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The spatial pattern of climate change during the spread of farming into the Aegean

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ABSTRACT

I examine the relationship between the spatial pattern of aridification in the northeastern Mediterranean ca 8600 years ago and the spread of Neolithic farmers into the region surrounding the Aegean Sea. I use a generalized additive model to downscale winter rainfall from a state-of-the-art paleoclimate simulation. The model performs well at reproducing the present-day pattern of rainfall in the northeastern Mediterranean, and it generates physically-interpretable estimates of past rainfall consistent with global and regional proxy records of early Holocene climate. Comparing modeled rainfall with Neolithic settlement patterns reveals spatially-heterogeneous regional impacts of this period of global aridification. Only the humid regions of the Aegean coast experienced major drought, while more inland zones temporarily experienced more rainfall. The result of this spatially heterogeneous climate event was, conversely, more homogeneous regional rainfall. Neolithic colonists from southwest Asia would have encountered new landscapes with a more familiar, and predictable, precipitation regime.

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1. Introduction

The early farmers of southwest Asia expanded into the Aegean littoral — western Anatolia, Greece, and Thrace — during a period of global climate change starting 8600 years ago. This period of cooling and aridification is distinct from the rapid-onset global cooling event beginning 400 years later (the "8.2 ka event", where ka is 1000 years before present) (Rohling and Pälike, 2005). Although the increases in aridity after 8.6 and 8.2 ka are often conflated in discussions of Neolithic dispersal, the former period of climate deterioration is more consistent with the chronology of the expansion of farming into the Aegean littoral and beyond (Düring, 2013; Weninger et al., 2014; Flohr et al., 2016). For thousands of years prior to this period, farming had failed to spread along the maritime and terrestrial networks connecting the Aegean to the Neolithic core zones of southwest Asia (Schoop, 2005; Brami, 2014); in the millennium that followed, founder populations of Aegean farmers gave rise to farming communities across the Mediterranean and Europe (Hofmanová et al., 2016).

Several studies have sought to connect this drought to the Neolithic dispersal directly, with a general focus on the potential social impacts of this climate event (Clare and Weninger, 2010; Düring, 2013; Lemmen and Wirtz, 2014). Less attention has been given to the nature of the drought itself, and its manifestation on the regional and local scales most relevant to Neolithic societies. Although there are clear spatiotemporal patterns in the initial expansion of farming from the Near East (Brami, 2014; Flohr et al., 2016), the current state of paleoclimate knowledge precludes a direct comparison between the archaeological record and patterns of regional climate change.

Previous studies examining the relationship between climate change and Neolithic dispersal (e.g. Weninger et al., 2014; Flohr et al., 2016) have been limited by the use of scattered, point-based paleoclimate proxy records such as speleothems and lake cores, coupled with an assumption that the spatial patterns of climate in the present are sufficient to understand climate patterns of the past. The use of point-based proxies restricts researchers to a one-dimensional perspective of climate as it changes over time and not across space. One method to spatialize proxy data is to select a set of "representative" proxy records from multiple regions of interest (Shennan et al., 2013; Lemmen and Wirtz, 2014). But extrapolating a climate signal from a single proxy to an entire region is unreliable, and imposes a spatial structure on the data *a priori*. Proxy data are noisy and variably time- and space-averaged records of an actual climate signal. Whether a particular proxy is sensitive to local, regional, or global climate varies with the type of proxy and its location. The geophysical and biophysical processes

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that formed a proxy record and the taphonomic processes that altered it are often uncertain. If the relationship between a climate signal and a proxy signal is nonlinear, this uncertainty can negatively impact the performance of statistical methods used to recover that climate signal (Tingley et al., 2012).

Proxy data are simply ill-suited to represent spatial heterogeneity in climate. But spatial heterogeneity drives ecological processes (Pickett and Cadenasso, 1995), and changes in the spatial pattern of rainfall can impact local ecologies without any change in the average values recorded in a proxy. Droughts in particular have a complex spatiotemporal structure, and ignorance of this structure will confound any attempt to model the social impacts of a drought event. To assess the role of such a drought in the spread of the Neolithic into the Aegean, we must know what rainfall was like across the landscapes settled by Neolithic groups before and after the onset of climate change 8600 years ago.

In this paper I use a general circulation model (GCM) simulation and statistical downscaling tools as an alternative to paleoclimate proxies to examine the spatial structure of winter rainfall over the northeastern Mediterranean from 10.5 to 7 ka. GCMs produce physically-consistent estimates of past climates by coupling representations of the Earth's atmosphere, ocean, and land surface systems (Gettelman and Rood, 2016). GCMs are spatially explicit, and thus better-suited to investigate the role of climate change in the spread of Neolithic communities into the Aegean. Statistical downscaling is a computationally inexpensive method to generate high-resolution fields from spatially coarse GCM outputs (Wilby et al., 2004; Maraun et al., 2010). After comparing the spatial pattern of downscaled model outputs to a dataset of Neolithic settlement locations, I find that the climate change in the northeastern Mediterranean around 8.6 ka would have led to a more regionally homogeneous winter rainfall regime and facilitated movement of Neolithic farmers through a range of previously distinct environments.

2. Methods

2.1. Statistical downscaling

The computational complexity of GCMs demands a trade-off between spatial resolution and the number of simulated years. Simulations spanning several millennia are generally run at resolutions of greater than 1° at the equator to minimize computational time. Output from these simulations must be downscaled to a higher resolution to detect climate patterns at regional scales. Two common downscaling techniques are dynamical and statistical downscaling.

Dynamical downscaling embeds a high-resolution regional climate model in a standard low-resolution GCM so that the region of interest is represented in much more detail than the rest of the globe (e.g. Brayshaw et al., 2011). Although regional models retain the dynamical nature of GCMs, they are even costlier to run than GCMs in terms of time and money. Furthermore, the choice of regional climate model parameters and boundary conditions introduces an additional level of uncertainty to the GCM outputs.

Statistical downscaling is a much more flexible alternative to regional climate modeling. These techniques build a statistical relationship between small-scale observed climate and large-scale GCM simulations of the same period, then use this relationship to infer small-scale climate from GCM simulations of a different period (Wilby et al., 1998). A generalized additive model (GAM) is one kind of statistical model that can effectively downscale GCM data (Brulhet et al., 2003; Vrac et al., 2007). GAMs are primarily data driven, in contrast to weather generators and other statistical downscaling methods that rely to a greater degree on external assumptions and parameterizations (Vrac et al., 2007). GAMs can also process gridded data; other techniques are often point-based and thus not spatially continuous.

In a GAM, an observed climate variable is modeled as a function of multiple explanatory variables. This technique is conceptually similar to multiple linear regression, but linear regression assumes linear relationships between observed and explanatory variables with normally-distributed errors, whereas a GAM uses smooth polynomial functions and "link" functions to account for nonlinear relationships and non-normal errors, respectively. GAMs have previously been used to downscale GCM simulations of the Last Glacial Maximum in Europe (Vrac et al., 2007; Levavasseur et al., 2011; Korhonen et al., 2013; Burke et al., 2014). These studies used GAMs to predict past climate conditions as a nonlinear function of atmospheric variables from a GCM, small-scale topography derived from a digital elevation model (DEM), and interactions between the two. The logic behind this implementation is that if local climate heterogeneity arises from the interaction of local topography and dynamic regional atmospheric circulation, and both topography and its statistical relationship to local climate are effectively static through time, then a statistical model calibrated on modern-day climates can downscale GCM atmospheric data from any time period (Wilby et al., 2004). GAMs have yet to be used to downscale Holocene climate simulations, but this time period is a more reasonable target then glacial climates because the assumptions of static topography and stable statistical relationships are better satisfied.

2.2. General circulation model

The GCM data to be downscaled were derived from the TraCE-21ka simulation of the Last Glacial Maximum to the present (He, 2011). This simulation used version 3 of the National Center for Atmospheric Research's Community Climate System Model (CCSM3). CCSM3 models the dynamic interactions between the atmosphere, ocean, sea ice, and land surface on a global scale (Collins et al., 2006). In the TraCE-21ka simulation, CCSM3 was run for the period from 22 ka to AD 1990 at a horizontal resolution of approximately 3.75° at the equator. It is a transient simulation in that boundary conditions and forcings were varied over time to simulate the real-world climate evolution over the past 20,000 years. This is in contrast to an equilibrium simulation in which climate forcings are held constant and the model is allowed to reach an equilibrium state without successive external inputs (an approach more common for Regional Climate Model applications to paleoclimates (Brayshaw et al., 2011)). Climate changes in TraCE-21ka were forced by greenhouse gases, changes in the Earth's orbit, and fluxes of glacial meltwater. The simulation's boundary conditions included ice-sheet extent and sea level. From this combination of transient and static inputs, TraCE-21ka reproduced key events of the last deglaciation including the Younger Dryas and Bølling-Allerød warm period (He, 2011).

Simulation outputs of decadal-mean winter averages of large scale precipitation (PRECL in CCSM3), convective precipitation (PRECC), and zonal and meridional wind velocities (U and V) were downloaded from the Earth System Grid Repository[1] for the periods 10.5 to 7 ka and AD 1950–1990 for GAM prediction and calibration, respectively. Winter rainfall was chosen as the specific downscaling target because most of the region's annual precipitation occurs in winter, and the paucity of summer rainfall would necessitate a more complex GAM that accounts for both the occurrence and amount of rain.

[1] https://www.earthsystemgrid.org/project/trace.html.

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