to grow a suitable winter cover crop (<14").

The final map shows suitability scores in all areas that are categorized a 'cropland' in the 2019 National Land Cover Database (Dewitz & U.S. Geological Survey, 2021). These areas are superimposed onto groundwater basins categorized as high priority in California's Sustainable Groundwater Management Act (California Department of Water Resources, 2020). Crop totals on land that was deemed suitable for tomato dry farm management in these areas were calculated using the 2021 Cropland Data Layer (USDA NASS, 2021).

3.4. Results

We conducted interviews with ten individuals that represented eight dry farm operations (likely at least half of the commercial dry farm tomato operations in the region), whose basic characteristics are summarized in Table 1. We found four unifying themes across business and management practices that led to dry farm success (*Dry farming defined: water vs quality, Motivations for dry farming: economic, environmental, and place-based, Dry farm tomatoes are a preferred crop, Diversified management is key in dry farm success*), as well as five themes identifying constraints on and opportunities for expansion (*Tomatoes hit a sweet spot, Environmental constraints, Economic constraints, Size and scope matter, Opening opportunities*). To be included, each theme had to be mentioned by at least four farmers, and representative quotes were pulled from responses that fit in each theme.

3.4.1. Current practice

3.4.1.1. Dry farming defined: water vs quality.

Though farmers have been dry farming tomatoes on the Central Coast for decades, there is no rule book for what that actually means.

> What is dry farming? There is no criteria, you know, do this and you'll succeed.

> To be completely honest, I sometimes am like, are we dry? Right? ... It's a very, very loose term.

Instead, the practice has been built through a colloquial understanding between both growers and customers in the region.

When asked to define dry farming, farmers took two, often overlapping, approaches. As one might expect, severe water restriction were at the heart of the concept for all ten of the interviewed farmers:

> At least for my limited experience, it's like once the fruit is there, like, no, definitely no more water.

with some farmers taking a truly purist approach:

> I'm in the camp of legit, like planted into dry, no water ever. I feel like I would advertise my products as dry farmed if they're truly dry farmed. And then if they're not, I would say 'minimally irrigated' or something like that.

However, farmers were just as likely to approach the question from the opposite direction, with eight of the ten farmers defining a dry farm tomato by its small size, thick skin, and concentrated flavor, and calling dry farming any means to that end.

> But really, when I think of a dry farm tomato, I'm all about the flavor... I don't care that, you know, it's a dry farmed tomato but it doesn't taste good. Well, then, for me, there's no point in doing that.

As one farmer succinctly put it,

> If you're telling me you're dry farming it, and it tastes like water, then you are not dry farming.

It is worth noting that the situation this farmer describes can occur when a farmer is growing tomatoes quite close to the water table, often on sandy soils. In these cases, farmers may never irrigate at all (dry farming in its purest sense) and still grow large, watery tomatoes. Similarly, farmers noted that if two operations use the same (severely restricted) amount of irrigation water, but one irrigates after fruit set and the other does not, the first is likely to have a higher yield of more watery tomatoes compared to the second.

> So in the beginning, I would do them drier consciously because I knew like when you're trying to develop markets, you got to have the best. And it's worth having less to have the best because you're getting new customers and you're trying to grow your base.

> We're focused on flavor and not so much on yield. That's where most of our customers are. That's what they're attracted to.

By focusing on the characteristics that limited water can give a tomato, these farmers highlight a recurring theme in understanding the functional definition of dry farming tomatoes. As the Central Coast faces increasingly limited water availability, the idea of dry farming has gained traction among policymakers purely by virtue of offering a means to continue farming while maintaining a restricted water budget. However, these farmers are quick to recognize that dry farming is only a management style that they can afford to choose for their operations insofar as it can excite customers and return a reasonable profit. In this way, the product that dry farming creates, which is valuable enough to consumers that they are willing to pay a significant premium for it, is the outcome that defines the management approaches farmers can use.

Farmers know that they could alter the schedule for the minimal irrigation they do put on their dry farm tomatoes to increase yields (this would involve watering after fruit set, as the first quote alludes to). However, while defining the practice by some maximum threshold of water application, and then choosing to allocate irrigation water to maximize yields, may be appealing from a water savings perspective, farmers recognize that they must define the practice in terms of outcomes and not inputs. Farmers must produce what consumers have come to expect from a dry farm tomato if they are going to make dry farming an economically viable choice for their operation.

3.4.1.2. Motivations for dry farming: economic, environmental, and place-based.

For nine farmers, the decision to include dry farming in their operations boils down easily to farm finances. These growers are quick to acknowledge that their motivations are

> Purely economic. I wanted to farm and I wanted to succeed, and that was perfectly obvious the crop that would make us get there... [We] wouldn't have much of a customer base without the dry farms.

However, seven farmers more holistically pointed out the rewards of dry farming both in terms of product quality and environmental benefit. Farmers related strongly to values of land stewardship,

> I would consider myself a very ecologically, you know, like a systems oriented grower, right? Not just the health of the farm, but also the health of the ecosystem and how we share resources. And, you know, this is something that just really fits into that category. And I know there's a lot of growers that feel that way too; this responsibility to care for the land that they're on, to make sure they're having minimal impact on the surrounding areas.

and also particularly appreciated that tending to this value facilitated growing a high quality product:

> I really like the tomatoes, and I like growing high quality. And also I like the horticulture, the actual farming; dry farming tomatoes, that just appeals to me. Doing it, saving water, saving electricity, saving plastic, saving this, saving that, you know, all kinds of stuff.

> In our case, it's really related to the quality–or I guess the attributes–of the fruit. And so yes, it's to minimize our water use, but it's also to grow the type of food that we want.

Four farmers also found a gestalt to the situation where land stewardship in this particular region creates a high quality product, taking pride in a truly place-based regional specialty:

> You need the microclimate. You need the soil, you need to put it in at the right time, you need to navigate the season to make sure that everything's okay. And then in the course of following that and really tuning in nature, you grow a really fantastic product. Yeah, you know, and that's kind of where I'm at, the niche that I'm at, is like, how do you grow the best of anything?

This satisfaction at mastering a true regional specialty belies not only the success that dry farming has had in the region, but a potential inflexibility in translating this success too literally to other climates or growing conditions.

3.4.1.3. Dry farm tomatoes are a preferred crop.

These economic, environmental, and place-based incentives were powerful motivators, and often resulted in farmers explicitly calling on dry farm tomatoes as a preferred crop grown on their operation.

For eight farmers, decreased labor made dry farm tomatoes preferable to other crops on the farm:

> Labor is like a huge part with dry farming. That's honestly the impetus for a lot of farmers, more so than the environmental reasons... If you don't irrigate, you don't have weeds. So yeah, weed saving and irrigation labor is huge.
>
> You only have to weed 2 or 3 times. It's less weeding; it's a pretty damn easy crop.

Beyond labor, there was a considerable appeal to a lower farming intensity, which differentiates dry farm crops from irrigated ones, and also differentiates these farms from the surrounding region, which is one of the most intensively managed agricultural landscapes in the world:

> One of the things that I like most about it is it's actually asking less input from you than more. Whether it be time or whether in the form of actual equipment,... it actually seems like this is sort of the best of both worlds.
>
> I think it's just, it's easier, you know, it's easier to manage a dry farm crop... Dry farming is not intensive in the way you would look at, like, lettuce and broccoli.

This perceived lack of intensity parallels the fit between region and crop that farmers described as a motivation for dry farming. With the right microclimate and soil, farmers do not have to manage intensively to mimic the appropriate conditions for dry farming, as they are already present.

While this could be said of many dry farm crops, farmers were also clear in their preference for tomatoes over other potential dry farm crops, again largely for economic reasons:

> Economically, it makes a ton of sense to do these dry farm crops, especially because they're so productive. You know, if you look at the dry farmed dry beans that we grow, that makes no economic sense... Dry farm tomatoes are a total win win. Like your costs are way down. The product is really good. And there's definitely a market for it, and we like it in rotation.

For farmers who had experienced water scarcity before, dry farming also provided an important aspect of stability for the farm, making it preferred over crops that could be a liability in dry years. As one farmer who shifted dramatically towards dry farm crops in their operation described it,

> We've decreased the water use; I think we use 75% less than the last farmer... I'm kind of scarred from not having water. Yeah, I'd rather not max out the pond every year ... I'd rather kind of go for consistency. 'Cause hopefully even if it's less each year, I know that I have a certain amount so that I can ... plan a little bit more.

Beyond all these practicalities, six farmers also had a soft spot for appreciating dry farming as an impressive and fascinating system:

> I don't really want to personally eat or sell non-dry farmed tomatoes. And I just think it's amazing to be able to grow stuff without water. That's why I really ... push the limits of the plants and just see what can hang without water. Because it's pretty crazy to see something grow all season long and not have rain for months.

3.4.1.4. Diversified management is key in dry farm success.

In addition to having the appropriate microclimate and soil, farmers engage in many management practices to successfully grow dry farm tomatoes. Some of these practices (e.g. dust mulches) are specific to dry farm management, while others (e.g. trellising) are specific to tomatoes. On the other hand, many practices, including cover cropping, crop rotation, and organic matter incorporation, are mainstays of diversified farm management and were cited by all farmers as key components of dry farm success.

Every farmer highlighted cover cropping as core to their dry farm regime. Though there has been considerable debate in California about whether cover crops use more water than they add to soils (DeVincentis et al., 2020; Mitchell et al., 2015), there was no doubt that they were necessary in this low water system. Among the benefits of cover crops, farmers described improved soil water holding capacity and infiltration, as well as general soil improvements.

> We disc [the field] and we let it over winter with a cover crop... And that helps the water percolate down.

> [With] cover cropping and stuff we've gone from like, one point something percent organic [matter] to like 3.7% organic. That's the cover crop and tilling that in and all that... The soil got so crummy at first, and it was hard to grow things over there. The soil's gotten better.

Four farmers also described using cover crops as an indicator of soil fertility that could help indicate a field's capacity to successfully grow dry farm crops.

> If the cover crop sucks and the year before sucks, then get nervous. But like this year, the cover crop looks great. We've worked so hard to make it good, so I feel pretty confident.

Because soil nutrients in the top 30cm do not seem to impact dry farm tomato health (Socolar et al., n.d.), as their roots quickly move deeper in the soil profile in search of water, it can be difficult for farmers to manage fertility in the regions of the soil where dry farm crops access nutrients. Rather than using surface-applied amendments, farmers have learned to rely on cover crops as an indicator of soil fertility at these lower depths. These cover crops' roots can also create channels that allow tomato roots to penetrate deep into the soil more quickly, allowing faster access to subsurface water at a lower metabolic cost (Acevedo et al., 2022).

Most farms also included their dry farm tomatoes in a diversified crop rotation, with two notable exceptions. For four farmers, rotation was an important measure for disease control. As one farmer said of growing dry farm tomatoes repeatedly on the same field,

> The disease pressure is the issue there. We haven't had hard and fast rotations, but the tomatoes have rotated with both other dry farm crops, like hard squash, and irrigated crops–zucchini or peppers.

Beyond the benefits to the tomatoes themselves, dry farm crops are particularly desirable in full farm rotations, due to their ability to lower weed pressure:

> We like it in rotation. We oftentimes say like, oh, this is where the dry farms were. We'll plant something that we want less weed pressure on, right, because we've been able to manage it so well: there hasn't been a lot of germination of weeds.

Dry farm crops therefore play an important role in diversified rotations both for the benefit of the tomatoes, and to the benefit of the full farm system.

Two farms, however, did not rotate their dry farm crops, but grew them repeatedly (10 years in a row and counting), or alternated between tomatoes and fallow. These management decisions to maintain fields as dry farmed rather than rotating irrigated crops through are particularly compelling in light of recent research on many of the same fields, showing that repeated seasons without any external irrigation result in soil microbial communities that are associated with improved dry farm tomato performance (Socolar et al., n.d.). To fully capture all of the rotation benefits described by farmers, it may therefore be necessary to develop dry farm rotations in which all of the included crops are grown with little to no external irrigation.

Eight farmers also described organic management in a more general sense as being necessary to optimize soil health and dry farm performance. This management style includes incorporating organic soil amendments (rather than synthetic fertilizers), in addition to cover cropping and crop rotation.

> You know, organic management is actually key, because we had to rehabilitate some of our fields at the very beginning... It did take some assiduous basic organic cropping management, a lot of years of cover cropping, incorporating a green manure to produce, you know, sort of the peak performance and system.

While these organic amendments may be critical for soil rehabilitation, most farmers also described using a much lighter fertility regime on their dry farm crops, cutting back on compost and often stopping pelleted fertilizers entirely:

> Did we do compost at [the field] last spring? No. We skipped the year–it's really expensive and seems questionable. No [fertilizers], not in the dry farms. Put the seedlings in and they just grow. That's like how it's supposed to be.

Between the organic amendments/green manures and a general decrease in fertilizer use, farmers are able to lower their use of off-farm inputs beyond just water restrictions, relying instead on on-farm ecology.

3.4.2. Potential for expansion

While farmers have found a clear and sustainable regional niche for tomato dry farming on the Central Coast, policymakers and the public are calling on the possibility of expanding dry farm agriculture in California with increasing urgency. Here we discuss the opportunities and possible pitfalls of growing dry farm tomatoes–and potentially other crops–on a broader scale.

3.4.2.1. Tomatoes hit a sweet spot.

When considering the potential for dry farm agriculture to expand beyond its current scope, an obvious option would be to increase the number of vegetable crops that are dry farmed. While many of the farmers in this study have experimented with other crops (see Table 1) to varying degrees of success, none have had the staying power of tomatoes in their operations.

From the very beginning of tomato dry farming and marketing in the Central Coast, dry farm tomatoes' superior quality–and consumers' response to it–have been integral to dry farm tomato success.

> That was a fortunate coincidence of ... the spectacular difference in quality of the product flavor [versus] the sad state of the rest of tomato culture at the time.

In the 1980's, farmers were able to build a consumer base around their dry farm products that has had an impressive staying power. Growers in this region are now known for these tomatoes, and continue to appreciate their charisma.

> It's something that we have a niche here on the Central Coast. Coastal growers have... a certain reputation. We have a certain customer base that's really looking forward to them... Yeah, it's the tomato.

Since the 80's, farmers have explored dry farming other crop options, but as of yet none have compared to tomatoes in their consumer appeal and versatility.

> Dry farm tomatoes are more charismatic, you know? I think people–the general public and chefs–don't care as much if you're like, 'Oh, these are dry farm winter squash'.
>
> You know, you don't want to have summer squash or winter squash every single week. But dry farm tomatoes you can have them every day; you can freeze them for winter and make it into sauces.

Though tomatoes have been a clear dry farm vegetable front-runner in the Central Coast region, it is important to note that farmers across the state have also found orchard fruits to be a desirable option, particularly in Humboldt County. These fruits have a similar charisma in terms of market appeal and quality premiums, making them economically viable where the other crops discussed by farmers in this study (beans, potatoes, winter squash) may falter.

3.4.2.2. Environmental constraints.

Due to tomatoes' particular success in the Central Coast region, we focus the following environmental constraints on tomato agriculture; however we also discuss the potential for success in dry farming less charismatic crops when considering policy and public opinion shifts that might boost their economic viability (see Economic constraints).

Each farmer was asked what they see as the climatic and soil constraints on dry farming tomatoes. Their answers are summarized in Table 2. Farmers consistently noted the importance of wet winters, and paid particular attention to the timing of rains, often providing caveats that 20" of soft rain over many months would likely sustain a dry farm crop, while the same amount of rainfall in short bursts–particularly early or late in the wet season–could easily render dry farming without supplemental irrigation infeasible. Farmers were less consistent in providing a temperature threshold, but did generally agree on the importance of cool nights and there being some upper limit on what temperatures dry farm tomatoes can consistently tolerate. These limits were then used to create model constraints for a suitability analysis (see Modeling).

In considering these stated constraints, farmers were also highly aware of changing climates and how those violate regional norms that have historically supported dry farming.

> The main thing that I'm thinking about in terms of our ecologically based system with climate change is that, you know, if we don't have rain at the right times, it really impacts how much biomass we can grow on our cover crop, and how long those plants are in the ground and how much root activity. I think there's a real potential stressor there that violates the logical foundation for the farming system.

Farmers have thus far handled these lapses by adjusting management to mimic historical climate, even when it no longer occurs.

> That's essentially what we're stuck in, I think now, is trying to manage ... to simulate what we used to have.
>
> When I was just starting doing this 20 years ago, dry farming, you know, we had to wait for the soil to dry out enough to even disk in the cover crop, right? So it was always the push of trying to get them in; the plants are ready. And you're going to disk them and put them in and then you're going to get in and you're going to wait and you're going to plant them right before there's a rain. And that to me is what I'm trying to simulate, is that general spring shower that waters them in, that normally, naturally would occur. But now we're just in the middle of drought.

This move to recreate the climate also opens possibilities that management could mimic the Central Coast's historic climate in regions that currently do not–and never have–met climate requirements. In particular, supplemental irrigation may be included in some areas to produce dry farm-quality tomatoes and drastically cut back on irrigation compared to other crops that might be grown on those fields.

3.4.2.3. Economic constraints.

While it may be possible to dramatically increase dry farm tomato production from a land suitability perspective, it is also crucial to consider the economic repercussions of–and limitations on–such an expansion. Dry farming allows farms to decrease labor costs and water inputs, making it particularly appealing in areas where water and labor prices are high. Premiums for superior quality can further boost revenues, particularly in the face of drought stress-induced yield declines.

However, land values are some of the highest in the country due to the high value of crops that are typically grown in areas that are suitable for dry farming (Moss & Schmitz, 2008), and large revenues are necessary for most farmers in the region to remain profitable. Therefore, if tomatoes are grown with little-to-no irrigation inputs but do not possess the classic dry farm characteristics, profits will decline and it becomes unrealistic to expect farmers to choose to grow them over a more water-intensive and lucrative alternative. Though farmers may ideologically have strong support for dry farming, they increasingly find themselves in situations where high returns are essential to keep up with rising land prices.

> The good farmland is going into berry production because they can get the most dollars per acre out of it. You have to put the most dollars in per acre as well, but you get a bigger return. And as a result, the rents are skyrocketing... So we have to compete with people that don't have to give a damn.

Premiums for dry farm tomatoes are currently entirely supported by consumers, rather than policies designed to support low-water agriculture.

> The government isn't incentivizing us to do this. It's all the consumer, because they're buying it. That's the incentive that we get.

Therefore, any expansion of dry farming onto soils or into climates that result in notably decreased fruit quality may not be an economically viable option for farmers, who would instead likely devote that land to an irrigated crop with higher returns (e.g. strawberries), or in the absence of water might choose not to farm the land at all. Efforts to increase production at the expense of fruit quality (e.g. shifting irrigation to after fruit set or growing on soils close to water tables) would likely meet a similar end.

Even if farmers are able to maintain quality, too large of a production surge could also topple the profits farmers have come to rely on.

> All of a sudden some giant growers are doing 500 acre blocks every two weeks or something? Yeah, definitely if it's no longer a specialty, then that'd be more of a concern.

Any increased production must therefore also consider whether the consumer demand exists to support current prices.

3.4.2.4. Size and scope matter.

Farmers were unanimously confident that tomato dry farming would be unlikely to occur at industrialized scales given current incentive structures. Interviewees did see potential for more small-scale operations to enter the market, though there are geographic limits to such an expansion.

All of the farms involved in the study cultivated less than 60 acres and grew less than 10 acres of dry farm tomatoes, and none knew of any larger operations. Small-scale farmers have found that dry farm tomatoes are a niche–and sometimes a crucial one–that their operations are able to fill.

> There's always been dry farming involved [in our operation]. Started off smaller percentage, but quickly realized it was the ticket for a small farm to succeed in our case.

As to why this niche is so well-suited to small operations, part of the explanation lies in the origins of dry farm marketing in the 1980's.

> Wholesalers and retailers had to be trained to understand what this was. And they were forced to by their customers who came in and said, 'Hey, I got these at the farmers' market. Like, can you get them? Can I find them here?' So I had to do a lot of training people in the produce business to understand that they could actually successfully sell a smaller, great, tasty tomato.

The first farmers to commercially sell dry farm tomatoes in the region relied heavily on direct interactions with consumers in order to build loyalty and trust in the superior quality of their product. Because the introduction of dry farm tomatoes coincided with the start of Santa Cruz's first farmers' market, farmers were more easily able to come face-to-face with consumers who learned to recognize and appreciate their produce. That consumer interest, along with farmer encouragement, was then able to convince local grocers that they could successfully sell more expensive tomatoes when shoppers recognized and trusted their increased value. To this day, dry farm tomato growers rely heavily on farmers markets, CSAs, and small grocers to sell to consumers who will recognize the value in their product, allowing farms to charge a premium for their trusted quality (Table 1).

However, there is a limit to both consumers' interest in expensive tomatoes, and to larger grocers' willingness to test the limits of what consumers might buy.

> So with Safeway right now, they're paying probably 60, or 50 cents a pound. Would Safeway be willing to pay two bucks a pound? I don't know if that's [something] they're willing to put on the consumer... Why would they rock the boat?

There is also a question of order of operations; large farms are unlikely to plant large areas of a crop without a guaranteed buyer, while large grocery stores are unlikely to contract a large tomato crop without having seen that there is consumer demand to sustain the elevated price. Therefore neither operation is able to test the waters before both commit.

Six farmers also pointed to their business models, which are entirely different from industrial-style growers.

> [Conventional farms] are in it for a different game, right? They want more quantity, more volume. And they will not even harvest their tomato ripe. So I think you're dealing with different segments of the market for tomato, where quality is not as important. And I think this farming technique is very much linked to a quality, appreciation for quality... When that's not your advantage or comparative advantage, then why bother?

Finally, there is also a question of capacity and capability. Even if a large farm were to develop an interest in growing dry farm tomatoes, they are less likely to use the diversification practices that these small farms have found key in dry farm management. Though it may be possible to approximate these practices or even commit to a full dry farm regime, the learning curve is steep and the product can be finicky. As one farmer put it,

> Yeah, more people come and compete; there are definitely more people showing up with dry farms. And that's inevitable, but most of them still can't do what we do.

and of the farms that are currently growing dry farm tomatoes, none expressed an interest in a significant expansion.

> Taking over this land four years ago was roughly a double in acreage, and so I feel like we've added a market or two since then. And then I feel like I've stabilized. We're at a good spot.

> We've just had a really hard time scaling up. I find you scale up with what we do and we have a really hard time keeping up quality.

Given that current dry farmers do not have interest in expanding their operations, without deep knowledge of dry farm management or the nimbleness that comes with growing and adapting management to a small acreage, large farms may simply not be able to produce a quality dry farm product at scale.

While scaling up production by increasing the size of individual operations may be unlikely given current markets, new small farms could take up the practice in the Central Coast and other regions. All of the farmers interviewed for this study agreed that they would not have trouble selling more dry farm tomatoes if they were to produce them, suggesting that the market is not yet saturated, even on the Central Coast. If small farms in other regions are able to grow dry-farm quality tomatoes, it therefore seems likely that the practice could easily expand in geographic scope. However, there are environmental constraints to how far the practice can spread (see Modeling below), even on small farms that can follow the Central Coast's economic model.

3.4.3. Modeling

To better understand where tomatoes might conceivably be farmed in California given the environmental constraints identified above, we modeled dry farm suitability on California cropland as a function of precipitation, temperature, and percent clay in soil. The resulting map shows what lands could potentially support a dry farm crop, with and without supplemental irrigation, using constraints that are relaxed to encompass the least restrictive farmer-elicited constraints (Figure 1). The map therefore errs on the side of including land that is not an ideal candidate for dry farming, rather than leaving off land that may potentially be a good fit. With rising temperatures and less reliable rainfall, this map, which is based off of 30-year normals, likely also systematically overestimates what areas might fall into these thresholds when projecting into future climatic conditions.

All areas in blue indicate land that meets a threshold where dry farming could be considered in a non-drought year without adding any irrigation. Areas in orange indicate that, while there is likely enough rain to sustain a winter cover crop, some amount of irrigation (and therefore water access) would often be needed to grow a successful dry farm crop. Areas in darker colors (blue or orange) connote land that falls in conditions that are closer to ideal, whereas lighter colors indicate that more conditions are tolerable, rather than ideal, for dry farming.

It is crucial to note that areas that show up as "suitable" on the map–including the most ideal locations–will likely require years of diversified management (cover cropping, organic amendments, etc.) for soils to build the water holding capacity and fertility that allow for peak dry farm performance. These areas should therefore be considered candidates for long-term dry farm management, rather than ready-to-go dry farm fields.

Because the constraints used to build the model were elicited specifically with regard to tomatoes, this of course is not a comprehensive map of everywhere that might be considered for dry farming non-tomato crops. Particularly when it comes to grains and perennials (e.g. orchards), the range of possible locations is likely much broader. In the case of grains, winter varietals can be planted that take advantage of rain in winter months, while tree crops have far more extensive root systems that can reach water well beyond that which might be available to a tomato, in both cases relaxing the temperature and precipitation constraints that tomatoes need to survive without irrigation. Tomatoes are likely a better proxy for other vegetable crops (e.g. squash, potatoes), though each will have its unique requirements (and economic limitations as discussed above).

As we imagine a shift towards dry farm agriculture in California, it is also important to consider how land that is suitable for dry farming is currently being used. Combining areas that are suitable for tomato dry farming with and without irrigation, we compiled a list of the top ten crops by area (as identified by the 2021 Cropland Data Layer) that are currently grown on these lands (Table 3). Some of them (grapes, winter wheat, and of course tomatoes) are currently being dry farmed with some regularity in the state and could signal particularly easy targets for a shift to low-water practices. Others (almonds, walnuts) are dry farmed in other Mediterranean climates and suggest an important opportunity for management exploration in lands that might be particularly forgiving to experimentation. The remaining crops (pasture, alfalfa, hay) are some of the most water intensive in the state and would therefore lead to substantial water savings if the land could be repurposed.

While unrealistic in the near future, calculating potential water savings from a complete conversion of suitable lands to dry farming allows for comparison with other water saving strategies. Even assuming that an acre-foot of irrigation is added to each acre of dry farm crops every year (an overestimate compared to the 0-10 inches that farmers in this study use), if all the land listed in Table 3 were converted to dry farming and irrigated to the statewide averages listed in the table (California Department of Water Resources, 2010), California would save 700 billion gallons of water per year, or nearly half the volume of Shasta Lake, the largest reservoir in the state. Given the overlap between suitable dry farm areas and high priority groundwater basins, these potential water savings are especially valuable as water districts scramble to balance their water budgets in light of SGMA.

Perhaps the largest caveat to these potential water savings–and any analysis of dry farm suitability that relies solely on environmental constraints–is the economic reality in which conversions to dry farming currently occur. As discussed above, while a dramatic reduction in irrigation inputs might be feasible from a crop physiological perspective, whether farms can remain profitable through such a transition is an entirely different question. Given a dramatically increased supply of dry farm tomatoes, the profits that current dry farmers rely on could easily crumble. When considering other, less charismatic crops that could be good candidates for dry farming (that might also thrive in these areas), customers' likely hesitance to pay as steep a premium for high quality produce as they do for tomatoes also casts doubt on the viability of a large-scale dry farm transition given current profit structures for farmers.

3.4.4. Opening opportunities

Though there are limits to how far tomato dry farming can expand as a regional specialty, and with its reliance on consumer excitement to support profits, farmers do also see enormous potential for dry farming to improve various aspects of the food system if given the proper support.

In an age of changing climates, farmers are all too aware of the challenges they will likely face as temperatures rise and water access becomes less reliable. With climate risk looming, farmers are looking to dry farm tomatoes as one of the safest bets they can make on their fields:

> I think of all the crops that would survive in climate uncertainty, this is the one that would be the cornerstone of resiliency.

Given dry farm tomatoes' ability to offer resiliency to coastal farmers, they are unsurprisingly looking to other crops and varieties that might be able to make the transition to dry farming. In addition to other crop species, farmers are also searching for tomato varietals (e.g. a dehybridized Early Girl called the "Dirty Girl") that would allow them to save seed and better adapt their crops to their local context, as the currently preferred Early Girl varietal is a hybrid and therefore cannot support seed saving.

> We could be adopting a lot more varieties for dry farming. Because Early Girls is like a fluke that they dry farm well, but then Dirty Girls is more intentional selection for dry farming. And we could be doing that with way more crops. I think like chili peppers–definitely. And beans for sure. There's a lot of stuff we could be pushing, like selection boundaries for a lot more melons.
>
> If somebody was like, 'this is a dry farm winter squash' and save seed from it, we could probably do it. But it hasn't been developed, right? And right now, we don't have the programming to support it. But I think it'd be really fun.

While this shift may be difficult to make in the current economic landscape, there may soon come a time when farmers' options are not between growing tomatoes or a more lucrative irrigated crop, but rather between growing a variety of dry farm crops or nothing at all. In the interim, policies that would allow farmers to make higher profits on less charismatic dry farm crops, as well as research support through breeding programs, could help farmers more smoothly transition to a low-water future.

Even in its current scope, dry farming offers farmers access to land that might otherwise not be arable, a possibility that will likely only become more appealing as more crops enter fields and markets as viable dry farm varietals. Eight farmers in the study had actively farmed in areas that would otherwise not be suitable for crop production:

> I'm here because I felt like I could dry farm and because there's very insufficient water to produce other stuff here. But on dry farming, I feel like all we got to do is water them in, and then we're good. You know, so that's a lot of times I take these pieces that have substandard water.

> It does give you some flexibility to grow things in certain areas where I wouldn't even consider growing something else.

This possibility of gaining access to marginal lands for vegetable cropping also opens opportunities for incoming and marginalized farmers who otherwise can face extreme difficulties securing fields to farm (Carlisle et al., 2019).

Farmers also expressed excitement about ways dry farming can help them better steward their land. Rather than use saved water to irrigate other crops, farmers were intrigued by the prospect of returning that water to natural ecosystems:

> We are rainwater catchment, but we're still diverting–ultimately it's water that would be going to the creek, so if we can figure out how much water we really need and it's way less, we could be doing more creek releases for fisheries. [It] would be awesome because supposedly there is salmon in [the] creek and we do certain creek releases right now with NRDC. Our obligation to do that ends next year, but it'd be great if we could keep doing that.

By aligning lands well-suited to dry farming with conservation goals, areas to target for dry farming could be optimized to serve non-human interests as well, particularly if the right policy support is provided.

Amidst the myriad opportunities and benefits dry farming offers, it also emerged as an important avenue for outreach and education. Farmers see dry farming as a key model for what climate resilience can look like.

> So educationally, that's the easy one. It just totally makes sense... It has roads into climate change. It has roads into agronomy, and soil science, and understanding soil water dynamics. And so I think it's a really important crop to contrast with the irrigated lands, you know, in an era of climate change and really climate unpredictability.

Several farms are already using dry farming as an education tool, and still more have benefited from learning about dry farming at organizations like the Center for Agroecology (formerly CASFS) that have served as hubs for understanding, refining, and teaching the practice. Eight of the farmers in this study could trace their dry farm lineage back to the Center for Agroecology in some way, highlighting the importance of farmer-to-farmer education and farmer field schools.

> They learned it from CASFS, I believe... So I feel like there's a lot of good that's come of that research hub.

Because tomato dry farming is such a localized specialty, education and research hubs may be all the more important in not only teaching farmers the practice in a final or static form, but for teaching more versatile principles and forging long-lasting learning communities where farmers can continually return and convene to hone the practice to fit new crops and landscapes.

3.5. Discussion

As policymakers increasingly focus on dry farming as a solution to California's water crisis, there is significant interest in expanding dry farm management beyond its current scope. Nonprofit policy advocacy groups have been calling for increased dry farm production in California (CAFF, 2015; DeLonge, 2022; Pottinger & Peterson, 2021), beginning conversations about how such a transition might be supported. We conclude by exploring how dry farming can act as a model for a transition to both low-water agriculture and a more agroecological food system, as well as the policies that hold the most promise for dry farm expansion.

3.5.1. Central Coast dry farming as an agroecological transition.

As agroecology–a form of agriculture based in small-scale, thought-intensive, diversified farming systems and the socio-political movements necessary to defend and advocate for their wider adoption–gains recognition as an alternative to industrialized agriculture, questions of how our food system might transition towards agroecology have gained considerable attention (Duru et al., 2015; Gliessman, 2016; Tittonell, 2020). We look at dry farming through the lens of the four key dimensions of agroecological transition–changes in production practices, changes in knowledge generation and dissemination, changes in social and economic relations, and changes in institutional framework (Gliessman et al., 2018)–on the small, diversified operations where it is currently practiced, asking how dry farming can further differentiate these farms from an industrialized agricultural system.

3.5.1.1. Changes in production practices.

The specialized management involved in non-irrigated vegetable production is perhaps the most obvious change in dry farm systems. From the lack of water inputs to the cover crops and dust mulches that allow dry farm tomatoes to thrive, a unique management regime sets dry farming apart from irrigated, industrial-style production practices in the region.

3.5.1.2. Changes in knowledge generation and dissemination.

Successful dry farming must tailor management decisions to the specific field that is being farmed and the weather conditions that year (see 'Motivations for dry farming' above). This localized knowledge is shared through farmer-to-farmer conversations and teaching farms that mirror the rich history of campesino-a-campesino exchange and farmer field schools that exemplify farmer-led agroecological knowledge exchange throughout the globe (Holt-Giménez, 2006; Waddington et al., 2014).

3.5.1.3. Changes in social and economic relations.

Farmers' ability to market products directly to consumers–who in turn developed trust in certain farms to provide particularly high quality tomatoes–was key to allowing farmers to charge a price that made dry farm tomatoes economically feasible to grow. The concurrent development of the Slow Food movement in the region, with its focus on local cuisine and calls for quality over quantity, and local chefs' praise for dry farm tomatoes' intense flavor gave them a staying power that farmers might otherwise have had trouble accessing (Waters, 2006).

3.5.1.4. Changes in institutional framework.

Dry farming follows a long history of agroecological transition in spite (rather than because) of government policy. As is all too often the case, farmers interviewed for this study could not point to a single government program that assisted in the development or continued viability of dry farming as a practice. Water shortages have already begun to encourage policy involvement (e.g. SGMA), begging the question of whether such involvement will actively support or undermine an agroecologcial transition (as has already been seen with organic strawberry farming in the same region; see below).

Thus far, these changes have followed a multi-level perspective in which agroecological transitions use exogenous shocks (e.g. water shortages) as windows of opportunity to enter a dominant agricultural regime (Blesh et al., 2023; Geels, 2002). With dry farm innovations creating a niche that supports small-scale farm diversification, we ask how institutional pathways may lead to a new regime of agroecological water saving.

3.5.2. A model for water saving.

Our suitability map shows potential for vegetable dry farming to be practiced on California croplands that are currently irrigated, though its expansion is inherently limited. Even if markets could be adapted to support an influx of dry farmed vegetables, our map indicates that climatic constraints will largely require dry farming to be practiced in coastal regions or other microclimates that can provide cool temperatures and sufficient rainfall. However, the Central Coast's tomato dry farming offers principles–but not a blueprint–for low water agriculture in other regions.

Based on themes from our interviews, these principles show a cycle of water savings that connect reduced inputs, management diversification, and market development (Figure 2). The cycle begins with lower irrigation (reducing water inputs), which can be accomplished in concert with soil health practices (e.g. cover cropping, adding organic amendments, etc.) that build soil water holding capacity and increase long-term fertility. Reduced weed pressure and lower biomass production can then lead to reducing other inputs, such as labor and fertilizers, while also allowing for further water savings. The combination of reduced inputs and soil health practices then gives rise to a product that is unique in its water saving potential, and may also be of unusually high quality. By encouraging consumers to appreciate the products, or through novel policy support, farmers can develop markets that will provide a premium for these low-water products–or payment for the practice itself–which in turn creates an opportunity to expand the practice, further lowering inputs.

3.5.3. A forking path.

As we ask how policies may impact dry farm production systems, we find a forking path in what types of expansion may result from different policies. An increase in production can be accomplished through both scaling size (increasing the size of individual dry farm operations) and scaling number (increasing the number and geographical scope of dry farm–or dry farm-infomed–operations). Both options can tap into the water saving cycle to decrease water usage; however, the search for just, agroecological transitions has pointed time and again to the need for scaling number (Anderson et al., 2019; Ferguson et al., 2019; Gliessman et al., 2018).

On the Central Coast, small, diversified farms have used this water saving cycle to both cut water use and develop a specialty product that allows growers to farm in areas with high land values by increasing their land access, profits, and resilience to local water shortages. Through these principles, small-scale operations have differentiated their management from both industrial farms and even other small farms in the region by creating a system based in localized knowledge, soil health practices, and thought-intensive management.

However, it cannot be taken as a given that this water saving cycle will continue to uplift the small-scale operations on which it started. Recent work highlights the potential for biophysical and socio-political conditions to combine to shrink–rather than grow–the use and viability of agroecological systems (Ong & Liao, 2020). In the case of dry farm tomatoes, socio-political attention is already beginning to target the biophysical need to decrease water consumption. If well-intentioned policy interventions designed to decrease irrigation water use build markets that value the fact of dry farming, rather than the high quality fruits it produces (e.g. labeling and payment for practice programs), growers will be able to scale the size of dry farm operations without needing to rely on the highly localized knowledge required to produce high quality fruits. As large grocers scale up dry farm produce sales without worrying about quality-based markets that may quickly saturate at industrial scales, the agroecological systems that originally produced dry farm tomatoes may be edged out of the market. On the other hand, if policies build guaranteed markets for small farms growing dry farm produce, dry farming may grow by scaling out to more small-scale operations.

Policies focused on water savings may then favor industrial or small-scale farms, depending on how interventions shape the "Market Development" aspect of the cycle. We therefore examine this cycle not only as a means to save water, but ask if and how it can enhance the viability of non-industrial farming operations as the food system adapts to restricted water availability. We consider the relevant policy recommendations outlined in Blesh et al.'s (2023) analysis of how institutional pathways can act synergistically with farmer networks to enable agricultural diversification (encourage tracking systems, cost share programs, seed/land access, research/education, and public procurement), asking which have the potential to point future dry farming towards scaling size vs scope.

3.5.4. The trouble with scaling size.

To better situate these policy options in the local context, we first look to the outcomes of institutional intervention in organic strawberry production in a very similar region on the Central Coast, and consider the analogous options for dry farm tomatoes.

Similar to dry farm tomatoes, organic strawberry production was launched into the spotlight by government-mandated input curtailments (water restrictions in the case of dry farm tomatoes, a methyl bromide ban in the case of strawberries). For strawberries, the development of an organic strawberry production system also coincided with the adoption of an organic certification process by the US Department of Agriculture. Growing public interest in organic strawberries and the methyl bromide ban led to the rapid expansion of industrial-scale organic strawberry production–blatantly scaling size of production (Arcuri, 2015; Guthman, 2016; Jaffee & Howard, 2010). As production increased, organic strawberry markets saturated and prices crashed, leaving an economic landscape where only the largest operations could remain viable selling strawberries at market prices (Guthman, 2004b). At this point, agroecological growers had to redouble their efforts to target local consumers with direct marketing strategies, as the organic label no longer added the necessary value to profitably sell their product.

3.5.4.1. Tracking systems.

In an analogous case for dry farm tomatoes, it is easy to see the immediate appeal of establishing a "dry farm" label that can incorporate the social value added to dry farm tomatoes into the price of the product without relying on consumers trusting and paying a premium based solely on higher qualities. However, by divorcing dry farm practices from quality premiums and trusting relationships with customers, a dry farm label would make it much easier for large-scale growers to enter the dry farm market. These larger operations–which may struggle to produce high quality fruits or maintain direct relationships with customers but can still decrease water usage enough to produce a certified dry farm tomato–could easily grow dry farm produce at large enough scales to edge smaller growers out of the label. As has been seen in the organic program, industrial growers could also lobby for an official relaxation–a literal watering down–of label standards (Guthman, 2004a). This sidestep of the dry farm practices described in the above interviews would not only further advantage large scale farmers, but would also undermine the very water savings that they are meant to encourage.

3.5.4.2. Cost share programs.

Larger scale growers may also be favored when farmers are paid to implement specific practices. Administrative costs involved in enrolling in payment-for-practice programs can be a cumbersome barrier to entry, while low payouts at small scales dissuade small farmers who implement the practice from enrolling (Cronin, 2023; Reimer & Prokopy, 2014). These patterns are currently seen in programs offering cost shares for cover cropping, where farm size is significantly larger for participants than non-participants (Sawadgo & Plastina, 2021).

3.5.5. Policy options for scaling the scope of dry farming.

Rather than replay the pitfalls of policies whose design is likely to increase dry farm adoption via larger growers entering the market, we ask instead which policies might encourage dry farming to "scale number," increasing production via more crop varieties and accessible land (seed/land access), more small growers (education), and more markets for them to sell to (public procurement).

3.5.5.1. Crop varieties.

Given farmers' interest and current experimentation with dry farming non-tomato vegetables, expanding the set of crops that can be dry farmed and adapted to local conditions is a clear target for future policies. Support for research and participatory breeding programs/variety evaluation could spur development of locally-adapted dry farm varietals. By compensating farmers for experimentation with diversified dry farm rotations and development of locally adapted varietals, policymakers can also absorb some of the risk inherent to on-farm experimentation and encourage innovation on the farms that are most familiar with the practice, while simultaneously lowering barriers for farmers new to the practice. To create a policy environment where experimentation feels more accessible to farmers, minimum lease terms (e.g. 10 years) could be set for farmland, allowing farmers to feel more secure in investing in localized practices (Stevens, 2022).

3.5.5.2. Land access.

Priority could also be given to creating programs that connect farmers–particularly new farmers and those who hold underrepresented identities–to available farmland. Without the burden of securing water access, lands that would otherwise be impossible to farm with summer crops could become arable, particularly in conjunction with the concurrent support of the other policies discussed here. Though many areas will still require some access to water to successfully dry farm (i.e. orange areas on suitability map), crops' need for water coincides with points in the season when surface water is most available (Schlenker et al., 2007), making areas with inconsistent water access over the course of the season likely candidates for dry farm success. Priority might initially be given to areas shown as suitable on the map, but as new and locally adapted crop varieties emerge, access may also extend.

3.5.5.3. Farmers.

In addition to land access, new and transitioning dry farmers will require education and support to successfully implement the practice. Funding for field days, demonstration farms, and farmer-to-farmer networking events can encourage the spread of knowledge to new farms and farmers (Carlisle et al., 2019; Teixeira et al., 2018).

3.5.5.4. Markets.

Finally, increased dry farming must be met with increased capacity for markets to accept dry farm produce at prices that support farmer livelihoods. While some market expansion is inherent to a geographical expansion beyond the Central Coast region, additional markets throughout the state can offer dry farmers more security in a production expansion. Public procurement programs (e.g. the Farm to School Incubator Grant Program currently aiming to expand farm to school supply chains) could serve to connect dry farmers to guaranteed markets, especially if they are prioritized for entry into the program.

3.6. Conclusion

As water shortages are exacerbated by changing climates in California and across the globe, there is an increasingly urgent need to adapt agricultural systems to use less water. By nearly or entirely cutting irrigation to tomato crops grown in the summer season, dry farming has particular appeal as a low-water alternative to irrigation-intensive agricultural systems. While tomato dry farming is an inherently localized farming practice, suitable only for implementation in a specific region, it also offers a global model for how farming systems might shift towards low-water agriculture. Beyond decreasing water use, with the right policy support, dry farming also presents an opportunity to support innovation on small, diversified farms, transitioning the food system towards an agroecological future.

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3.9. Figures

Figure 1. Dry farm suitability in California. Areas shown in blue indicate cropland that meets all farmer-provided constraints for non-irrigated dry farm production. Areas in orange indicate cropland that meets all other constraints, but would likely need supplemental irrigation in most years. Darker colors (blue and orange) indicate areas that fall within optimal ranges for each constraint, while lighter colors indicate that some constraints were tolerable but not ideal.

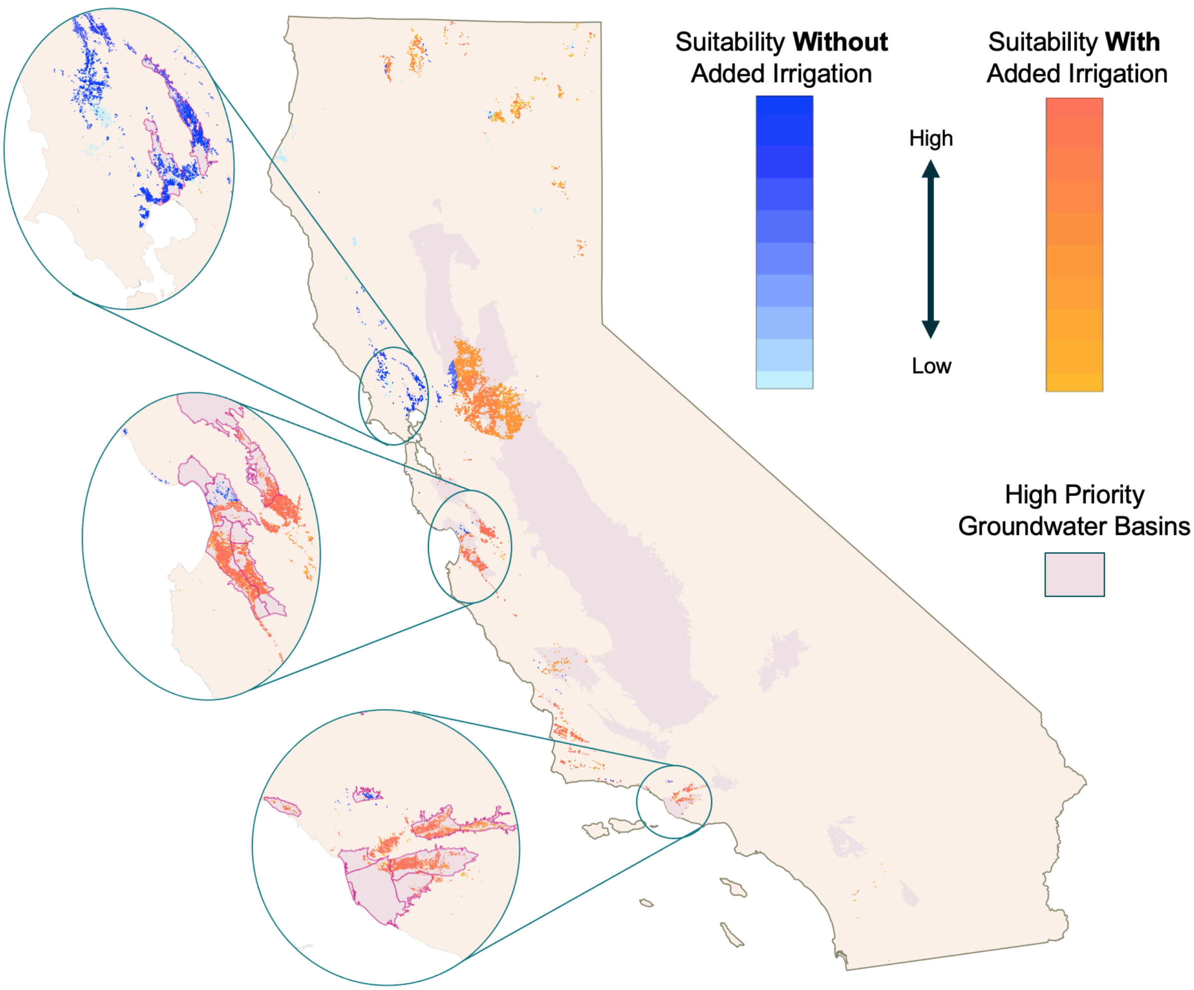
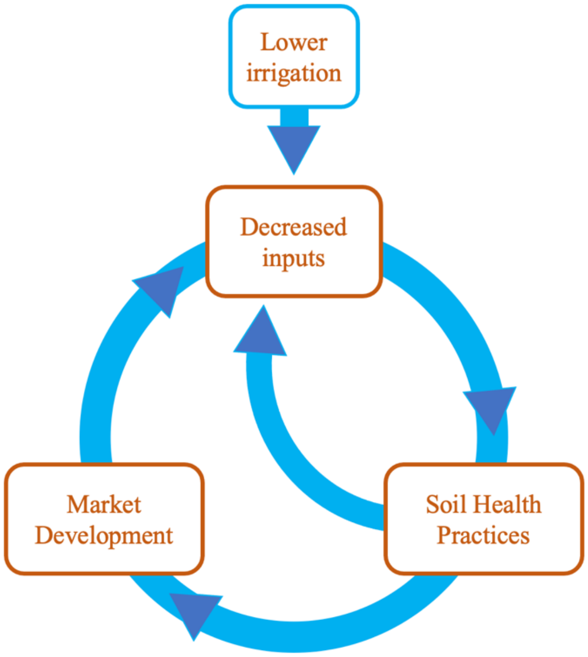


Figure 2. The water saving cycle modeled by dry farm tomato systems.



3.10. Tables

Table 1. General characteristics of farm operations associated with each interviewee. Where cells are empty, interviewee could not provide information.

Farm	Area cultivated (ac)	Area in dry farm tomatoes (ac)	Percent farm income from dry farm tomatoes	Water Source	Main markets	Price (full price/ wholesale)	Non-tomato dry farmed/low water crops	Self-described farming style (all farms are certified organic)
A	10	4.5	65%	Groundwater	Farmers markets	$4/–-	Winter squash	Diversified organic
B	60	4	5%	Groundwater	Farmers markets, CSA, you-pick, value added products	$3/$2	Potato	Organic
C	42	6-10	30%	Groundwater	Farmers markets, wholesale	$4.50/$2	–	Small scale organic
D	1.5	0.5	40%	Groundwater, storage tank	Farmers markets, restaurants	$4/$2	Winter squash	Certified organic
E	13	0.25	2%	Surface water/reservoir	CSA, wholesale, restaurants	$5/$2.50	–	Diversified organic
F	12	0.2	2.5%	City water	CSA, basic needs program	$3.50-$4/–	Hopi dry beans	Agroecological
G	25	2	50%	Groundwater	Farmers markets	$4/–	Winter squash, watermelon	Organic
H	5.5	0.2		Reservoir	Farmers markets	$5-$8	Winter squash, melons, shallots	Diversified

Table 2. Farmer-provided environmental constraints. The table is left blank where farmers either did not volunteer information about a given constraint or explicitly stated that they did not feel confident in giving an answer. Farmer responses were synthesized into model constraints that were relaxed to encompass the least restrictive estimates in order to cover all areas potentially suitable for tomato dry farming.

Farm	Precipitation	Temperature	Soil
A	At least 15”	Not more than 90 consistently in the summer	–
B	–	Can’t get above 100-110	Clay loam
C	At least 24” (non-irrigated); have to do a lot of pre-irrigation if less than 16”. Timing of rain matters.	Can’t get above 110	Clay is important; too much sand relies on close water table and leads to poor quality
D	20” (well-timed)	Not more than upper 80’s consistently in the summer	–
E	–	Can’t be too hot	High enough clay content, soil management history
F	19” is our threshold for dry farming; timing of rains matters a lot. Need enough in winter to grow cover crop.	Has to cool off at night	Clay is important; would be hard if too sandy
G	At least 15”	No sustained spells >105	Having clay is important, not too sandy
H	–	Santa Cruz is pushing it (too hot); has to be warm enough to grow tomatoes	–
Model Constraint	Suitable without irrigation: >22” Suitable with supplemental irrigation: 14-22” Not suitable: <14”	Max temp Good: <86 Tolerable: 86 - 95 Intolerable: >95 Min temp Intolerable: >59	Good: 10-50% clay Tolerable: 5-10% clay Intolerable: <5% clay

Table 3. Current uses of cropland (as classified by the 2021 Cropland Data Layer) within high priority groundwater basins that our analysis indicates as suitable for dry farming. Water usage data from the California Department of Water Resources.

Crop	**Area (ha)**	**Average annual water use (Acre-foot/Acre)**
Grass/Pasture	98138	4.05
Grapes	86340	1.86
Alfalfa	84520	5.05
Other Hay/Non Alfalfa	45625	1.39
Almonds	40507	3.54
Fallow/Idle Cropland	36240	NA
Walnuts	33661	3.30
Winter Wheat	31355	1.39
Shrubland	26088	NA
Tomatoes	21878	2.15

3.11. Supplementary information

DRY FARM PARTICIPANT INTERVIEWS

Guide for Semi-Structured Interviews

Part I: Introduction

1. Thank you for participating! I know some of these questions will be redundant with what we've talked about this past summer, but trying to get it all in one place.
2. Brief summary of research project and objectives. We will go over preliminary results before the interview!
    1. same goals as we've already talked about
    2. Trying to get a sense for who is dry farming and why
3. You are not obliged to participate at all or answer any questions you do not want to answer, we will not share your name with anyone, and we will not associate your answers with your name.
4. This interview process is completely voluntary and confidential.
5. We would like your permission to record this interview. Recording allows us to confirm our notes are correct and be sure we represent your comments exactly as you say them – they are for backup purposes only. We will keep the recordings until the end of the project and then destroy them. Do you mind if we record this conversation?
6. Please know that there will be pauses between questions as I catch up in my notes from your answers.

Part II: Farm history and Dry farm practices

Farm History
How long have you been farming; have you always been a farmer?
Farm Characteristics
Do you have a full crop list of what you grow on your farm (and can I have it)? Any livestock?
Acres managed for crops, by ownership (owned, private leased, public lease, etc.)?
What are the sources of your irrigation water? How reliable are these sources?
What varieties of tomato do you dry farm? How much space do you give to each?

Where do you get starts from?
What do you call your style of farming? (organic, regenerative, etc.)
Dry Farm Management
What does "dry farming" mean to you?

Describe your field and bed prep
• Typical plant dates (earliest and latest)? How do you decide?
  o Staggered plantings?
• Bed spacing?
• Plant spacing? Density (plants per acre)?
• How large are your fields (min-max)?
• Do you have a set rotation with your df tomatoes?
  o What crop came before them last year?
  o The year before that?
  o This coming year?
• What amendments do you add to the soil?
  o When do you add them and how much do you add?
• How deep do you try to incorporate the amendments?
• Mulches?
• Cover cropping?
• Do you ever fallow?
• Typical harvest interval? How do you decide when to stop?

Do you dry farm anything besides tomatoes? How does your field/bed prep differ?
Are there crops you aren't currently dry farming that you think would be good candidates?
Describe your water management • What type of irrigation? • How many acre inches of water were applied on your earliest planting last year? (or any info you have on irrigation)   o What was the timing? • How do you decide when to water?
How has your dry farm management changed over time?

Why does dry farming work well for your farm? (Tomatoes and otherwise)
What do you see as the climatic constraints of dry farming tomatoes?
Management Motivations
What motivated you to start dry farming? (environment, water concerns, economics, neighbors?)
Do you prefer dry farming to other management styles? Why?
Was it difficult to transition to dry farming?
Do you manage with any ecological goals in mind? If so, please describe.
Management Repercussions
Have you noticed any changes on your farm since you implemented dry farming practices?
Did you experience any challenges (institutional, social, ecological) to adopting dry farming? Please describe
What are the challenges/barriers to adoption that you think are most prevalent among farmers who have NOT adopted the practice?

Part III. Community, Marketing, Institutions and Policy

Where did you learn to dry farm? Who taught you/how did you learn?	
Where do you go when you have questions? • Do you consult with any organization or institution to inform your method of farming? • Which organizations?	

Have you relied on any government, state, or NGO conservation programs to help pay for implementation of sustainable practices?	
Are you certified organic? Any other certifications?	
Do you feel like your farming practices have impacted other farmers' practices? Have you been engaged in learning about and/or spreading new techniques?	

Part IV: Water and Land Access

Has dry farming changed your ability to access land?	
Has dry farming changed how much water your farm uses?	
Has dry farming changed the way your farm would respond to a drought/water restrictions?	

Part V: Economics

What are the main markets you target with your produce (DF and otherwise)?	
How many farm workers do you hire each year? I.e. how many people are working for you?	

Price
• What price do you typically get for your dry farm tomatoes?
    ○ Direct to retail
    ○ Wholesale
• How does that change over the course of the season?
• What price do you budget for?	

If you grew more dry farmed tomatoes than you do now, could you likely find a market for them at a similar price to the ones you grow now?	
Is farming your main occupation, or do you have other off-farm jobs?	
If you also work off-farm, what proportion of your income comes from on and off the farm?	
What percentage of your farm income comes from dry-farmed crops?	

Part V: Personal Information

Respondent Number	
Respondent, Age	
Respondent, Gender	
Farm role/title	

Part VI: Conclusion

- Is there anything else you would like to add before we conclude the interview?
- Express appreciation for his/her participation
- Review permissions for quotes, and any media taken during the interview

Conclusion

In my dissertation I demonstrate that locally adapted, diversified management systems can serve as a model for shifting agricultural production towards resilience to water scarcity, and that policy must be carefully designed if it is to support this transition. I have highlighted the current reality that policy, economics, and environment are aligning in ways that constrict agroecological transitions in the US Midwest. In listening to farmers' voices and collaborating on building a research program, I have also built a clearer picture of dry farm management on California's Central Coast as an example of an agroecological transition that is at an inflection point when it comes to policy support. I have begun to explore the soil health practices and fungal communities that allow dry farm systems to thrive, and also the environmental, economic, and policy landscapes that dictate the bounds of current production, and where/how it might expand.

These findings have begun to answer the three central research questions that have guided my work so far, and that will continue to set the trajectory for my career:

1. How does policy go wrong, leading farms towards simplification and industrialized growing practices when there is an increasingly urgent need to diversify farming systems?
2. How do these diversified systems function ecologically, and what management practices might enhance their performance, particularly in the face of water scarcity?
3. How could policy go right, supporting agroecologcial transitions as climate shocks open opportunities for food systems change?

In the above pages, I use mapping, participatory research, field data, lab analyses, and farmer interviews to chip away at understanding answers to these questions, as applied to corn-based crop rotations in the US Midwest and tomato dry farming on California's Central Coast. Here I highlight key findings in response to each question.

How does policy go wrong?

In my first chapter, I found that farmers are most likely to implement simplified crop rotations on the most fertile soils in the US Midwest. After looking at rotation patterns on over 1.5 million fields and accounting for spatial autocorrelation using bootstrapped linear mixed models, clear patterns of rotational simplification emerged that clearly mapped onto repercussions of federal policy. Crop insurance[1] and livestock/biofuel production[2] have created an economic environment in which corn is more reliably profitable than any other crop that can be grown in the region, incentivizing farmers to grow corn as often as possible. Recent biofuel policy has further boosted demand for corn, which can be seen in price spikes near biofuel plants[3], leading to our finding that there is a positive association between simplified rotations and proximity to biofuel plants.

Because crop rotation is a key diversification practice that builds soil health, government programs that create conditions that lead to rotation simplification run counter to long-term soil health and production stability in the region. As rotation simplification leads farmers to grow fewer crops in a given year, they are less able to take advantage of the portfolio effect, whereby farm yield and income is stabilized by growing a diversity of crops that respond differently to stressors[4]. Additionally, as soil health benefits accrue, diverse rotations can stabilize yields from a single crop in seasons with adverse growing conditions[5]. The lack of effort to change these incentive structures is therefore surprising as changing climates make simplification all the more risky in the region.

Nevertheless, policy options do exist that can better align practices that support farm resilience with economic incentives. For example, farmers and advocacy groups have pointed to the Conservation Stewardship Program as a policy that has successfully increased diversification practices, and a target for expansion[6,7]. I have also begun to work on a project that will adjust agricultural lending to account for the risks inherent to simplified rotations, which I hope may eventually lead to updated federal crop insurance programs that consider simplification risks. These and other policy options must both consider which practices to encourage, and address where and how these practices might expand through our agricultural system.

How do diversified systems function ecologically, and what management practices might enhance their performance?

Rotational simplification in the US Midwest is not an isolated story; US policy has overwhelmingly led our agricultural system towards industrialized forms of agriculture[8,9]. Yet pockets of diversification exist throughout the country and could flourish with thoughtful policy intervention[10]. In order to understand what practices policy can support to make agriculture more resilient to water shortages, I looked to a system that has thus far been relatively untouched by targeted policies, growing instead out of farmer innovation, consumer demand, and savvy marketing approaches: tomato dry farming on California's Central Coast. Dry farming allows farmers to grow produce with little to no irrigation water, relying instead on winter rains to support crops through rain-free summers, and is made possible with careful soil health management.

I asked the farmers who developed and continue to practice dry farming what would be helpful to know about the system, and together we explored management-relevant questions in a field experiment on these farms. Given that surface soils dry early in the season in these systems, quickly forcing roots deep into the soil profile, farmers wanted to know what depths of nutrients impacted harvest outcomes. Farmers were also interested in the growing body of research about soil microbial communities, and were curious both about symbiotic fungal inoculants that had been advertised to them, and also the impact of dry farming on soil fungal communities more broadly. In finding that plants only access nutrients below 30-60cm, and that commercial arbuscular mycorrhizal inoculants are ineffective on these farms, we were able to provide farmers with immediately actionable information about how dry farm systems function and their management implications (avoid AMF inoculants, focus on fertility changes below 60cm). We also found that dry farm soils develop a fungal signature that supports tomato fruit quality, suggesting a longer term goal to develop dry farm rotations that allow soils to be irrigation-free for multiple years in a row.

Together, these findings also begin to shed light on policy involvement that could most directly benefit dry farming and the farmers that practice it. For example, funding for both farmers and researchers could be allocated to explore varieties and support breeding programs through community based participatory research that would allow crops beyond tomatoes to be incorporated into dry farm rotations (a project that I hope to pursue in my future work). By better understanding how dry farm systems function, we can better target policies that are most needed and have the highest chance of succeeding as interest in dry farming spreads throughout the state.

How could policy go right?

Beyond these targeted interventions, it is also crucial to understand the broader environmental and economic context in which dry farming arose to create an appropriate climate for its wider adoption. Dry farming is an example of a management system that has allowed small, diversified farms to further transition towards agroecology in the absence of policy intervention. The core tenants of dry farmings' context on the Central Coast that allowed it to begin an agroecological transition must be preserved to avoid its cooptation towards an industrial model of water savings.

Interviews with the same farmers I developed relationships with in the second chapter gave me context to understand the environmental and economic conditions in which dry farming currently operates. After synthesizing the themes from these interviews, I created a map that can guide future geographic expansion. I also developed a proverbial policy map to guide dry farm expansion towards scaling the number of agroecological dry farm operations and their geographical scope, rather than scaling the size of a few industrialized operations. A central tenet of both maps was maintaining the conditions and principles that originally allowed dry farming to flourish, rather than altering physical and economic landscapes to force a practice that does not fit local contexts.

Providing more options for farmers to shorten supply chains (e.g. expanding to new farmers markets or connecting farms with farm-to-school programs) allows and incentivizes farmers to profit from dry farm tomatoes' superior quality, while other interventions (e.g. labeling programs or payment for practice) create a disconnect between profits and quality. Because an intimate understanding of soils and climates is required to grow high quality tomatoes, maintaining profit structures based on quality puts a natural cap on a dry farm operation's size, requiring the practice to spread via increasing the number of operations that dry farm and their geographic scope. Keeping this in mind, policies that allow growers who are committed to dry farming to more easily access land–with everything from minimum lease terms to new farmer entry programs–hold particular promise for dry farm expansion. Similarly, funding demonstration farms that can spread the practice to more interested farmers can support an increase in dry farmed land and operation numbers, rather than the acres that are farmed by a single operation.

After thousands of soil samples, thousands of pounds of harvested tomatoes, hundreds of hours spent in conversation with farmers, and more long days in the field and late nights in the lab than I wish to count, I have constructed a foundation of answers to the questions that guided my dissertation research. These answers explore specific, place-based examples of on-farm diversification practices, how they work, and how policy can create or curtail opportunities for them to serve as the basis of a transition towards agroecology in the United States. In future work, I hope to deepen my ties to the farmers, landscapes, and practices I connected to in my dissertation research. I also hope to broaden the scope of practices and policies I consider, while maintaining accountability to communities of current farmers, hopeful farmers who are excluded from current agricultural systems, and eaters whose wellbeing is impacted by the health of our food system.

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