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The dynamics of risk perception in a Mediterranean agroecosystem

Nicolas Gauthier 1 ·

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Abstract Small-scale agriculturalists in the Mediterranean Basin rely on multiple strategies including diversification, intensification, and storage to maintain a stable food supply in the face of environmental uncertainty. Each of these strategies requires farmers to make specific resource allocation decisions in response to environmental risks and is thus sensitive to variability in both the spatiotemporal pattern of risk and the ability of farmers to perceive that pattern. In this chapter, I present an agent-based model of a Mediterranean agroecosystem. By driving the model with realistic environmental dynamics derived from simulations of mid-Holocene Mediterranean climate, and by allowing the psychology of risk perception to vary among individual farmers, I explore the hidden vulnerabilities of traditional risk-management strategies to periods of rapid climate change. I show that even when farmers are able to manage risk "optimally" in light of past experience, unanticipated changes in the spatiotemporal pattern of rainfall can still lead to major food shortfalls.

Keywords belief-based agents · drought risk · crop diversification · rapid climate change ·

1 Introduction

The distinct climate and ecology of the Mediterranean basin afforded both challenges and opportunities to the earliest farming communities. Here, water is the primary limiting resource for traditional agroecosystems. Agricultural droughts – where growing season precipitation is low enough to cause crop

Nicolas Gauthier 1
Laboratory of Tree-Ring Research & School of Geography and Development, University of Arizona
E-mail: ngauthier@arizona.edu

failures, are a constant threat. Precipitation is highly variable in space and time and droughts are difficult to predict with any certainty. How were Neolithic farmers able to adapt to, and even thrive in, such an uncertain environment?

Over the past 10,000 years, small-scale subsistence farmers have relied on a suite of strategies to maintain stable food supplies given uncertain rainfall. These strategies includes practices like crop diversification, storage, mobility, and exchange (Halstead and O'Shea 1989)). Crop diversification in particular is an excellent example of a widespread and effective risk management strategy that is well suited to Mediterranean agroecosystems. In the Mediterranean, land-use strategies involving a diversified portfolio of wheat and barley have been employed by even the earliest sedentary farmers, and continue to be used to this day (Gould 1963, Slafer1999, Abbo2009a, abbo2010,weiss zohary 2011,Marston2011190).Relying on a mix of food types with different climatic tolerances is an efficient way to maintain a robust food supply (**???**). Wheat is high yielding but drought sensitive, while barley is lower yield but drought tolerant. Planting a mix of high yield, high risk and low yield, low risk crops, either in the same plot or in a combination of plots, is an effective means of diversifying the annual supply of staple food crops (**???** et al 2019). By dynamically adjusting the ratio of wheat to barley in their fields, farmers can adapt to a variety local climate conditions with different drought risks.

Risk-managing strategies like crop diversification require farmers to make specific resource allocation decisions in response to specific environmental risks, so are sensitive to variability in both the spatiotemporal patterns of risk and the ability of individual decision-makers to perceive and act on those patterns. Here, I focus this discussion on two main questions:

1. How likely are droughts to occur each year in the eastern Mediterranean, and how did these risks change over the Holocene?
2. How might Neolithic farmers have perceived these changing risks, and what were the consequences for Neolithic farmers' collective ability to manage them?

To address these questions, I first use results from a long-term paleoclimate simulation to estimate the changing risks of past agricultural droughts in the eastern Mediterranean over a 4,000 year period in the early to middle Holocene. Then, I use a simulated population of Bayesian "belief-based" agents to explore the extent to which individual farmers would have been able to perceive these long-term changes in drought risks, given their finite life experiences and limited information processing capacities. This computational approach allows for a more nuanced understanding of the sensitivity of risk-management strategies to changes and climatic variability and imperfect human perceptions of those changes.

2 Decision-making in a game against nature

The basic decision-making problem facing a farmer seeking to diversify their crops can be thought of as a game against nature. We can represent this

Table 1 Estimates of yield volume (t/ha) for ancient wheat and barley varieties derived from [@Slafer1999].

	Dry Year	Normal Year
Barley Yield	0.93	1.18
Wheat Yield	0	1.60

simplified decision context as a "game" in a game theoretic context (**???**). The "game" in this context is the farmer's decision of which crops to plant and in what proportions, given uncertainty in the future "state-of-nature", and nature varies between several possible states such as dry and wet years (Table 1). In reality continuous, but people often intuitively solve an easier problem when faced with a complex real-world situation (**???**). The exact values in the payoff matrix here are less important than the relative payoffs in each quadrant. We can think of this game as being the culturally-inherited object. So in this case the cultural norm would be to mix wheat and barley, but individuals need to choose the precise ratio given their perception of risk. Our question is how do individuals make decisions here?

How should an early farmer make a decision in light of this uncertainty? The basic logic of crop diversitication is Portfolio of crops ala modern portfolio theory: Blank2001 Sometimes best to think of nature as a sentient opponent out to get you, and play strategically based on that assumption. Gould 1963, Beckenkamp 2008 quick overview of criteria without risk, then say that a better option is to estimate the probabilities of the different state of nature Agrawal1968 talks about the strategies in the context of agriculture being a game against nature here I can slip in the cool thing about acting like the weather is out to get you being a good idea in states of complete uncertainty transition – the problem becomes easier if you have at least some idea of nature's moves, because then you cna work to get the highest yeilds given the risk of drought. Decision strategies as choosing different points – plot of decisions

$$a^2 + b^2 = c^2 \tag{1}$$

If an individual can learn about their environment, such as the risk of drought in any given year, then they can behave more rationally by trying to maximize their subjective expected utility. If the probability distribution of nature's moves is known, the farmer can choose the crop mix that simply maximizes the expected crop yields given the empirical frequency distribution of nature's moves. In the language of game theory, this strategy is known as a game of "fictitious play" against nature. While this is can be an effective risk-management strategy, like all strategies adapted to a specific pattern of variability it is vulnerable to changes in the pattern of variability (Janssen eta al 2007)

This strategy works well when the environment is stationary – nature plays from a fixed probability distribution, but is vulnerable to environmental non-

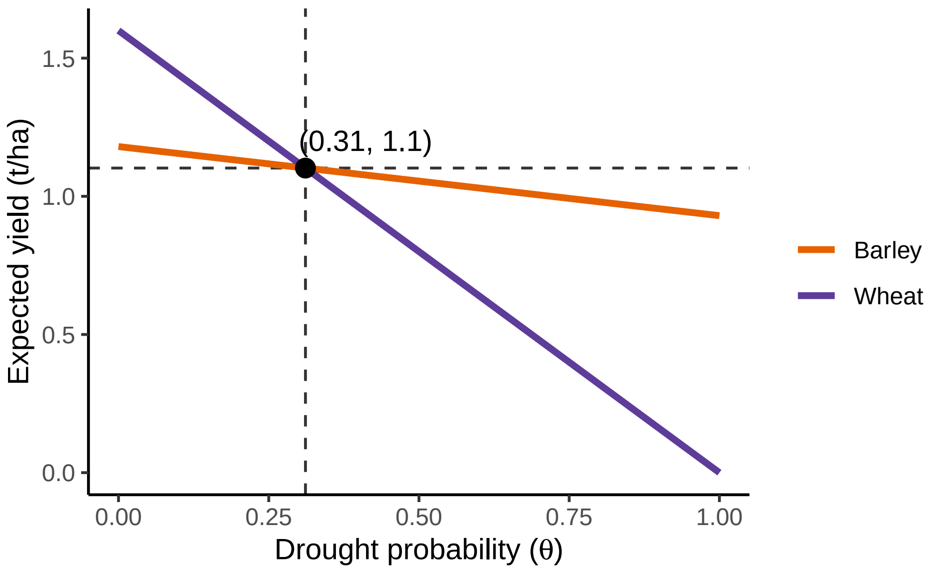

Fig. 1 Expected wheat and barley yields under increasing drought risk with the point of indifference highlighted.

stationarity. That is, when the mean or higher order moments of the rainfall distribution shift, playing a game of fictitious play can backfire because as agents get too stuck in their ways while the world changes around them. Thus it is important to understand the dynamics of risk perception – how subjective risks, and thus subjective expected utility – rise and fall in uncertain environments.

3 Early to mid-Holocene drought risks

In order to estimate drought risks in the past, we cannot rely on present-day observations alone. Not only does precipitation vary from year-to-year, but it is also subject to centennial and millennial-scale trends and cycles throughout the Holocene that are unresolved in the observational period. Estimating not only the risks of drought in the eastern Mediterranean is therefore not sufficient, and this information must be supplemented with estimates of the *change* in drought risks over time. Climate dynamics are non-linear, non-stationary, and non-ergodic, which means sudden, unpredictable variability is the norm in the region rather than the exception. Using the simulated paleoclimate, rather than modern-day weather station observations or paleoclimate proxies, allows us to estimate not just the first order statistics of the climate system (e.g. the mean and variance of dry years) but also the higher order patterns such as the serial persistence of wet and dry years. This presents a much more realistic picture of the inherent year-to-year uncertainty in the climate system, and presents a realistic challenge to simple risk-managing strategies that assume climatic risks are fixed.

3.1 Paleoclimate simulation

Estimates of changing Holocene drought risks were derived from the TraCE-21ka paleoclimate simulation (He 2011). TraCE-21ka is a state-of-the-art simulation that uses a coupled atmosphere-ocean general circulation model to recreate the transient response of the global climate system to changes in the Earth's orbit and greenhouse gas concentrations from the Last Glacial Maximum to the present. The simulation generates physically consistent spatiotemporal climate dynamics, driven by current best estimates of external climate drivers (e.g. orbit, greenhouse gasses, glacial meltwater flux). The model simulates these dynamics on a six hourly timescale, and model outputs are archived at a monthly resolution.

Monthly TraCE-21ka precipitation outputs were extracted from the 3.75° grid cell covering Central Anatolia. This location was selected to sample climate patterns typical for key archaeological sites in the region such as Çatalhöyük and Aşıklı Höyük, and for the eastern Mediterranean more broadly.

3.2 Estimating drought risks

Using the climate model output, I divided each model year into dry years and normal years. A dry year was any year where less than 300mm of rain fell during the wet season (October-May), the threshold below which wheat crops will generally fail (**???**), and a normal year was defined as any year above this threshold. Given the modeled patterns of normal and dry years, the "objective" climatic drought risk $\hat{\theta}$for any particular year was defined as the proportion of the previous 50 years that were dry year as

$$\hat{\theta} = \frac{\sum_{n=t-1}^{t-50} P_n < 300}{50}, \tag{2}$$

where P_n is the growing season precipitation accumulation in millimeters for year n.

The simulated risks of crop failure due to drought ranged between 10% and 46% during the period from 9.5ka to 5.5ka, with a median risk of 24% (Figure 2). This means that, on average, a Neolithic farmer in Central Anatolia could expect their wheat crops to fail two or three times a decade, punctuated by even drier periods in which wheat crops could be expected to fail roughly every other year. The simulation also reveals a long-term trend of decreasing drought risks, in particular with higher drought risk in the early Holocene giving way to lower drought risk in the middle Holocene.

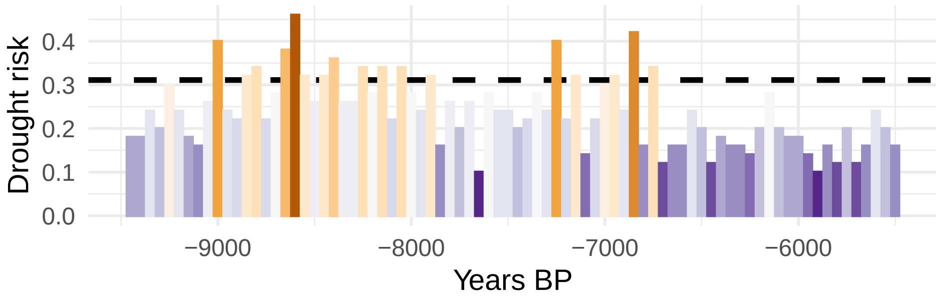

Fig. 2 Annual risk of wheat crop failure due to drought aggregated by fifty-year period. The dashed line indicates the level of risk beyond which one would plant barley over wheat to maximize subjective expected yields (after Figure 1), given the payoffs defined in Table 1.

The TraCE-21ka simulation confirms that drought risk in the eastern Mediterranean was non-stationary and, in fact, quite volatile during periods of climatic disruption in the early Holocene. This volatility would have had severe consequences for early farming communities whose risk-managing practices depended so heavily on accurately perceived local climatic risks.

4 Modeling risk perception

In order to properly manage drought risk, a farmer must first be able to perceive that risk. Yet, a farmer's perception of risk reflects more than just the objective, empirical risk observable in the world around them (Tucker et al. 2013). Individual risk perception is inherently subjective – influenced by a person's past experience of dry and wet years as filtered through memory – and can reflect varying levels of uncertainty. Likewise, the distribution of individuals' perceived risks within a population influences the collective perception of drought risks and the potential aggregate societal-level response to those risks (Moussaïd 2013).

But how best to model risk perception at the individual level? The human brain does not record every bit of perceived information in memory, rather it stores a "compact encoding" of that information which it uses for future decision-making. The tools of Bayesian statistics provides an elegant solution to the compact encoding problem. Instead of recording detailed memories of each year, a "Bayesian agent" can compactly store their beliefs about the world around them in the form of a prior probability distribution. These agents thus develop beliefs about the risk of drought in their environment through their personal experience of the weather, and their perceptions go on to impact their successive decision-making by altering their subjective expected crop yields from planting different crop mixes.

4.1 Prior beliefs and Bayesian Agents

It is possible to capture the influence of risk perception on decision making computationally by simulating a population of "belief-based" Bayesian agents. A Bayesian agent is one whose subjective beliefs can be represented as a probability distribution over possible states of nature (Kahvalti et al 2019 and others????). This approach has a clear computational efficiency – for both modelers and decision-makers – and even if real-world decision makers are not Bayesians in a literal sense the basic algorithmic problem faced by the brain, and the solutions it has evolved, reflect the same constraints on information processing in the heads of decision-makers (Sanborn and Chater 2016).

Here, the probability of a drought occurring in any given year can be treated as a coin flip (i.e. a draw from Bernoulli distribution) with parameter θ representing the drought probability. The beta distribution is a natural choice for representing knowledge about probabilities because it is constrained to fall between 0 and 1. Hence, an individual agent's prior belief about the value of θ can be represented as

$$\theta \sim \mathrm{Beta}(\alpha, \beta), \tag{3}$$

a beta distribution with the parameters α and β corresponding to the number of dry and wet years previously experienced by that agent. Varying these two parameters thus allows us to represent a variety of different personal experiences of drought risk. For example, if an agent recalls having lived through 5 dry years and 25 normal years, their prior belief about the chance of a drought occurring in the following year would be represented as a Beta(5, 25) distribution with mean value 0.2 equivalent to the empirical drought risk for that period, $\hat{\theta}$.

Using probabilities to represent agents' beliefs also allows for estimation of the *uncertainty* in those beliefs (Figure 3). A simple Bayesian agent becomes more certain in their beliefs with age. For example, an agent who experienced 5 wet and 10 normal years and one who experienced 25 wet and 50 normal years would both agree that, on average, droughts occur 50% of the time. Yet the latter agent would be much more certain in this belief because it is drawn from a larger range of experience (i.e. a larger sample size). We can thus represent the exact information content of each individual agent's subjective experience of droughts using the diffusion of this prior belief. How, then, should an agent update its beliefs in light of new experience?

4.2 Bayesian updating and the weight of past experience

As a Bayesian agent moves through time and observes each successive year's weather, it must be able to update its beliefs accordingly. It does does by comparing the information in this year's observation with the cumulative weight of their past experience. The agent combines its prior beliefs about drought risk with the likelihood of observing a drought this year in order to generate a posterior distribution representing its updated beliefs about the world.

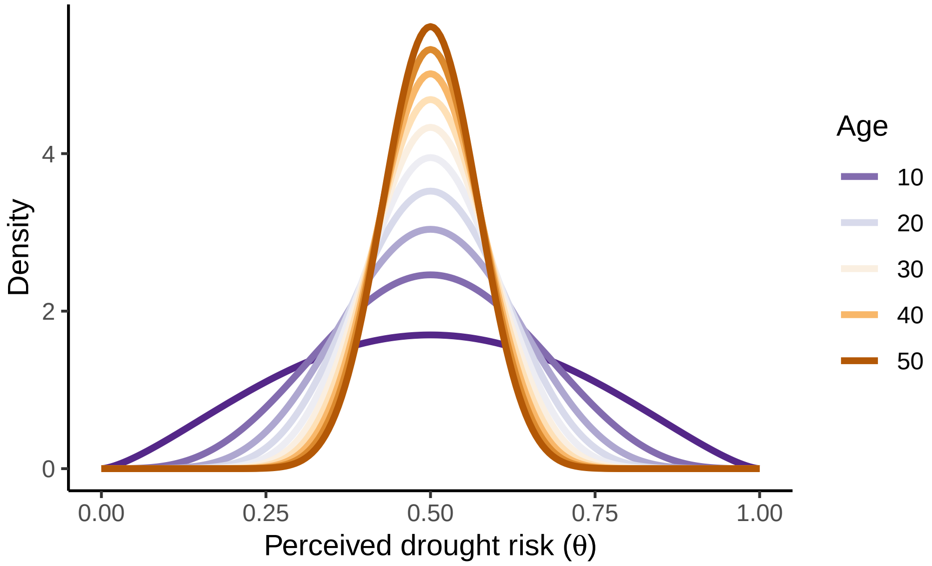

Fig. 3 Development of an individual's perceived drought risk with time, assuming a fixed drought risk of 0.5. Beliefs are represented as Beta probabiity distributions, and the increased certainty with age reflects the varying effective sample size of the Beta prior.

Crucially, the strength of one's prior beliefs determines how much weight is given to new information (Figure 4). For example, assume two agents – one aged 15 and the other aged 50 – who have only ever experienced a moist climate where droughts happen on average two out of every ten years. The mean value of θ for both agents would thus be 20%, but the degree of certainty varies because the older agent is basing this inference on many more years of experience. Now assume the climate suddenly changes such that the drought risk is doubled to 40% for the next 25 years – not an uncommon occurrence in the simulation of early to mid-Holocene climate. Because the prior beliefs of the agents were so different, their subjective beliefs after the drought are also different *even though both experienced the same climate.*

For young agents with weak priors, the information of each new year can thus strongly influence their beliefs. For older agents who have experienced many more years their priors will be stronger, and they will be less likely to update their beliefs when balancing the information from a single year's weather with previous decades' worth of accumulated experience. Although neither agent may perceive the "true" climatic drought risk exactly, they nevertheless reflect perfectly rational beliefs about the world. Both agents have perfectly rational beliefs and differ only in their prior subjective beliefs - their relative conservatism or flexibility are not biases but rather varying perspectives on an inherently uncertain world.

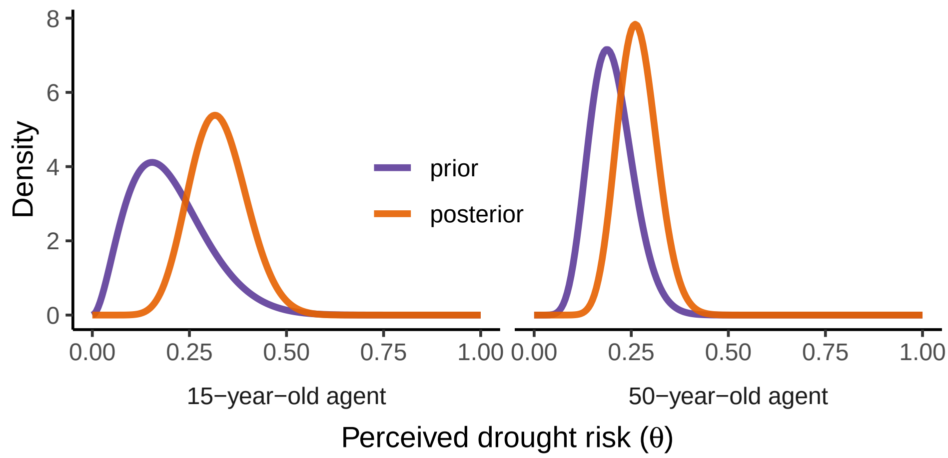

Fig. 4 Change in perceived drought probability in an older (50) and younger (15) agent before and after a 25-year dry period.

As was the case in the game of "fictitious play" discussed in Section 2, having conservative beliefs is fine when the environment is stable and risks do not vary. But when there is volatility in the environment, and risks can indeed change, the ability to change one's mind is crucial. Being too inflexible in one's priors can lead being too optimistic when things really have changed for the worse, or alternately being too conservative when conditions ultimately improve.

5 Risk management and the dynamics of risk perception

While the above example helps establish some basic intuition for how agents with varying subjective beliefs can perceive risk differently, it represents an idealized situation where agents update their beliefs retrospectively after a many-year dry period. Farmers, on the other hand, must update their planting decisions each year and continuously monitor the weather around them. The transient, year-to-year changes in perceived risks can thus have major consequences for how a population responds *during* a dry period. How do Bayesian learners perform in such an uncertain, unpredictable time?

To explore these dynamics we can simulate a population of Bayesian agents responding to a random sequence of wet and dry years. Here, observations are made about the world sequentially, and the agent must continuously update its beliefs accordingly. As in the previous section, an agent's prior belief about drought risk is updated in light of new experience to generate a posterior perception risk. Now, this update occurs every year and thus only a year's worth of new information is incorporated into the agent's beliefs each time step. The learning process is iterative, as an agent's posterior distribution in one year becomes their prior following year and the updating process repeats itself. Formally, this iterative process is known as "online" learning from Bernoulli observations, where "online" refers to the sequential, year-to-year updating (Bissiri and Walker 2010). In this learning environment, isolating signal from noise becomes critical for accurately perceiving evolving drought risks.

Now we can simulate a time series. As above, we'll use a scenario not uncommon in the paleoclimate simulation – a baseline drought risk of 20% punctuated by a 25 year dry period when risks rise to 40%. The results of such a simulation reveal the importance of the subjective experiences of individual decision makers on the population-level perception of risk (Figure 5a).

Translating the uncertainty in drought risk to a particular crop diversification strategy (Figure **??**b).

6 Conclusion

In this chapter, I explored the consequences of individual heterogeneity in risk perception on the risk-management practices of a simulated Neolithic farming community in the eastern Mediterranean. I used a long-term paleoclimate simulation to estimate the changing risks of agricultural drought over a 4,000 year time period spanning the early to middle Holocene. Over this time span, the risk of a wheat crop failing from drought varied from once every ten years to nearly once every two years. Changes of such magnitude would have severely impacted Neolithic agroecosystems in the long run, but would have been difficult for any individual farmer to perceive in the short run.

To explore these dynamics, I simulated a population of Bayesian "belief-based" agents who use their subjective perception of annual drought risks to decide what mix of crops will best manage those risks. During periods of climatic stability, allowing past experiences to influence decision making helps farmers minimize the impacts of *predictable* drought. But past experiences are less informative during periods of rapid climate change, and even farmers who manage risk "optimally" in light of their prior beliefs can experience food shortfalls. Cognitive diversity and life experience can be as or more important than the exact mix of crops planted for a population's long-run survival under extreme uncertainty.

These dynamics have implications for understanding risk management and food production in the Neolithic. Two points arise that this model helps clarify our understanding of the earliest farming communities in the Mediterranean and can inform future simulation work:

1. **Risk perception is hard.** The climate system inherently chaotic. Annual forecasts are fundamentally uncertain, even in the era of modern supercomputers and numerical weather prediction. For prehistoric farmers, this uncertainty would have been a existential challenge. With the end of the Last Glacial Maximum and the advent of the Holocene, precipitation became increasingly volatile on multiple time scales. This uncertainty in

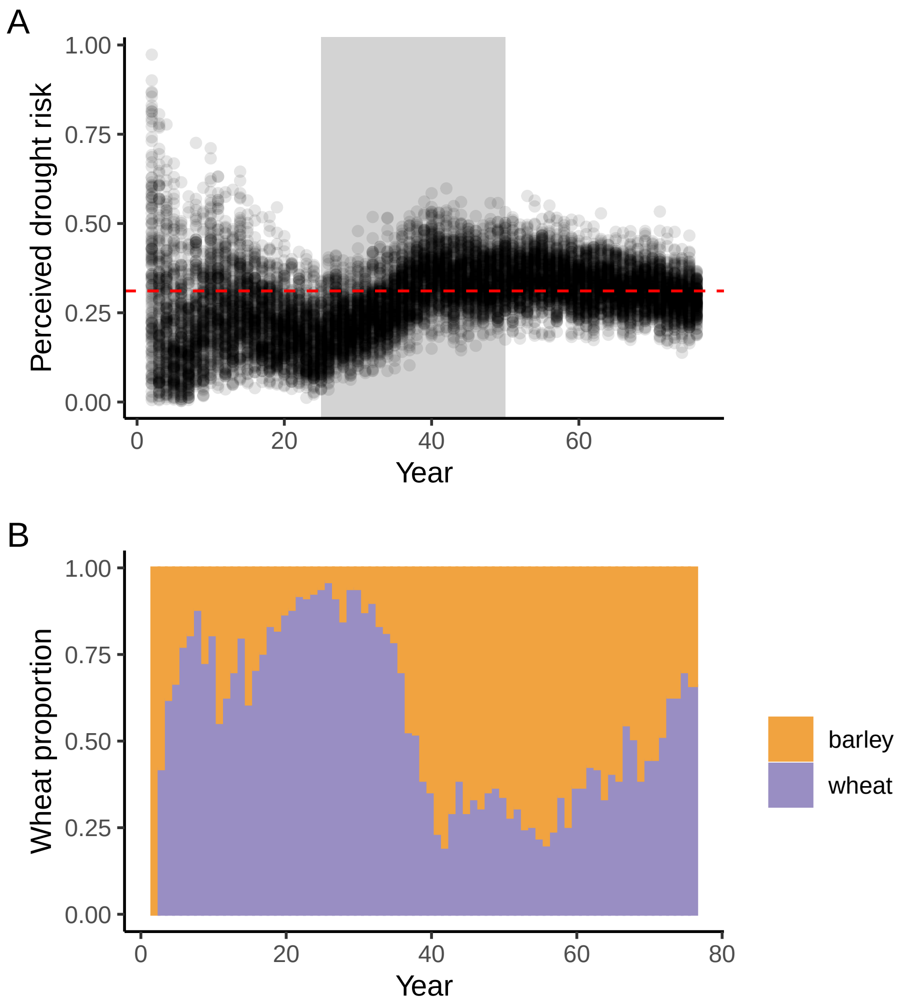

Fig. 5 A: The dynamics of risk perception. B:

the objective drought risk is only compounded by uncertainty in individual farmers' subjective perception of drought risk. Any individual would have experienced only a brief snapshot of this complex period. The rhythm of a single human lifespan is out of sync with the centennial to millennial scale oscillations in the climate system, so even the predictive value of one's own experience is itself unpredictable. This fundamental uncertainty would have influenced far more than the choice of which type of crops to plant – and would have pervaded all kinds of decision-making under risk.

2. **Individual risk perception has consequences for collective risk management.** Individuals of different ages may perceive the same dry period depending on their prior life experience. Younger individuals are more likely to perceive a run of dry years as a trend, rather than a temporary deviation from the norm, and older individuals are likely to do the opposite. By extension, the age structure of a population will influence how quickly it is able to perceive and adapt to a changing climate. For example, a young, fast growing population will have a different collective memory of a past drought event then an older population. Likewise, baby booms and busts associated with famines, or any mortality crisis that afflicts specific age classes like warfare or epidemics, will alter the time horizon of that population's collective memory. Individual heterogeneity in risk perceptions can thus play a key role in broader social responses to climatic risks.

Although social learning and cumulative cultural evolution has not been a focus of this paper (see (**???** and Richerson 1998, 2001)), these findings provide insight into the individual learning dynamics that underlay those broader social processes. Relating collective knowledge to individual cognition is essential for understanding human behavior in complex social-ecological systems (Beratan 2007). This chapter has focused primarily on the physical and cognitive dimensions of risk and risk perception. The social context of risk and risk perception can be equally consequential (Rogers 1997). The balance of individual learning with social transmission determines the collective perception of risks and its impact on collective memory (Moussaïd 2013, candia2019). Our finite lifespans ultimately keep the skill of individual learning low over the long term – cumulative cultural evolution is required.

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