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Measuring movement in cultural landscapes

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ABSTRACT

Culture is often conceptualized as a landscape, where the peaks represent popular beliefs, institutions or practices, while the valleys represent those that receive infrequent attention. In this article, we build on this metaphor, and explore how individuals navigate these cultural landscapes. Using longitudinal data from the National Study of Youth and Religion, we follow participants' survey response trajectories across three cultural domains, each with particular topographical features. We show that movement across cultural landscapes is adequately captured by a gravitational model of change, which specifies transition probabilities among cultural positions as a function of the distance between them and how populated they are. Nonetheless, the kind of movement that such a gravitational model would predict varies widely depending on the initial topography of the landscape. Our work highlights that charting landscapes is not only useful cartography, but also an analytical tool that helps us understand the kind of cultural trajectories we should expect individuals to follow.

1. Introduction

One useful metaphor to think about culture is to conceptualize it as a "landscape," where certain cultural objects—personal beliefs, daily practices, or institutional structures—are closer to some than others. We intuitively know that various positions within those landscapes are densely populated: despite their many differences, moral discourses or religious doctrines, across history and social groups, share certain features. We recognize, for instance, that most such doctrines have proscriptions against murder and theft, but fewer against the consumption of animals with cloven hooves. Hence, the landscape metaphor is somewhat literal: once we examine a given cultural space, we recognize the shared features that make certain positions adjacent to one another, and we can tell that there are populated areas and relatively sparse regions.

In this article, we build upon this metaphor and explore *personal culture*—the bits of culture that are manifest in individual beliefs and preferences (Lizardo, 2017). We propose an approach to formalizing cultural landscapes using survey data and show that this approach is useful for understanding how personal culture is organized. Moreover, we argue that the landscape metaphor is not just useful cartography that allows us to see how different positions are connected or not, but also an analytical tool to explore how people change their positions over time. Building on a variety of interdisciplinary sources ranging from biology and cultural evolution to ecological frameworks and the idea of duality in cultural sociology, we propose a formal procedure to explore how cultural positions evolve across time and issues.

Using panel surveys from the National Study of Youth and Religion (NSYR) and simulation studies, we ask whether the organization

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of cultural landscapes predicts cultural trajectories. We show that cultural landscapes allow us to understand the dynamism of cultural change: people's probability to change or remain stable varies according to the organization of the initial cultural positions and the distribution of people in different regions of the landscape. We argue that knowing how people are distributed across cultural positions is informative to predict subsequent states, as some distributions make particular trajectories more or less likely.

A key contribution of this article is to highlight the importance of an ecological understanding of cultural change and stability. We show that the population structure of cultural objects might be as consequential as their substantive content, emphasizing the social distribution of ideas as an information constraint for cultural movement. We argue that the particular mechanisms of cultural change—say, influence, contagion, or selection—occur in a cultural space with a given layout, and that this organization itself informs the kind of cultural shifts individuals make. This implies that social scientists should develop a toolkit for analyzing, not just individual trajectories of change, but how the cultural space as whole is organized and how it develops—i.e., to take the *set of possible trajectories* seriously, rather than just focusing on *the observed movement*.

We begin by reviewing several common threads within the interdisciplinary efforts to represent culture as a landscape. We conceptualize trajectories across time as a Markovian process, where each position in the landscape is associated with a set of transition probabilities. This allows us to specify several generative models of cultural change. We test these models against the empirical data from the NSYR and use simulations to emphasize that these models imply different trajectories depending on the initial topography of the landscape. We conclude by examining the implications of this exercise, emphasizing its resonance with ideas of duality in cultural sociology.

2. Understanding culture as landscape

2.1. An approach for cartography

The metaphor of *culture as landscape* has become influential across scientific disciplines, the general idea being that cultural objects, whether they are writing instruments or religions, can be laid out in a common space, defined by certain parameters (Introne, 2023; Poulsen & DeDeo, 2023a, 2023b). The first of these parameters is *cardinality*, i.e., the total number of positions that make up the territory. Cardinality allows us to understand the relationships among cultural objects in terms of proximity and distance: fountain pens are somewhat closer to ballpoint pens than they are to chalk, and Zoroastrianism is closer to Christianity than to Buddhism. The second parameter of interest is *topography*, i.e., the relative height of each position in relation to others. This means that a landscape has some volume, which can represent many characteristics, from something's perceived utility—you would probably rather take notes with a pencil than charcoal—to mere occupancy—Christianity has currently more adherents in the world than Zoroastrianism.

The value of this metaphor lies partly in the fact that it is useful for understanding several biological and social phenomena. For researchers interested in evolutionary dynamics, the landscape metaphor points towards where potential attractors—i.e., high points in the landscape—might lie (Falandays & Smaldino 2021; Introne 2023), an example being the relatively low number of positions occupied within the set of all potential positions among world religions (Norenzayan 2013; Poulsen & DeDeo 2023a).[c] In studies of social structure, understanding the relationship between individual actors and the positions they occupy in a given landscape is essential (Blau 1977). Several important insights from the sociological study of culture have come from the deceptively simple idea that people who occupy proximate positions in cultural landscapes tend to share other social characteristics as well (DellaPosta, Shi & Macy 2015; McPherson, Smith-Lovin & Cook 2001).

To formalize these ideas, we rely on an algebraic approach that has been implemented across different disciplines to represent landscapes (Kauffman & Weinberger 1989; Mohr 1998; Wiley & Martin 1999). The key idea is that it is possible to use binary strings of length n, where n refers to the number of features that constitute a given cultural system. In these strings, a 1 represents the presence of a feature and a 0 represents its absence. All the possible combinations of 1s and 0s for strings of length n lay out the entire set of positions that make up that landscape (Kauffman & Weinberger 1989; Poulsen & DeDeo 2023a, 2023b). Going back to the example of religion, we might think about different elements that describe the cultural system of a religion: the institution of monotheism, the belief in an afterlife, or practices of dietary restrictions. The number of these elements would be equal to the length of a string, and the presence or absence of such elements would be denoted by 1s and 0s, respectively. Hence, if we were to characterize Christianity based on the three features just selected, it would occupy the position $C = \{1, 1, 1\}$ in a three-dimensional space, and this position would imply that all features within the landscape exist in the cultural position of Christianity.

This algebraic representation is simple and effective. It allows us to define cardinality as the number of elements n being mapped to the number of potential positions, 2^n. Hence, in a 3-dimensional landscape of religion, we have 8 potential positions. Similarly, it allows us to define topography as the number of units in a particular position. If there are 100 hypothetical religions, 40 of which are situated in the position $P = \{1,1,1\}$, this would mean that P represents 40 % of the mass in the landscape. Finally, this approach allows us to define a measure of distance between positions as the absolute value of the Hamming distance between each string, $D_{p_1,p_2} = |p_1 - p_2|$, such that, e.g., two positions $P_1 = \{1, 1, 1\}$ and $P_2 = \{1, 1, 0\}$ are considered to be adjacent with distance $d = 1$.

Fig. 1 uses these properties and represents a set of hypothetical positions in a graph, where each node indexes a position and the edges between nodes capture the adjacency.

The central analytic utility of cultural landscapes lies in the difference between the left and the right panels of Fig. 1: cultural

[c] In other words, given the almost infinite combination of features a religion could have, it is quite striking that most look broadly similar. Most religions, then, are concentrated in a relatively small region of the cultural landscape.

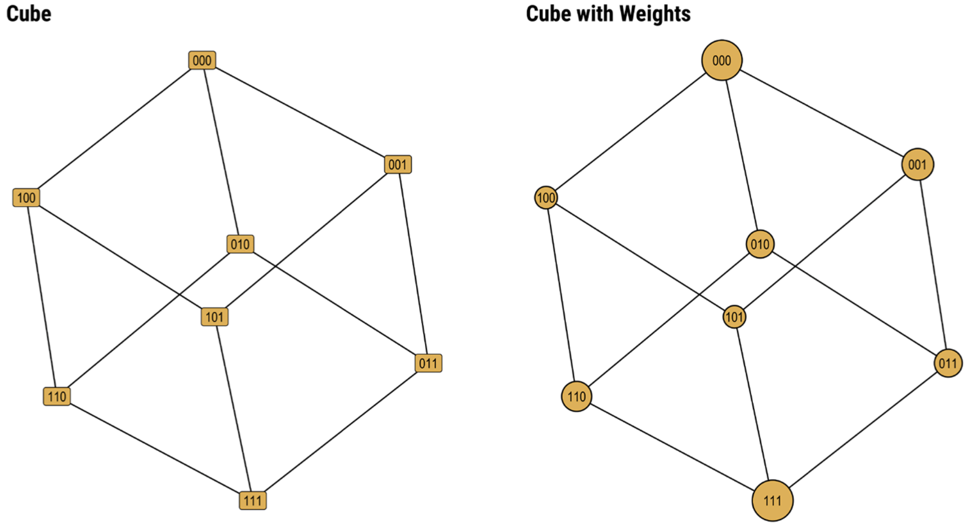

Fig. 1. Cubes from Three-Dimensional Landscape.
Notes: The figure shows two hypothetical cubes emerging from a cultural landscape. Each node indexes one potential position and the node size captures the number of units defined by that position. The left panel presents a cultural landscape with no mass attached to nodes while the right panel presents a cultural landscape where positions have varying volumes.

landscapes are often not flat, but rather have volume, meaning that they have topographical features. This is where the landscape approach departs from other algebraic representations (Mohr 1998)—it considers the relationship between the relative height of positions and their cardinal location. This relationship is captured by the parameter of *ruggedness*, a central element of the NK model (Kauffman & Weinberger 1989), one of the most famous methods for generating these binary representations of landscapes. In this model, ruggedness represents the correlation between the heights of adjacent positions. A landscape with minimal ruggedness implies that height across positions increases or decreases in expected ways, and the height of one's current position is predictive of what one might expect in adjacent positions. Thus, we expect there to be one global peak, and walking towards the highest adjacent position is a useful strategy to reach that peak. In a maximally rugged landscape, however, the height between positions is unrelated, and one step might lead to a giant increase or a sharp drop. This time, the same strategy—walking towards the highest adjacent position—would likely lead us to be stuck in a local optima. The landscape metaphor, then, owes part of its usefulness to being able to capture these dynamics.

2.2. Spatial approaches to culture: landscapes in context

To argue that culture can be represented as a landscape is to align oneself with the longstanding sociological goal of understanding the organization of cultural objects. As mentioned above, there is a robust tradition among sociologists of culture of using binary strings to outline the positions that constitute a given cultural space (Mohr 1998; Wiley & Martin 1999). Nonetheless, a great deal of illuminating work has come from methods that—rather than imposing a structure on a given set of cultural items—let spatial logics emerge from either empirical data or from other criteria, exogenous to the cultural items themselves. We believe that the culture as landscape approach represents a good compromise that retains the key advantages of each line of work.

A good example of spatial work that does not impose a given structure *a priori* is the "ecology of affiliations" framework (McPherson 1983). This line of work notes that different cultural institutions compete for potential members. To continue our running example, we could think about Christianity and Zoroastrianism vying for a pool of members who are sympathetic to monotheism. This latter group would represent the *niche* of these institutions. The organization of a given cultural space here comes precisely from the idea of niche: institutions that compete for a similar pool of members should be closer in that underlying space. The determinants of cultural proximity, then, are not features of the institutions, but rather exist outside of them.

While it may be useful to let cultural proximity emerge from an external, common criterion, this makes it difficult to think about the distance between items in a given cultural space. Think of voluntary associations (McPherson 1983). It would be possible to argue, for instance, that young individuals are *at risk* for an athletic youth organization and a religious youth organization. Both of these organizations would be culturally proximate. But the question of just *how much* proximate they are remains unclear. The landscape approach, in turn, explicitly quantifies the *distance* between the two. In a landscape of three dimensions, $\{Youth, Religious, Athletic\}$, the former occupies $\{1,0,1\}$ while the latter occupies $\{1,1,0\}$. It also allows us to see that there are other potential cultural positions, such as $\{0,1,1\}$ or $\{1,1,1\}$, occupying distinct areas of the larger landscape.

Another common approach is to let the co-occurrence of certain items—or their features—map their proximity in cultural space. For instance, in their seminal work, Mohr and Duquenne (1997) show that commonalities in the way different relief organizations describe their missions places them in a structured semantic space defined by how they conceptualize those in need. Other work has used the co-occurrence of different survey responses to build belief networks (Boutyline & Vaisey 2017), with the proximity between beliefs is their correlation in a given sample. In similar fashion, co-occurrence of items is also conceptualized as ordered pairs of relationships (Wiley & Martin 1999).

The landscape approach incorporates these observed co-occurrences, while also mapping a more complete layout of the terrain. We collapse features to positions and establish fully-connected networks (see the left panel of Fig. 1). This allows us to construct *theoretical* relationships between different positions based on their proximity and distance. We then define landscape topography through the empirical distribution at the position level (see the right panel of Fig. 1). Given how landscape topology is explicitly defined through the volume of each position, this allows us to examine two elements, theoretical relationships between features and empirical regularities within specific landscape positions, in the same analytical setting.

One underlying principle that governs these various research streams is the notion of *duality*, the idea that actors are defined through groups and groups are defined through actors (Breiger 1974). Voluntary associations are close together when they compete for the same membership pools; poverty relief organizations are united by their common definition of those deserving of help; and beliefs are connected through the agents that jointly profess them. This principle also underpins the culture as landscape approach. As actors cluster around similar regions, we can draw two insights. First, we learn about what kinds of actors end up connected by sharing a cultural position. Second, we can examine the kind of cultural positions that go together because they share the same occupants.

These discussions have an analytic payoff. The principle of duality is often used to provide cultural cartographies, with an explicit aim to *represent* social world, though we believe that our approach might provide information about cultural *movement*. As Martin (2000) emphasizes, a picture from a low-orbiting satellite would give us the map, but also would help us figure out where the roads are. If duality is indeed the underlying principle, these cartographies might not just help us see what culture is like, they might also store "information about [potential] paths that [people will] take" (Lee & Martin 2018:19). The fact that we (a) quantify distance and (b) incorporate empirical distributions in the same analytic scheme is consequential in achieving this goal.

2.3. A markovian model of cultural movement

We propose that the organization of a cultural landscape—i.e., the distribution of cultural positions and the emergent topography at time t_0—is instrumental to understanding the landscape at time t_1. This trajectory can be formalized as a Markov process, where a landscape changes from one state to another. This is effectively an *accounting* of transitions: we observe the number of people occupying a position at each time point, and analyze the movements—say, from position $\{1,1,1\}$ to position $\{1,1,0\}$—within and between landscape positions. Each of these movements is associated with a transition probability; when put together, these probabilities constitute a *transition matrix* that provides information about the future states of the landscape. With this framework, we can examine whether actors tend to stay put in their initial positions, hover around adjacent locations, or make long-distance jumps, all representing the dynamics that underpin the development of the landscape, and all represented in a simple matrix.

Let us go through a basic example, following a three-feature landscape, like the one we saw above. Assume three features, f_1, f_2, f_3, with 1s and 0s denoting the presence and absence of each feature, respectively. This gives us $2^3 = 8$ unique positions in the landscape:

$$p_{t_0} = (\{0,0,0\},\{0,0,1\},\{0,1,0\},\{1,0,0\},\{1,1,0\},\{1,0,1\},\{0,1,1\},\{1,1,1\})$$

Assume also that there are 50 individual actors, distributed across these positions unevenly:

$$v_{t_0} = (13,\ 6,\ 3,\ 3,\ 5,\ 2,\ 3,\ 15)$$

The first piece of information in this Markovian system is a vector v_{t_0} of equal length L to the number of positions that constitute the landscape, p_{t_0}. Our hypothetical v_{t_0} indicates that this is a landscape with two high peaks at $\{0,0,0\}$ and $\{1,1,1\}$, with all the other positions sparsely populated.

Suppose now that we observe this landscape in a second discrete period, t_1, and it turns out to be a completely stationary system. If we were to tally up movements in a matrix, where each cell $\{i,j\}$ represents an observed movement from position i to position j, we would have a matrix with a diagonal equal to v_{t_0}, and zeroes everywhere else. This would be our *realization matrix*:

$$P_{t_{0,i},t_{1,j}} = \begin{pmatrix} 13 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 6 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 3 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 5 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 15 \end{pmatrix}$$

The central idea in this article is that we can think about this *realization matrix* as the product of a generative model, i.e., a specific set of probabilities that indicate the likelihood of certain movements between and within landscape positions. As stated above, the set of probabilities that is most likely to have produced this *realization matrix* is one of complete stationarity. We can represent this generative model using the same structure, this time populating cells with transition *probabilities* instead of position *volumes* as our unit for the construction of the matrix:

$$T_{t_{0,i},t_{1,j}} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

This is what we will call a *transition matrix*, which stipulates how likely certain movements are among these positions. In this matrix, $T_{i,j}$ represents the probability of moving from position i to position j. In our example, an individual located in any given position has 8 possible moves: they can either stay put or move to the other seven positions. Each of those 8 moves will have a probability associated with it, and these will be encoded in the row associated with the position where the actor is located at time t_0. Given that our system is fully stationary, all probability is concentrated in the diagonal. Note that, since we specify positions i in the rows and positions j in the columns, each row and each column need to sum to 1.

The power of this model is that we can go back and forth between *realization matrix* and *transition matrix*. After observing a given set of movements, we can ask what set of transition probabilities are likely to have produced it. Likewise, we can start from some transition probabilities—and a starting configuration of the landscape—and ask what patterns of movement are more compatible with them. Thus, if we start with the *transition matrix* presented above and the vector of initial weights v_{t_0}, we expect that this is compatible with complete stationarity, given that each individual remained in their position in the second iteration of the system. We have a rather unique case where only one *realization matrix* is compatible with a specific generative model.

Now, let's consider another model, where all movements between any two positions are equally probable. See the transition matrix on the left below. In this case, we can think of each row as representing a fairly weighted 8-sided die. We roll the die as many times as there are occupants in the corresponding position at t_0, and record the new positions. For instance, if we get the number 3 twice for the first row, we record 2 in the cell $P_{i=1,j=3}$. This would mean that 2 individuals moved from $p_{t_0,1} = \{0,0,0\}$ to $p_{t_1,3} = \{0,1,0\}$. Since the observed transitions are probabilistic, we have *many* realizations that are compatible with the transition matrix. The matrix on the right shows one stochastic example.

$$\begin{pmatrix} \frac{1}{8} & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \frac{1}{8} \\ \frac{1}{8} & \frac{1}{8} & \cdots & \cdots & \cdots & \cdots & \cdots & \frac{1}{8} \\ \frac{1}{8} & \cdots & \frac{1}{8} & \cdots & \cdots & \cdots & \cdots & \frac{1}{8} \\ \frac{1}{8} & \cdots & \cdots & \frac{1}{8} & \cdots & \cdots & \cdots & \frac{1}{8} \\ \frac{1}{8} & \cdots & \cdots & \cdots & \frac{1}{8} & \cdots & \cdots & \frac{1}{8} \\ \frac{1}{8} & \cdots & \cdots & \cdots & \cdots & \frac{1}{8} & \cdots & \frac{1}{8} \\ \frac{1}{8} & \cdots & \cdots & \cdots & \cdots & \cdots & \frac{1}{8} & \frac{1}{8} \\ \frac{1}{8} & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \frac{1}{8} \end{pmatrix} \dashrightarrow \boxed{\text{REALIZATION}} \dashrightarrow \begin{pmatrix} 3 & 1 & 2 & 0 & 2 & 1 & 4 & 0 \\ 0 & 1 & 1 & 0 & 1 & 1 & 2 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 2 & 1 & 0 & 2 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 2 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 3 & 2 & 2 & 2 & 3 & 2 & 1 \end{pmatrix}$$

In the diagonal, we see how many actors stay in their original positions. Excluding the diagonal, the column sums capture the amount of inflow towards a particular position. Conversely, the row sums capture how many people leave a given location in the landscape. Hence, the realization matrix allows us to chart the inflows to, and outflows from, a particular position. Correspondingly, the transition matrix allows us to specify generative models of change from t to $t+1$.

In essence, transition matrices can be described as *generative models*, and given what we observe between different time periods, the natural question is to ask whether we can know the underlying generative model, conditional on our observation of a particular set of realizations. This seems rather easy in the example where we have complete stationarity: since positions did not have inflows or outflows and everything remained stable, our generative model very likely is *position stability*. Yet, see the realization matrix after the random change described above: simply by chance (although with very low probability), we could end up with the same stationary matrix. Therefore, to recover the underlying generative models, we need to exploit the fact that certain realization matrices will be more compatible with some transition matrices than others in expectation, allowing us to adjudicate generative models given realized empirical distributions.

2.4. Adjudicating between generative models

One straightforward procedure to adjudicate generative models is to compare multiple models using the sum of the absolute differences between the observed transitions in data—what we call the empirical matrix—and the realization matrix predicted by a given movement model. This strategy assesses how well the generative model fits the observed data.

First, we construct the position-by-position matrix, $P_{t_{0,i},t_{1,j}}$, from the empirical data, using two time periods t_0 and t_1. Then, we build the transition matrix, $T_{t_{0,i},t_{1,j}}$, based on the generative model under consideration. The next step is to simulate one potential realization, let's call it $R_{t_{0,i},t_{1,j}}$, as a function of the configuration of the landscape in the first time period, $P_{t_0,i}$, and the probability vectors specified in $T_{t_{0,i},t_{1,j}}$. This leaves us with two matrices: one with the observed transitions and one with the simulated transitions based on the generative model. Then, we take the sum of the absolute difference between the entire matrices by subtracting one from the other and taking their absolute values, or, more precisely:

$$\text{Prediction Error} = \sum \left| R_{t_{0,i},t_{1,j}} - P_{t_{0,i},t_{1,j}} \right|$$

Therefore, lower differences will indicate a better fit between the specified movement model and the observed data.

Here again, it would be useful to walk through an example. For illustration, assume that we have empirically observed the matrix we provided as an example of a realization for the model where all transitions are equally likely. Say we want to assess how compatible these observed transitions are with another generative model, which we will call *one move at most* model. This model states that moves with one step or fewer have equal probability, while those with longer distances have 0 probability. Here is the implied transition matrix:

$$T_{t_{0,i},t_{1,j}} = \begin{pmatrix} \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & 0 & \frac{1}{4} & 0 & 0 & 0 \\ \frac{1}{4} & \frac{1}{4} & 0 & \frac{1}{4} & 0 & \frac{1}{4} & 0 & 0 \\ \frac{1}{4} & 0 & \frac{1}{4} & \frac{1}{4} & 0 & 0 & \frac{1}{4} & 0 \\ 0 & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & 0 & 0 & 0 & \frac{1}{4} \\ \frac{1}{4} & 0 & 0 & 0 & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & 0 \\ 0 & \frac{1}{4} & 0 & 0 & \frac{1}{4} & \frac{1}{4} & 0 & \frac{1}{4} \\ 0 & 0 & \frac{1}{4} & 0 & \frac{1}{4} & 0 & \frac{1}{4} & \frac{1}{4} \\ 0 & 0 & 0 & \frac{1}{4} & 0 & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \end{pmatrix}$$

We can now compare our hypothetical, empirical matrix with some realization matrices produced by this proposed model. Considering that there is stochasticity involved in moving from the transition matrix to the realization matrix, we want to iterate over this process several times to build a reliable picture of what model of movement is more compatible with the data we have observed. In this example, we iterate this process 10,000 times. Fig. 2 shows the distribution of prediction errors we calculated.

Once constructed, these prediction errors can be compared across different generative models to assess the extent to which a given model best approximates the observed data. Models whose distributions of prediction errors are lower can be deemed as more compatible with the observed data.

3. Understanding cultural formation

What is the utility of the landscape approach for understanding cultural formation, change, and stability? Studies on *personal culture*, culture manifest in beliefs and preferences (Lizardo 2017), show how individual differences in personal culture might be captured in an *n*-dimensional "belief space" (Martin 2000), much like the hypothetical religion landscape discussed above. One consistent observation in these studies is that people's cultural positions usually overlap: we observe clusters of people sharing similar positions within the overall belief space. If this is indeed the case, the landscape approach, used properly, might shed light on how individuals come to cluster in certain regions, and how, once those peaks have been formed, the topography of the space might make certain enculturation trajectories more or less likely.

Given the durability of cultural orientations during adulthood (Kiley & Vaisey 2020; Lersch 2023) and the relative dynamic changes in adolescence and early adulthood (Keskintürk 2022), we turn our focus to cultural formation, i.e., the processes of socialization (Guhin, Calarco & Miller-Idriss 2021). We claim that culture as landscape can be instrumental to understanding why actors, with a rough set of starting values, end up in specific positions given a generative model of socialization.

A key promise of the landscape approach is its ability to contrast observed data with underlying generative models, but this brings up the question of what exactly these models should capture. We contend that—at least as a starting point—it is worth contrasting generative models that seek to operationalize some of the main findings in current work on social learning and attitudinal formation. We begin with three broad assertions that currently enjoy ample empirical support in the literature. First, individuals tend to inherit similar worldviews to those of their parental figures (Jennings & Niemi 1968; Jennings, Stoker & Bowers 2009). Second, either by virtue of increased exposure or conformity bias, popular worldviews attract more adherents (Efferson et al. 2008; McElreath et al. 2005). Third, individuals may pay attention to how their beliefs fit together with one another (Converse 1964). Drawing from these basic ideas, we outline four broad generative models for cultural formation: the *vertical transmission model, conformist model, logical consistency model,* and *gravitational model.* Each of these emphasizes different aspects of social learning—from conformism to content-based consistency—and provides diverging predictions about how stability and change are realized in cultural landscapes.

The *Vertical Transmission Model* relies on the claim that vertical transmission, organized mostly at the family, determines people's

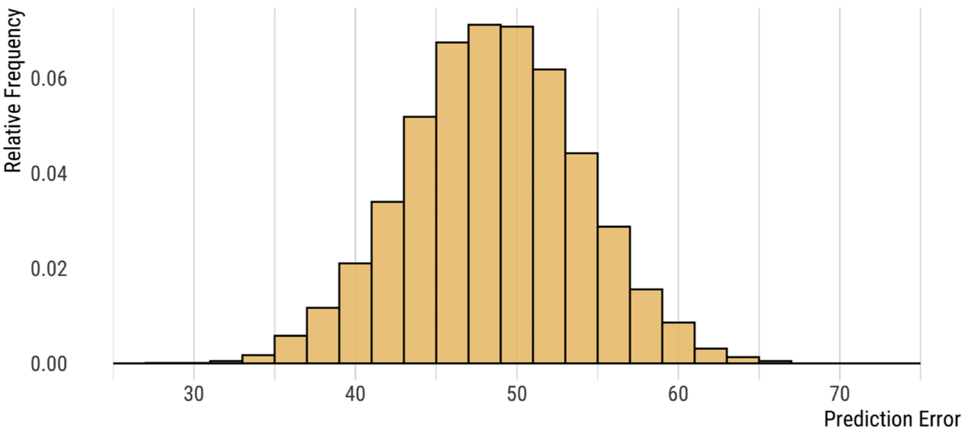

Fig. 2. The Distribution of Prediction Errors Across Simulation Runs.
Notes: The figure shows the prediction errors, calculated as the sum of differences between a hypothetical empirically observed matrix and model-predicted simulations across 10,000 simulation runs.

subsequent cultural orientations (Jennings & Niemi 1968; Jennings, Stoker & Bowers 2009). According to this view, people acquire their cultural positions through a combination of learning and imitation, and these experiences shape the extent to which people subsequently travel across different cultural positions. Thus, the model proposes that when an individual moves, they tend to stay put within particular regions of the cultural landscape, meaning that long-distance transitions within the landscape are increasingly less likely. We operationalize this idea via two generative processes: (a) *the distance model*, where the transition matrix T is constructed such that positions are less likely to attract respondents as a function of increasing Hamming distance from initial positions, and (b) *the one move at most model*, which is a simplified version of the distance model where respondents are only allowed to move one step away from their initial cultural positions (see Kiley 2023).[d]

The *Conformist Model* model, in turn, invokes frequency-dependent cultural transmission as a driving mechanism of social learning (Efferson et al. 2008). The underlying idea here is that people converge on beliefs and practices that have the most adherents in a given population. Conformity has a long history in sociology, both as an explanation (Parsons 1951) and as an explanatory target (Wrong 1961). Our operationalization of this idea is rather flexible: conditional on a landscape with one or more peaks, people are more likely to move towards higher peaks in a stochastic manner, each peak having attraction probabilities as a function of occupants. This means that more populous positions are both more likely to keep their current occupants and to attract newcomers from less populated positions.

An alternative model—*Logical Consistency Model*—involves the substantive *content* of the specific features, rather than initial conditions or topographical features. Actors might update their positions such that the target cultural position is logically more consistent—or, *constrained*—than the initial position (Simon, Krawczyk & Holyoak 2004). This means that individuals might only move to positions where personal culture is more consistently organized (Keskintürk 2022). Of course, when highly populated areas and highly consistent areas converge, this is reduced to the conformist model. But if there are discrepancies, this generative process assumes that people, over time, would rather end up in logically consistent stances rather than highly populated regions.[e]

For the final generative process, we propose a *gravitational model*, synthesizing ideas from vertical transmission and frequency-dependent social learning. According to this model, populous positions represent cultural ideologies that attract people, though the extent to which people can move towards these positions is mediated by the total distance from their socialization imprints. We see here a sort of compromise between conformist social learning and a reticence to explore distant positions. Mathematically, this is a gravity model where the probability of moving to a target position is proportional to the current occupancy of that position divided by the squared distance from the initial location. Thus, this model incorporates information from both the theoretical relationships

[d] In all model specifications, whenever we invoke "distance," we refer to the squared values of whatever unit we are referring to. This is to ensure that the higher the distance, the more pronounced its effects are.

[e] This assumes that there *is* a logical consistency between features that can be recovered without population patterns. We assume logical consistency across features to the extent that those features are positively correlated. After checking that these features are indeed positively correlated in the empirical data, we assign $P_1 = \{0, 0, \ldots\}$ and $P_2 = \{1, 1, \ldots\}$ as the positions of highest logical consistency, with the highest probability of attraction under this model. Note that this is based on, but inherently different than, the use of constraint commonly employed in sociology (e.g., Boutyline and Vaisey 2017) that mainly relies on pairwise linear dependencies between different items. Given that our theoretical strategy heavily relies on Martin (2000) and works at the level of N-dimensional belief space, the use of pairwise measures is not suitable for specifying generative models in this case. Hence, rather than the general understanding of constraint as belief dependence, which is the main idea underlying Converse (1964), we opt for the more modest approach of looking at logical dependencies derived from population correlations. Of course, the choice of logical consistency, to the extent that it relies on positive correlations, is rather limited, and we expect that the future research will improve upon this point.

between positions and the topographical features of the landscape as a whole.

4. An analysis of cultural movement

We now turn to our empirical analysis. We examine which of the generative models outlined above is more accurate in predicting patterns of movement across three landscapes with distinct topographies. We do this in three steps. First, we describe three landscapes whose patterns of development we will trace. Second, we analyze the predictions from six generative models against the empirically observed transitions for each landscape. In the last step, we turn to simulation models to explore the implications of these predictions.

4.1. Data and analytic strategy

We use panel surveys from the National Study of Youth and Religion (NSYR), a longitudinal and nationally representative survey of adolescents and early adults in the United States.[f] The first wave of the NSYR was fielded in 2002 and 2003 with 3,370 respondents aged 13 to 17. In approximately two-year intervals, the NSYR conducted three subsequent surveys (2005, 2007–2008, and 2012–2013), which allows us to follow the trajectories of personal culture among adolescents and early adults—a demographic that tends to display some durable change. Moreover, the questions touch on a wide array of subjects, from religion and gender attitudes to abstract questions about morality. This allows us to build different cultural landscapes with varying topographies, and examine how actors move across them.[g]

We analyze movement across three landscapes with widely different structures. The first is made up of seven questions around religion—e.g., whether respondents believe in angels, miracles, and the afterlife (N = 1,684). The second features seven items as well, this time related to gender and sexuality. These encompass questions about whether mothers should work and unmarried sex is permissible (N = 1,621). The last landscape consists of an eclectic set of items with equal length, ranging from moral relativism to the respondents' belief in God (N = 1,512). Our choice of these landscapes is deliberate: we want to build cultural landscapes that have different topographical features. Table 1 documents the full set of items,[h] while Fig. 3 depicts their topographical layout.

To show the topographical layout of each landscape more clearly, we simplified their representation by plotting bar plots in Fig. 3. Since there are 128 potential positions implied by the 7 features that make up each landscape, the horizontal axes in the figure represent all these positions, ranging from $\{0,0,0,0,0,0,0\}$ to $\{1,1,1,1,1,1,1\}$. At the same time, each position captures the percent of people occupying the particular response configuration at Time 1 of the NSYR. There are striking differences across landscapes. The *Religion* landscape, for instance, has two visible clusters—organized around all 0s and somewhere close to all 1s—that mark two distinctive peaks in the structure. In contrast, the *Sexuality and Gender* landscape has one highly populated peak, whose adjacent positions also enjoy considerable occupancy. This resembles what scholars of rugged landscapes call a *mount Fuji* terrain: a landscape dominated by one global peak. Finally, the eclectic terrain is quite "disorganized," meaning that the organization of participants across positions in the landscape follows no clear pattern. Thus, it is possible to argue that the latter is the most "rugged" of the three.

We test a total of six models against the empirical data to evaluate how well the generative processes capture the observed transitions in each landscape. Suppose $T_{k,w}$ captures the target position k with occupancy (i.e., the number of people) w at t_0. Further, d_k captures the distance from the target position to the initial position P_0, L captures the amount of positions in a landscape, and F the amount of underlying features—which can be either 0 or 1—that make up the positions. Accordingly, each target position receives the following probability scores in their respective transition matrix cells:

- Gravitation: $\frac{T_{k,w}\times\frac{1}{d_k^2}}{\sum_k^N T_{k,w}\times\frac{1}{d_k^2}}$
- Conformist: $\frac{T_{k,w}}{\sum_k^N T_{k,w}}$
- Hamming Distance: $\frac{\frac{1}{d_k^2}}{\sum_k^N \frac{1}{d_k^2}}$
- 1 Move at Most: $\begin{cases} 0 & \text{if } d > 1 \\ \dfrac{1}{F+1} & \text{if } d \leq 1 \end{cases}$
- Logical Consistency: $\frac{Consistency\times\frac{1}{d_k^2}}{\sum_k^N Consistency\times\frac{1}{d_k^2}}$
- Random: $\frac{1}{L}$

[f] The replication files for the article are stored in Open Science Framework: https://osf.io/dsj95

[g] Since most of these questions had been included as of Wave 2, we use Waves 2, 3, and 4 in the upcoming analyses. To mitigate confusion, we refer to these waves as Time 1, Time 2, and Time 3.

[h] Since we need binary features to index positions, we binarized the items such that individuals get a 1 if they say they agree or 0 otherwise. In some cases—e.g., *viewrel*—this involves selecting the most salient categorical response and coding that as 1, with 0 representing other categories.

Table 1
The Items Used for the Analyses.

Landscape	Item	Label
Landscape 1		
Religion	*aftrlife*	Belief in Afterlife
	angels	Belief in Angels
	astrolgy	Belief in Astrology
	demons	Belief in Demons
	god	Belief in God
	miracles	Belief in Miracles
	reincar	Belief in Reincarnation
Landscape 2		
Gender and Sexuality	*abstain1*	Waiting for Sex Until Marriage
	divrceok	Couples Should Stick to Marriage
	mandecid	Man Make Important Decisions
	menwrk	Man Earns the Living
	unmarsex	Unmarried People Having Sex
	wommar	Women's Life Without Marriage
	wrkngmom	A Working Mom's Relationship with Child
Landscape 3		
Eclectic	*god*	Belief in God
	spiritua	Spiritual But Not Religious
	wrldorig	The Origins of the World
	moralrel	Moral Relativism
	viewrel	The Views About the Truth of Religion
	relprvte	Religion: Private or Public
	okayconv	Converting Others to Religion

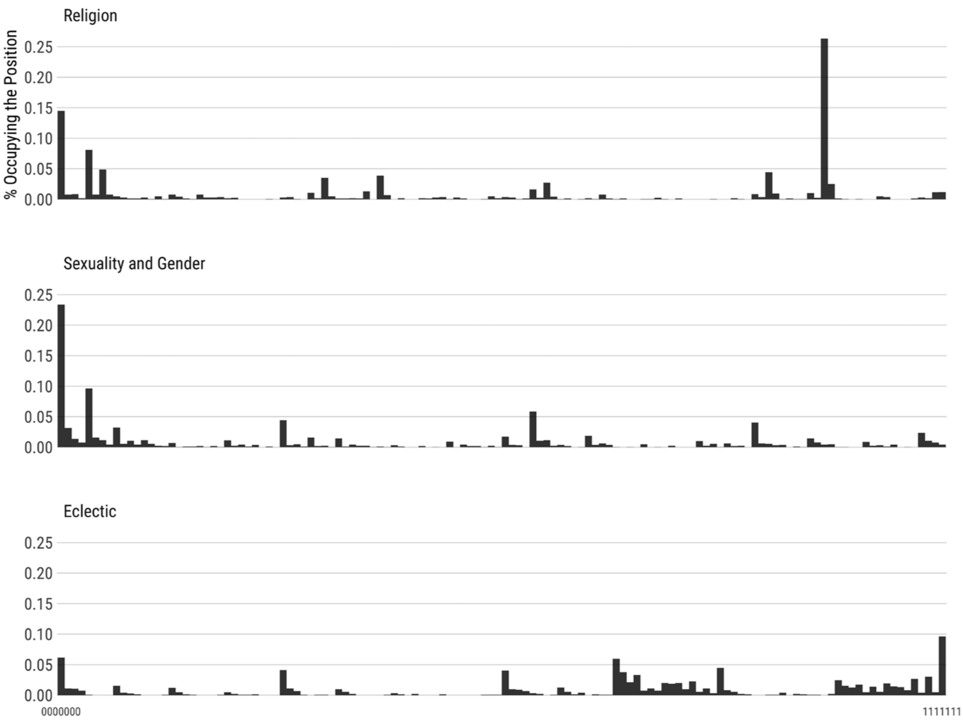

Fig. 3. Representation of Three Cultural Landscapes.
Notes: The figure shows three landscapes constructed using the National Study of Youth and Religion data. Each facet shows bar plots, where the x-axis indexes 128 potential positions implied by the 7 survey features for the particular landscape, while the y-axis indexes the percent of individuals occupying each position at Time 1.

It may be useful to walk through each equation more carefully. The equation for the Gravitation model has the current occupancy of the target position divided by the squared distance in the numerator, and the sum of those quantities for all possible target positions in the denominator. It captures the idea that a position should be attractive if there are more people holding it and if it is closer. The conformist and hamming distance equations are similar, but they only consider one of those two elements: either the current occupancy or the distance. The 1 Move at Most equation assigns a probability of 0 to all positions that are further than 1 step away, and then splits probability evenly among the F + 1 remaining positions. The Random Model just assigns the same probability to all possible moves. Finally, the Logical Consistency Model looks very much like the Gravitation Model, but instead of the current occupancy of the target position, we use the logical consistency of the elements within each position. We calculated consistency by fixing positions to two ideal-typical strings, $P_1 = \{0, 0, ...\}$ and $P_2 = \{1, 1, ...\}$, and calculated the distance from these positions.[i] The positions closer to one or the other receive higher weights, again, normalized by the distance from the initial position.

We then examine how likely each generative model—with their respective transition matrices—is to have generated the transitions we observe in our empirical data. In doing this, we generated 10,000 potential realization matrices for each model in each landscape, compared these realization matrices to the observed empirical matrices, and calculated the prediction errors across all runs by summing the errors across all cells.

4.2. Empirical results

Fig. 4 presents the distribution of prediction errors across six models, three landscapes, and two transition periods. The first striking observation we can make is that the gravitational model is the one that best captures the patterns of movement in the data across all landscapes. Looking at the aggregate, taking into account gravitational patterns reduces the prediction error by half when we set our baseline to *random*, which, incidentally, has the highest inaccuracy among all models. Taken together, these findings imply that knowing the structure of the landscape is substantively important for understanding what kind of transitions people will make across time.

The greater explanatory power of the gravitational model is perhaps expected, given that it is the model that incorporates the most information. The gravitational model has more parameters—it takes into account information about the distance between positions *and* the current occupancies—and, therefore, is the most flexible among our candidates. Nonetheless, precisely because of this flexibility, the gravitational model might result in vastly different predictions depending on the structure of the initial landscape. It is thus useful to examine how discriminative the predictive power of the gravitational model is, both in relation to the second most informative model, and to the overall predictions across all candidates.

Note that the discriminative power of the gravitational model decreases when we go from *Religion* to *Gender and Sexuality*, and even more so when we go to *Eclectic*. Once we take the *Religion* as our baseline, the predicted distance between the gravitational model and the random model is 20 % lower in the *Gender and Sexuality* landscape, while it is 52 % lower in the *Eclectic* landscape. Similarly, the standard deviation of predictions gets cut >50 % when we move from the *Religion* landscape to the *Eclectic*. This indicates that the topographical differences between landscapes are important in assessing how gravitational model performs in the aggregate.

We see that the gravitational model seems to have a different relationship with the other models, and this varies across landscapes as well. In the *Religion* landscape, we find that the second most explanatory model is the *Conformist*. This hints at the fact that stasis might be the central driving force here, given that the two peaks in the *Religion* landscape captures the consistent believers and consistent disbelievers in supernatural elements. In fact, stasis would be the most likely outcome in a system where there are highly occupied positions away from each other. Their gravitational pull is nullified by distance and by the countervailing forces of other attractors—stasis, then, is the compromise. As we mentioned above, this is precisely the topography of the *Religion* landscape.

The *Conformist* emerges again as the second model candidate in the *Sexuality and Gender* landscape, though this time the implication is different: looking at the raw counts, the strongly consistent position $P = \{0, 0, 0, 0, 0, 0, 0\}$ and positions 1 Hamming distance away from it accounts for the 64 % of the entire landscape—moving from 48 % at Time 1 and 55 % at Time 2—suggesting the formation of a Fiji Mount structure around strongly liberal positions. This means that the main structuring power of the gravitational model in this landscape is the single peak that pulls the surrounding positions to itself. This is also the reason why we see the *Consistency* model as the second alternative: features become consistent over time around one of the two most logically constrained positions.

Finally, the *Eclectic* landscape shows the least discrimination in terms of model power. This time, the *Conformist* loses its predictive power given the strong entropy within the landscape. Note, for instance, the two most consistent positions, $P = \{0, 0, 0, 0, 0, 0, 0\}$ and $P = \{1, 1, 1, 1, 1, 1, 1\}$, as well as positions that are 1 Hamming distance away from them, account for <50 % of all occupants, suggesting strong heterogeneity across the board. This means that the topographical features are less predictable and, correspondingly, the movement is much more erratic.

Our central finding is that the gravitational model is the most predictive, but this model implies different patterns of movement depending on the layout and topography of the initial landscape. Knowing the current organization of a landscape—the distance between positions and how these are occupied—is thus highly useful for predicting how actors will move. But the kind of patterns of movement we expect depends on the organization of the landscape itself.

4.3. Simulation studies

To further reinforce our central argument, we now examine simulations where we start with the initial organization of each of our landscapes constructed using the NSYR and let the system develop one time-step according to a gravitational model of movement. Fig. 5 provides one such simulated development: we simulate data as if it was produced by a gravitational model, and examine the

[i] All features with significant correlations at Time 3 are positively correlated.

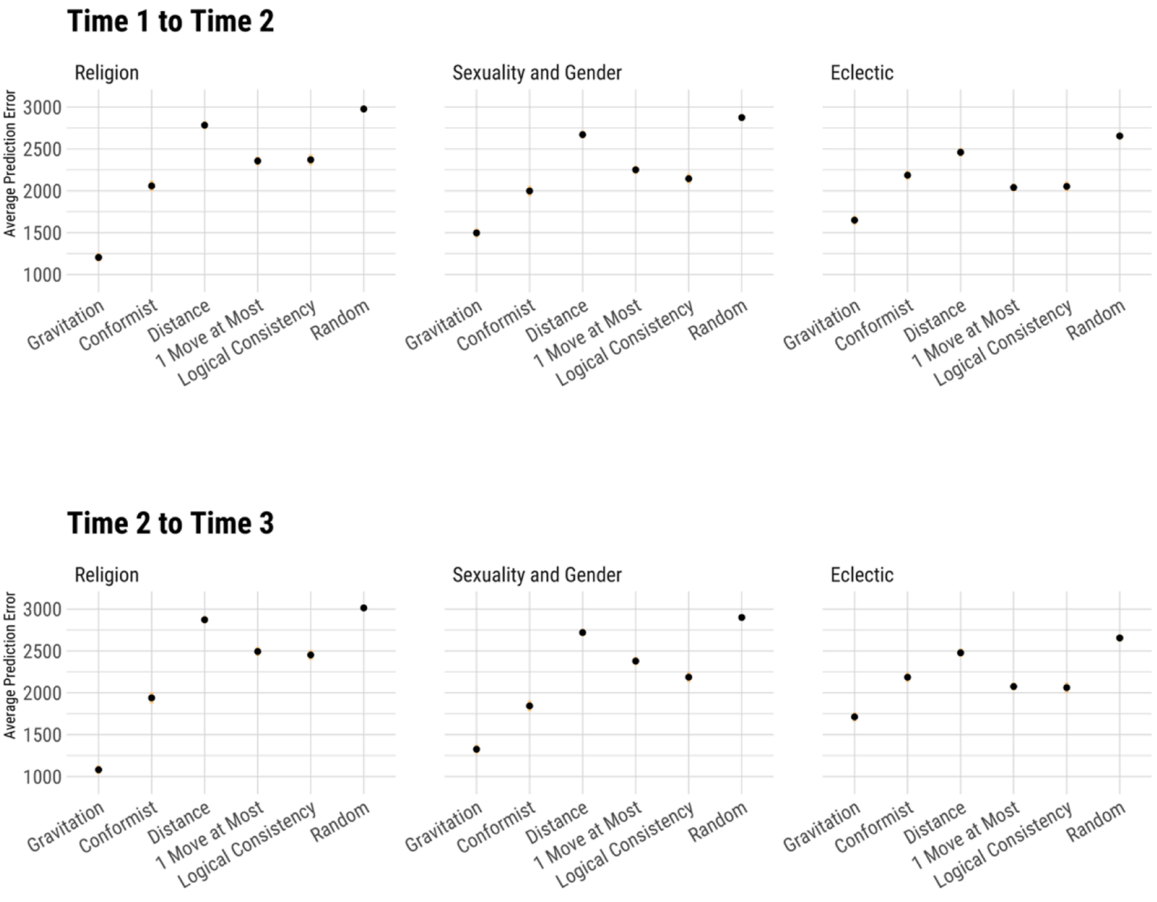

Fig. 4. Prediction Errors from Empirical Models.
Notes: The figure shows the distribution of prediction errors. These scores are calculated by summing over the differences between the observed matrices and the realization matrices generated by varying transition probabilities. The estimates average over 10,000 runs, with shaded lines represent 95 % confidence intervals.

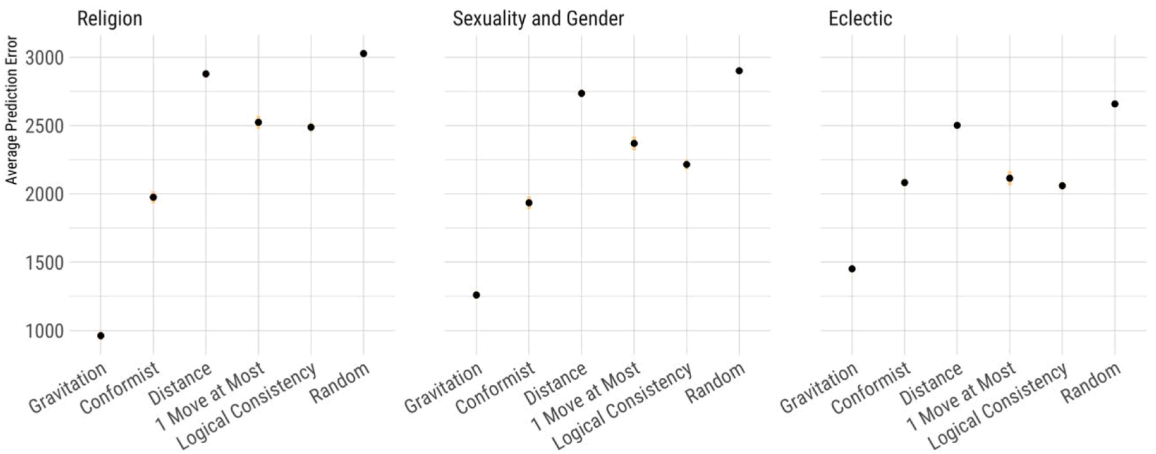

Fig. 5. Prediction Errors from Simulated Models.
Notes: The figure shows the distribution of prediction errors. These scores are calculated by summing over the differences between the observed matrices and the realization matrices generated by varying transition probabilities. The estimates average over 100 iterations of 100 simulation runs, with shaded lines represent 95 % confidence intervals.

explanatory power of each of our generative models. For these simulations, we run 100 iterations and take the median prediction error. Then, we repeat this process 100 times.

Again, we see similar patterns, suggesting that, even if the gravitational model is the "true" data generating process of these transitions, we should expect to see different patterns of movement in each landscape. In a landscape with one peak, like the *Sexuality and Gender* landscape, we should expect to see a lot of people staying at that peak, but also some inflow towards that global attractor. In a landscape with a few peaks that are far apart, like the *Religion* one, we expect stasis. Finally, in a relatively disorganized and flat landscape, like our *Eclectic* landscape, we expect erratic movements.

5. Discussion

In this article, we argued that the common metaphor of culture as landscape is not only useful for understanding how culture is organized—i.e., as a cartographic exercise—but also for analyzing how people travel across cultural positions. We noted that different disciplinary efforts have converged in certain algebraic representations of cultural landscapes, where binary strings represent the presence or absence of a certain set of features that define the positions of the landscape. These landscapes have two central parameters: cardinality and topography. The former refers to our ability to enumerate the positions that constitute a landscape and to know how close or far they are from each other. The latter, in turn, is concerned with the spatial organization of the positions, like how efficacious they are or—in our case—how well-populated they are. Following Martin (2000), we emphasized that capturing the layout of these landscapes is also helpful for understanding how people will move across time.

To test these ideas, we examined trajectories of cultural movement in the NSYR. We argued that understanding movement across landscapes of personal culture can be captured by a Markovian process where each position in the landscape is associated with a set of transition probabilities. By varying these transition probabilities, it is possible to build generative models of movement that are explicit about the kind of trajectories we expect to see in a given landscape. We then compared the predictions made by different generative models with the observed empirical data in order to adjudicate their explanatory power. We found that a gravitational model—one that calculates transition probabilities according to the occupancy of positions and the distance between them—is the most adequate model for explaining the observed trajectories in empirical data from the NSYR.

That said, we found that the kind of generative trajectories that such a gravitational model would predict depend heavily on the initial layout of the cultural landscape. Supplementing our empirical analyses with simulations, we showed that the organization of the landscapes is informative for understanding the patterns of movement that we should expect to see over time. In general, we noticed that the *ruggedness* of the landscape is particularly relevant for understanding the patterns of movement that we should expect within them.

Hence, our analyses emphasize the importance of an ecological approach to culture. Processes of belief change at the individual-level—via vertical learning or peer-influence—take place in more or less organized cultural landscapes. The layout and topology of these spaces makes certain shifts more probable, while dampening the likelihood of others. Thus, how culture is spatially organized at one point is instrumental to understanding subsequent development of cultural positions at the population level.

5.1. Different models of movement

In this article, we build and contrast different models of movement that—although rooted in contemporary work on socialization—remain relatively simple. For instance, we do not incorporate information about the social networks in which respondents are embedded. This omission might seem particularly glaring, as discussions of cultural transmission inevitably have to wrestle with the question of selection and influence, i.e., whether individuals create ties with like-minded individuals or whether they adopt the attitudes of their peers. Our omission is partly theoretical, given that the processes in question happen at different levels of analysis. While questions about social influence examine cultural items as they flow through social networks, or the creation of social ties themselves, we examined how actors move across cultural positions. This does not mean, however, that one cannot examine how both processes coevolve—how behaviors spread across networks and how this, in turn, reshapes the topology of cultural landscapes, or how movements in a cultural landscape reshape existing social structures. It would be possible, for instance, to build movement models that capture information about ego's social ties, perhaps giving priority to positions that are more common among ego's peers. Even though the NSYR contains some sociometric data, we lack the data necessary to build complete social networks and thus to test the relationships between social networks and cultural landscapes. We see this as an important next step in this line of work.

A similar consideration applies to the fact that, even in our first wave of empirical data, where we have rather young respondents (aged 16 to 20), the cultural landscapes they are embedded in are highly—and non-randomly—structured. While our analyses show that the current organization of the landscapes affects the kind of cultural shifts we can expect across them, we draw our conclusions from observing cultural terrains that are already structured. This means that our capacity to tease out the mechanisms that have led to that structure—and to its continued development—is limited. This is a broad limitation for trying to understand the development of cultural landscapes: the fact that we rarely get to observe the nascent stages, where the structuring forces would presumably be more apparent.

Similarly, our analyses do not use any sociodemographic information about the respondents. It might be the case that certain social groups are less conformist or less reticent to long-distance exploration than others. This could potentially be operationalized by exploring the adequacy of different models of movement for different social groups. Here, we decided to keep the discussion as general as possible to showcase the general principles of our approach. However, we think that exploring whether socio-demographic characteristics are associated with different patterns of movement across cultural landscapes is an exciting avenue for future research.

The simplicity of our analyses could be regarded as reassuring for a landscape approach to cultural movement. In the article, we have shown that just by taking into account the initial topography of a cultural landscape, it is possible to better understand the types of trajectories that individuals are most likely to take. The approach is informative even before taking into account some of the data that is most predictive of individual-level outcomes, like social networks and socio-demographic characteristics. This means that being able to incorporate these pieces of information to an analysis of cultural landscapes could lead to even more insights about how actors navigate culture.

5.2. The duality of what?

One important implication of this study extends to the debates around the notion of duality in general (Breiger 1974) and the duality of people and cultural beliefs in particular (Boutyline & Vaisey 2017; Martin 2000). Sociologists have used the idea of duality to understand belief systems, cultural schemas, and affiliation networks. Most of these studies, however, have examined these cultural structures as *static*. The benefits of this approach notwithstanding, understanding cultural trajectories requires us to reconceptualize cultural landscapes as *evolving* and *dynamic* set of cultural positions. This means that relying on one approach or the other—individuals connected by the pieces of culture they share or cultural elements linked by the individuals that internalize them—might provide only a partial understanding of cultural systems. We argue that the framework of duality also shapes how we should expect the system to look like in the future: how actors are distributed across the landscape makes up the topology of the landscape, while at the same time the topology of the landscape is informative for understanding how those actors will move.

A framework for *dynamic landscapes* requires a formally adequate understanding of how dynamism might endogenously emerge, though we should not lose sight of the fact that it is wrong to see landscapes with a fallacy of misplaced concreteness. The aim of this article was to simplify our understanding of cultural change as a process of social learning. We shied away from arguing whether individual change is a conscious process of deliberation, calculation, or position-clarification, or whether it is mostly an unconscious trajectory of learning and habituation (Lizardo 2017; Vaisey 2009). Instead, culture as landscape is aimed for understanding the socially structured information environment, where people are situated in certain positions with an intuitive sense of *distance* and *popularity*. This necessarily implies a learning process, where (1) people's initial conditions—say, socialization—and (2) the extent to which they are exposed to certain configurations—say, ideological reproduction—matter for movement. But these theoretical commitments are flexible enough to accommodate different theories of attitudinal development – e.g. they could represent individuals deliberately ruling out cultural items that are distant from their current positions or more automatically disregarding any such distant objects. Crucially, the landscape approach shifts the explanatory onus behind spatial approaches to culture from *cartography* to *models of movement*.

5.3. The movement of what?

Measuring the dynamics of cultural landscapes is quite appealing. However, the price is two strong assumptions. First, the model assumes that the processes of cultural change and stability depend on the public opinion field, meaning that the social distribution of ideas is central to understanding belief dynamics. Yet, two conflicting models can explain this phenomenon: it might be that actors learn this structure early on, and the landscape changes through the replacement of old actors with the new ones, or the *zeitgeist* or *learning* can push them to new positions (Vaisey & Lizardo 2016).

In this article, we specifically modeled a process of individual change using panel data, and we saw that the gravitational processes are informative about personal change. That said, the formal framework we developed can be applied to the individual *and* the group level processes. In that sense, two periods might involve the same set of people observed in different times, or different sets of people representing generational replacement or cultural transmission. Therefore, we need larger time frames involving multiple cohorts to assess the extent to which the public opinion field can reorganize when gravitation—pull and push dynamics—in cultural positions take place.

Second, algebraic representations suffer from important measurement problems. First, the assumption of binary positions is restrictive, as it often involves arbitrary cutoffs that eliminate the original variance. Second, the list of the number of elements N that defines the features of our landscapes is unlikely to be exhaustive. Third, and perhaps most importantly, the survey responses can become too volatile or uncertain to reliably infer one's position in a belief space.

The measurement problem is a trade-off between recovering *true* states or ensuring that we get the benefits of being able to locate positions spatially. Sociologists often build latent state models that associate cultural profiles not to a specific position in the landscape, but rather to a set of probabilities that produce a given set of responses (Kiley 2023). This allows us to bypass potential measurement errors resulting from a number of factors (Alwin & Krosnick 1991; Ansolabehere, Rodden & Snyder 2008), as well as ensuring that the potential movement we observe is not due to errors. This fends off uncertainty, but comes with several costs. For instance, given that latent states are defined qualitatively, we cannot understand the directionality or distance of trajectories. In other words, we do not know what transitions are large or small, and whether certain latent states are closer to others. In this sense, our proposal for measuring cultural landscapes comes with important caveats, though we believe that the gains might be useful nonetheless.

CRediT authorship contribution statement

Nicolas Restrepo Ochoa: Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Turgut Keskintürk:** Writing – review & editing, Writing – original draft, Visualization,

Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

None of the authors (Nicolas Restrepo Ochoa and Turgut Keskintürk) have any conflicts of interests to declare. We have received no funding linked particularly with this study and have no reason to suspect there are conflicts of interests associated with this work.

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