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Epidemiology and Pedagogy: Approaches to examining disease dynamics and developing anti-racist teaching practices.

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Epidemiology and Pedagogy: Approaches to examining disease dynamics and developing anti-racist teaching practices.

By

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A dissertation submitted in partial satisfaction of the

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of the

University of California, Berkeley

Committee in charge:

Professor Damian Elias, Chair
Professor Céline Pallud
Professor Justin Remais

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Abstract

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Doctor of Philosophy in Environmental Science, Policy, and Management

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Professor Damian Elias, Chair

My dissertation integrates theories and methods from pathogen ecology, infectious disease epidemiology and anti-racist pedagogy. For the first part of my dissertation, I focus on two environmentally- mediated, infectious diseases impacting the respiratory system, COVID-19 and coccidioidomycosis. My first chapter reviews key environmental features that characterize the soil niche of the two known fungal species in the *Coccidioides* genus, the etiologic agents for coccidioidomycosis. In this chapter, I aim to understand the environmental biology of *Coccidioides* species, *C. immitis* and *C. posadasii,* and factors that influence the pathogens' life history. My second chapter explores the most important health, social, and environmental factors impacting transmission and mortality rates in US counties to determine the sectors of society most vulnerable to infection and mortality during the COVID-19 pandemic. For the last part of my dissertation, I outline a pedagogical framework which integrates social theories in methods for anti-racist praxis. In my third chapter I present a pedagogical framework with anti-racist principles for developing a course centered on uplifting racially minoritized groups in higher education.

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Introduction

My dissertation examined concepts related to the epidemiology and etiology of infectious, respiratory diseases (COVID-19 and coccidioidomycosis) as well as anti-racism in environmental sciences and higher education.

COVID-19 and Coccidioidomycosis

Infectious diseases are a constantly evolving threat to public. The impact of infectious disease on human populations is a function of many factors including environmental conditions, pathogen biology, social and cultural behaviors, and public policy. For environmentally-mediated infectious diseases, there are many aspects to disease lifecycle to consider for disease management, including emergence from reservoir populations, zoonoses transmitted through unconventional agents, and impact on human societies. Using dynamic approaches for analyzing disease systems, I examined the environmental and population-level mechanics that influence transmission of the virus SARS-CoV-2, the etiological agent for COVID-19. Also, I examined breadth of literature to summarize our understanding of the soil niche for the pathogenic fungal species *Coccidioides immitis and Coccidioides posadasii*, the etiological agents for coccidioidomycosis.

It's important to note that COVID-19 and coccidioidomycosis are both known to disproportionately impact racially marginalized communities in the US due to differences in susceptibility for severe outcomes and inequitable exposure. For example, data indicates that black and brown communities in the United States are more likely to suffer severe illness and mortality from COVID-19 [1–4]. Likewise, coccidioidomycosis is a major environmental justice concern. Coccidioidomycosis impacts the experiences for those who suffer the risk of high exposure of dust particles which carry the infective fungal spores produced by the *Coccidioides* species (henceforth *Coccidioides*) which typically includes individuals with occupations that are based outdoors and incarcerated individuals in endemic areas [5–8]. Additionally, it has been shown that people identifying as Black or Filipino appear to be at higher risk for disseminated disease after contracting coccidioidomycosis in California [9–12].

In Chapter 1, I synthesize literature describing environmental factors driving establishment, growth, and persistence for *Coccidioides*. I discuss current evidence on associations between climate and meteorology and the spatiotemporal distribution of *Coccidioides* and interpret these findings according to specific life stages of the fungus, including spore establishment, mycelial growth, and spore dispersal. Next, I summarize evidence on soil properties that may support *Coccidioides* growth. Then, I discuss specific *Coccidioides* traits that may provide the fungus with a competitive advantage in harsh soil conditions that characterize the arid and semiarid environments where it grows. Finally, I describe key gaps in our knowledge on *Coccidioides* ecology in soil, including the potential role of small burrowing mammals as important reservoir hosts for *Coccidioides*.

In Chapter 2, looks at COVID-19 outcomes across the United States (excluding counties in Alaska, Puerto Rico, and Hawaii) to explore the relative importance of different types of social, physical, and environmental factors on COVID-19 transmission and mortality [13]. I quantify the relationship between per capita COVID-19 outcomes and county-level physical and mental health, environmental pollution, access to health care, demographic characteristics, vulnerable population scores, and other epidemiological data.

By pursuing the gaps in our understanding of county-level features related to COVID-19 incidence and mortality as well as the environmental niche and biology of *Coccidioides*, I hope to offer information that can improve management of COVID-19 and coccidioidomycosis.

Anti-racism in Higher Education

For my final chapter, I detail a key example of pedagogical anti-racism efforts in higher education. During the initial days of the COVID-19 pandemic in 2020, there was an uptick in media-covered deaths of unarmed Black men and women in the US [14–16]. Academic departments across the United States saw an increase in efforts to integrate belonging, diversity, equity, justice, and inclusion initiatives into their programs. In this vein, I was part of a team that developed and led a 16-week semester course in the Environmental Science, Policy and Management (ESPM) department at the University of California, Berkeley, "ESPM 290: Critical Engagements in Anti-Racist Environmental Scholarship". The course sought to cultivate anti-racism mindsets through collaborative learning and anti-racist action in academic contexts from individual researchers to the College.

In this chapter, I draw on my experiences from two years of developing and teaching the course to present a theoretical and pedagogical framework for course design aimed at long-term, action-oriented ant-racist engagement. First, I outline our theory of change and provide an overview of our teaching philosophy, which includes attending to curriculum, classroom structures, and teaching practices. Then, I highlight elements that were critical to the course's impact: (1) engaging with a lexicon around anti-racism, (2) centering the knowledge of Black academics, (3) flattening institutional hierarchies in academia, (4) exploring anti-racist principles in mentoring, research, the classroom, and other settings, and (5) developing action plans for long-term anti-racism praxis. Overall, this chapter offers a model for those seeking to implement anti-racist praxis through coursework and long-form professional development training for academics.

References

1. Rozenfeld Y, Beam J, Maier H, et al. A model of disparities: Risk factors associated with COVID-19 infection. *Int J Equity Health*. 2020;19(1):1-10. doi:10.1186/s12939-020-01242-z
2. Maness SB, Merrell L, Thompson EL, Griner SB, Kline N, Wheldon C. Social Determinants of Health and Health Disparities: COVID-19 Exposures and Mortality Among African American People in the United States. *Public Health Rep*. 2021;136(1):18-22. doi:10.1177/0033354920969169
3. Adeoye EA, Rozenfeld Y, Beam J, Boudreau K, Cox EJ, Scanlan JM. Who was at risk for COVID-19 late in the US pandemic? Insights from a population health machine learning model. *Med Biol Eng Comput*. 2022;60(7). doi:10.1007/s11517-022-02549-5
4. Garg S, Kim L, Whitaker M, et al. Hospitalization Rates and Characteristics of Patients Hospitalized with Laboratory-Confirmed Coronavirus Disease 2019 — COVID-NET, 14 States, March 1–30, 2020. *MMWR Morb Mortal Wkly Rep*. 2020;69(15). doi:10.15585/mmwr.mm6915e3
5. Wheeler C, Lucas KD, Mohle-Boetani JC. Rates and risk factors for coccidioidomycosis among Prison Inmates, California, USA, 2011. *Emerg Infect Dis*. 2015;21(1). doi:10.3201/eid2101.140836
6. Laws RL, Cooksey GS, Jain S, et al. Coccidioidomycosis Outbreak Among Workers Constructing a Solar Power Farm — Monterey County, California, 2016–2017. *MMWR Morb Mortal Wkly Rep*. 2018;67(33). doi:10.15585/mmwr.mm6733a4
7. McCurdy SA, Portillo-Silva C, Sipan CL, Bang H, Emery KW. Risk for coccidioidomycosis among hispanic farm workers, California, USA, 2018. *Emerg Infect Dis*. 2020;26(7):1430-1437. doi:10.3201/eid2607.200024
8. Sipan CL, Portillo-Silva C, Bang H, McCurdy S. Coccidioidomycosis Knowledge and Behaviors of California Hispanic Farm Workers. *J Agromedicine*. 2022;27(2):197-206. doi:10.1080/1059924X.2021.2002223
9. Kupferwasser D, Miller LG. Sociodemographic factors associated with patients hospitalized for coccidioidomycosis in California and Arizona, state inpatient database 2005-2011. *Epidemiol Infect*. 2020. doi:10.1017/S0950268820002836
10. Flaherman VJ, Hector R, Rutherford GW. Estimating severe coccidioidomycosis in California. *Emerg Infect Dis*. 2007;13(7). doi:10.3201/eid1307.061480
11. Ruddy BE, Mayer AP, Ko MG, et al. Coccidioidomycosis in African Americans. *Mayo Clin Proc*. 2011;86(1). doi:10.4065/mcp.2010.0423
12. Rosenstein NE, Emery KW, Werner S Ben, et al. *Risk Factors for Severe Pulmonary and Disseminated Coccidioidomycosis: Kern County, California, 1995–1996*. Vol 32.; 2001. https://academic.oup.com/cid/article/32/5/708/358336.
13. McCoy D, Mgbara W, Horvitz N, Getz WM, Hubbard A. Ensemble machine learning of factors influencing COVID-19 across US counties. *Sci Rep*. 2021;11(1):1-14. doi:10.1038/s41598-021-90827-x
14. Stack M. The murder of George Floyd and the mediatization of solidarity by top-ranked universities. *Lang Intercult Commun*. 2021;21(6):749-764. doi:10.1080/14708477.2021.1985133
15. Dong B, Wu X. *Reaching and Engaging People: Analyzing Tweeting Practices of Large U.S. Police Departments Pre- and Post- the Killing of George Floyd*. Vol 17.; 2022.

doi:10.1371/journal.pone.0269288

16. Nguyen TT, Criss S, Michaels EK, et al. Progress and push-back: How the killings of Ahmaud Arbery, Breonna Taylor, and George Floyd impacted public discourse on race and racism on Twitter. *SSM - Popul Heal*. 2021;15:100922. doi:10.1016/j.ssmph.2021.100922

Chapter 1 | The soil niche of *Coccidioides*: implications for coccidioidomycosis epidemiology and ecology

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Included as a dissertation chapter with permission from co-authors.

Abstract

Coccidioidomycosis is a fungal infection caused by species of the *Coccidioides* genus, *Coccidioides posadasii* and *Coccidioides immitis (*henceforth *Coccidioides)*. *Coccidioides* grows as a filamentous fungus in soil and is dispersed *via* airborne spores, inhalation of which can lead to infection in humans. Coccidioidomycosis incidence has increased dramatically across the Southwestern United States in recent decades, yet the climatic, meteorological, and edaphic (soil) features that describe the distribution of *C. immitis* and *C. posadasii* in soil remain unresolved. Here, we synthesize literature describing environmental factors driving *Coccidioides* establishment, growth, and persistence in soils of the Southwestern United States. First, we discuss current evidence on associations between climate and meteorology and the spatiotemporal distribution of *Coccidioides* and interpret these findings according to specific life stages of the fungus, including spore establishment, mycelial growth, and spore dispersal. Next, we summarize evidence on soil properties that may support *Coccidioides* growth. Then, we discuss specific *Coccidioides* traits that may provide the fungus with a competitive advantage in harsh soil conditions that characterize the arid and semiarid environments where it grows. Finally, we describe key gaps in our knowledge on *Coccidioides* ecology in soil, including the potential role of small burrowing mammals as important reservoir hosts for *Coccidioides*.

Introduction

Coccidioidomycosis, commonly known as Valley fever, is a granulomatous fungal infection [1–5]. More than 95 percent of cases are reported in Arizona and California is endemic [6,7]. Disease typically presents as a mild respiratory illness or pneumonia but can lead to rare forms of disseminated disease or death [5]. Much research has focused on the environmental and social factors associated with coccidioidomycosis incidence in humans, but examination of the ecological factors that determine where, when, and under what conditions the fungal pathogen thrives in soil has been limited.

The etiologic agent for coccidioidomycosis a group of soil-dwelling fungal species in the *Coccidioides* genus. The *Coccidioides* species are spore-forming ascomycetes in the Onygenaceae family [8,9], which include a group of keratin-consuming fungi often associated with animals [8,10]. There are two species within the genus *Coccidioides* that are recognized, *C. immitis* and *C. posadasii*. The *Coccidioides* species (henceforth *Coccidioides*) is a thermally dimorphic fungus that grows as spore-forming mycelia consisting of septate hyphae in soil, and spherules encasing endospores in mammalian hosts [11–13]. These morphologies constitute the two potential life cycles of the fungus: the saprobic and the parasitic (Figure 1). During the saprobic life cycle, arthroconidia grow within alternating hyphal septa. As conditions dry and hyphae desiccate, the light weight arthroconidia may become airborne following soil disturbance caused by natural processes (e.g., burrowing, windstorms, or earthquakes) or anthropogenic processes (e.g., construction, agriculture, or excavation of archeological sites) [14–19]. Airborne arthroconidia may settle in a conducive soil environment and germinate, thus continuing the saprobic life cycle, or may be inhaled by susceptible mammalian hosts, initiating the parasitic life stage. Once within the host, the parasitic phase begins with the production of thick-walled spherules that develop endospores as maturation progresses (Figure 1). *C. posadasii* has been isolated from soils across a broad geographic range, including in Arizona, Nevada, New Mexico, western Texas, Mexico, and Central and South America. *C. immitis* occupies a smaller geographic range, and is typically found in the desert regions of central and southern California, extending into Baja California, and as far north as Washington State [20,21]. Overlap in the two species' distributions has been observed in southern California and Baja California [22].

While the life cycle and geographic range of *C. posadasii* and *C. immitis* is well described, information on their ecology in soils is lacking. Broadly, detection of *Coccidioides* has been linked to undisturbed and uncultivated soils [23], and several outbreaks of coccidioidomycosis have been documented following the excavation of undisturbed soil*s* [14,24–28]. Where the fungus has been isolated, it has been observed to be unevenly distributed, and no one set of physical, biological, and biogeochemical characteristics has thus far consistently described its soil niche [12,29]. Moreover, *C. posadasii* and *C. immitis* may have evolved ecological niches unique to their geographic ranges (e.g., differential thermotolerance observed between the two species may reflect adaptation to different climates) [30]. As incidence of *Coccidioides* infection rises across the southwestern United States, and as concern that the *Coccidioides* range may expand under future climate change scenarios grows [31], it is essential to synthesize current knowledge on the ecological soil niche of *Coccidioides* to support scientific and public health efforts to better understand and predict *Coccidioides* growth in soil, and mitigate human infection risk.

Here, we review literature describing biotic and abiotic factors that support *Coccidioides* establishment, growth, and persistence in soils of the southwestern United States. We assess climatic, meteorologic, and edaphic (soil) properties that influence the saprobic *Coccidioides* life cycle, as well as biological interactions with other fungal species that altogether define the ecological niche of *Coccidioides* in soil. First, we focus on how key climatic and meteorologic (e.g., precipitation, temperature, humidity) characteristics might broadly explain the distribution of *Coccidioides* in space and time, with specific focus on climate and meteorologic influences on different stages of the saprobic cycle (spore establishment, mycelial growth, and arthroconidia dispersal). Next, we consider edaphic properties (e.g., soil texture, soil porosity, soil moisture, nutrients, salinity, alkalinity, and presence of animal burrows) that may influence the distribution of the fungus at a finer scale within the soil matrix. Then, we explore potential competitive advantages that *Coccidioides* may possess under certain climatic and edaphic circumstances that allow it to survive in harsh arid and semiarid environments [29,32–34]. Last, we discuss key research gaps needed to provide a deeper, quantitative understanding of the organism's soil niche. Ultimately, we aim to provide a comprehensive description of our current understanding of the

Coccidioides soil niche, which is crucial to inform environmentally targeted public health interventions and control strategies.

Review and Synthesis

Climate and Meteorology

Meteorological and climate variables play a key role in the saprobic phase of the *Coccidioides* lifecycle. Soil moisture initiates mycelial growth[35], as moisture enables spores to germinate into branching, filamentous structures called hyphae. The network of hyphae creates the mycelium. Analysis of genes involved in metabolic processes suggests that mycelia derive nutrients from nonliving organic matter and animal keratin [8]. Within individual hyphal cells, barrel-shaped arthroconidia (spores) grow. Over periods of prolonged dry conditions, hyphal cells desiccate, and dead, empty, autolyzed cells split down their middle, leaving half of the dead cell on each end of the living arthroconidium. When dry, contaminated soils are disturbed, such as through wind erosion or construction, arthroconidia can be become airborne and disperse *via* soil and dust dispersion. This phenomenon of alternating wet and dry periods influencing *Coccidioides* mycelial growth (moist soil during relatively cool, moist weather) and spore dispersion (dusty, windy surface soil conditions and relatively warm, dry weather) has been referred to as the "grow and blow" hypothesis [36,37]. This suggests soil moisture is a major limiting factor that influences *Coccidioides* populations and, subsequent, disease burden.

In accordance with *Coccidioides'* climate-sensitive life cycle, changes in precipitation, temperature, and drought conditions have been identified as important predictors of *Coccidioides* presence in soils [31,35,38,39]. While most soil fungi thrive in conditions that maintain a moisture rich soil environment, *Coccidioides* are typically found in arid environments with distinct wet seasons with mild temperatures and distinct dry seasons with high temperatures in which there is little to no rain [40]. Alternating wet-dry climate conditions lead to seasonal periods of mycelial growth and arthroconidia "spore" production, which may in turn produce seasonal patterns of human infection. Nearly half of the annual precipitation in the southern U.S. falls between October and March [41], with distinct seasonal patterns across the endemic states. California exhibits a singular seasonal peak in precipitation, receiving over 80-90 percent of its precipitation during this cool winter period [41]. Precipitation in Arizona has two distinct seasons, with about 50-60 percent falling during winter, and another 40-50 percent during the summer (July – September) monsoon months [42]. Regional and interannual differences in rain intensity (e.g. monsoons) and precipitation timing may drive spatio-temporal differences in observed seasonality of coccidioidomycosis in people [38]. Here, we review the impacts of precipitation and soil moisture, ambient temperature, and drought conditions on the *Coccidioides* soil niche in more detail.

Precipitation and soil moisture

Precipitation and soil moisture are critical determinants of fungal growth in soil [12,36,39,43]. While directly measuring the relationship between soil moisture content and *Coccidioides* presence in soil is challenging due to the sporadic distribution of the fungus in space and time, there is evidence that *Coccidioides* is more likely to be detected in soil following wet periods as compared with dry periods [44]. In a study by Egeberg and Ely (1956) conducted in the southern

San Joaquin Valley, roughly 16 percent of soil samples (19/120) collected at the end of the wet season (April) were positive for *C. immitis* versus 4 percent of soil samples (16/380) collected at the end of the dry season (January)[44]. The depth at which *C. immitis* was detected also varied between the two seasons: at the end of the dry season, three of the four positive samples came from soil depths of 10-30 cm, whereas at the end of the wet season, all but one positive sample (15/16) were collected from surface soils [44]. This distribution corresponds to soil moisture dynamics, where moisture is retained at sub-surface levels in dry conditions, but across the entire soil column when soil is saturated. Thus, *C. immitis* hyphae may seek moisture at greater sub-surface depths when soil moisture is limited during dry periods [45–47]. Soil moisture content may also influence spatial (rather than spatio-temporal) *Coccidioides* presence: locations adjacent to stream beds and stream banks have been linked with *Coccidioides* presence, both in soil and in air samples collected adjacent to stream beds.[3,48,49]

While soil moisture is a fundamental requirement for *Coccidioides* growth, the fungus is not known to grow in soils that are frequently saturated. Waterlogged pores in soil may restrict space and oxygen needed for filamentous fungi to extend or grow [50], and abundant moisture may stimulate competitive microbial activity [12,36,39]. Studies assessing mean annual precipitation in California suggest mean annual precipitation in excess of 600 mm decreases the disease burden and, therefore, the prevalence of *C. immitis* in soils [38]. However, within this range of precipitation, fine-scale distribution of *Coccidioides* is impacted by many factors that further influence its soil niche, including soil texture (i.e., proportion of sand, silt, and clay), presence of small burrowing mammals, organic matter from flora and fauna, and abundance of microbes [24,43].

Temperature and humidity

Temperature and humidity play a major role in defining the soil niche for *Coccidioides*, both directly and indirectly influencing the viability of un-germinated spores, hyphal growth, and the lysis of hyphae and subsequent release of infectious arthroconidia [31,37,38,50–57]. Evidence suggests that *Coccidioides* spores are adapted to the thermal rigors of arid habitats, and possess hardy cell walls and protective enzymes to withstand extreme environmental conditions [58]. Laboratory studies found that *C. immitis* arthroconidia can remain viable across a wide range of temperatures, from -15°C to 37°C, as well as a wide range of relative humidity, from 10 to 95 percent [53]. However, the viability of arthroconidia may be reduced by extreme environmental conditions, including intense ultraviolet light and high surface temperatures [44,59]. For instance, in another laboratory study, temperatures near or greater than 50°C inactivated *Coccidioides* spores and the number of viable spores decreased by 45 percent over a one month period and nearly 100 percent over a six-month period when low humidity (10 percent) was coupled with high temperature (37°C) [53]. Increasing humidity prolonged spore viability across all temperatures tested. For instance, increasing humidity from 10 percent to 95 percent, while keeping temperatures at 37°C was associated with only a 9 percent loss of viable spores over one month and a 48 percent loss over a six-month period [53].

Areas known to harbor *Coccidioides* have been classified as hyperthermic (overheated) arid, thermic (heated) arid, and semiarid [50]. Fisher et al. (2007) provide data on the ranges of annual ambient air temperatures across government weather stations in Arizona, California, and Utah locales with known *Coccidioides* habitats [50]. The average annual low temperature values ranged from -0.5°C to 12.7°C while the average annual high temperature values ranged from 17.7°C to

27.7°C [50]. While the annual air temperature range provided by Fisher et al. may approximate the optimal soil temperature range for *Coccidioides* growth, mycelial growth rates may vary substantially along gradients of soil depth according to the temperature profile of the soil column [50]. Also, spore survival may be low within soils that reach very high temperatures, particularly at the surface where energy transfer is highest, due to heat and pressure sensitivity [50]. Indirect effects of temperature on *Coccidioides* survival and growth, mediated through soil moisture are discussed in the next section.

Seasonal soil moisture deficit and drought

Temperature and precipitation interact to determine soil moisture [60,61]. Because precipitation in the southern US follows distinct annual (California) or biannual (Arizona) seasons, endemic regions experience periods with low soil moisture, during which the surface soil no longer provides sufficient moisture for growth of soil microbes [62–65]. Under such conditions, microbes may suffer osmotic stress, a rapid or sudden change in the movement of water [66,67]. Organisms cope with osmotic stress in various ways, and certain fungi have specific adaptations to withstand very low water levels, including production of spores [66,67].

Accordingly, soil moisture deficits influence the short-term production of arthroconidia. During seasonal dry periods, the hyphal fragmentation and subsequent production of arthroconidia begins near the soil surface [50,59,68]. This morphological change is in direct response to the depletion of nutrients, moisture, or other resource deficits or environmental stresses [59]. Thus, while soil moisture deficits may delay hyphal growth in the long-term, it may accelerate arthroconidia production in the short-term. There is limited research on the physiological responses to soil moisture deficit and drought demonstrating this phenomenon for *Coccidioides* mycelia and arthroconidia. Particularly absent is research that might confirm the degree and duration of moisture deficit necessary to initiate the fragmentation of hyphae, and research characterizing the conversion time from hyphae to arthroconidia at given degrees of dryness.

Beyond inter-annual soil moisture deficits, the southwestern US is prone to extended periods of drought. A drought is defined as a period of anomalously dry conditions that results in water-related problems and can be classified into types. Agricultural drought is defined by anomalously low soil moisture [69] and, thus, thought to be most relevant for *Coccidioides*. While periods of low precipitation have been historically common, anthropogenic warming may have exacerbated droughts in recent years [70–73]. Indeed, the emerging 2000-2021 megadrought occurring in the southwestern US is thought to be rapidly intensifying due to record high temperatures and, has already resulted in the driest 22-year period in California since 800 CE [74]. As spore-producing fungi that can persist in arid soils, it is speculated that *Coccidioides* have a competitive advantage over competing organisms within the soil niche following a prolonged absence of moisture and water at the soil surface [34,52,75].

This hypothesized competitive advantage may be conferred *via* various pathways. For example, researchers suspect that if resources are limited (low water availability) or local conditions change (increased surface temperatures), the hyphae "retreat" or grow away from the soil surface by means of 1) inactivating hyphae near the surface and 2) continuing growth of hyphae along those protected from extreme dry, resource poor conditions in lower strata [44,46,57,76]. In this sense, *Coccidioides* may seek refuge for lower temperatures and increased moisture conditions in deeper soils. While the actual distance traveled by *Coccidioides* in seeking refuge is not known, *Coccidioides*-positive samples collected from the southern San Joaquin Valley during the dry season were more likely to have been found at depths of 10.16 to 30.48 centimeters beneath the surface as compared to positive samples collected from the wet season [77].

Another idea is that other microbes that compete for resources are eliminated by harsh conditions that *Coccidioides* can tolerate. Observations of the interactive (e.g., symbiotic, competitive, antagonistic) behaviors of *C. immitis* with differing microbes in the mixed cultures of soil isolation plates support the hypothesis that *Coccidioides* may be a poor competitor for nutrients and biological space when compared with certain fungi or bacteria [51,78]. Microbes including bacteria such as *Bacillus subtilis* and *Streptomyces* spp., may exhibit strong anti- *Coccidioides* properties in the soil [78]. Additionally, a plant endophyte, *Phialocephala*, was negatively associated with detection of *Coccidioides* DNA from soils in Washington state [79]. However, laboratory studies demonstrate that *C. immitis* spores can remain viable through climatological extremes, including low precipitation and intense heat, which may inactivate other species [53], and field study confirms that the same strain of *Coccidioides* can persist in soils for over six years [79]. As a filamentous fungus, *Coccidioides*'s hardy cell structures and ability to branch to more favorable depths may enhance its survival during extremes, among other factors. Thus, elimination of some competitors from the soil may permit *Coccidioides* to expand more freely when favorable conditions return. Taken together, these ideas form what is called the "soil sterilization" hypothesis [12,35,38,54,80].

Large die-offs of mammalian populations have been observed during drought [81], providing a third potential pathway yielding a competitive advantage for *Coccidioides*. Rodent hosts produce granulomas to entrap the parasitic spherules of *Coccidioides* within their lungs. When the rodent dies, the granuloma no longer functions and the rodent body temperature drops, permitting released spherules to convert to hyphae, either directly or *via* endospores [82]. The host's body may provide moisture and nutrients for hyphal proliferation. This hypothesis is termed the "endozoan, small-mammal reservoir hypothesis", and is discussed later in the review [83]. Both the "soil sterilization" and the endozoan hypothesis suggest that *Coccidioides* may proliferate when precipitation wets the soil following drought periods, but field evidence to confirm each theory is lacking.

Epidemiologic evidence supporting *Coccidioides'* climatic niche

A large body of epidemiologic evidence has demonstrated an association between human coccidioidomycosis incidence with climatic and meteorologic conditions, including precipitation, temperature, and drought, as well as climate-influenced factors like dust storms [35,55,84–87]. For example, several studies have identified a seasonal trend whereby incidence is associated with alternating seasonal periods of high and low precipitation [38–40,49,88].This association supports the idea that wet periods promote *Coccidioides* growth in soils [24,25,35,50,51]. It is thought that subsequent dry periods allow for dispersion of spores that can infect people and cause disease [40,88]. There are likely several direct and indirect contributing factors related to climate, including vegetation biomass, small mammal population cycles, vegetation and animal-derived soil nutrients, agricultural land usage, and seasonal trends in employment involving outdoor work.

Observed spatial and temporal heterogeneity in seasonal infection patterns may reflect spatiotemporal variations in the local climate conditions that influence mycelial growth and dispersion. In Arizona, where roughly two-thirds of US cases are reported [89], annual precipitation follows a bimodal cycle, and there are typically two coccidioidomycosis "seasons" [38]. In contrast, California's Central Valley, which accounts for much of the remaining 25 percent of cases, experiences a unimodal precipitation cycle and a single coccidioidomycosis "season" [38,89]. This may suggest that *C. posadasii* (which causes most cases in Arizona) undergoes two moisture-aided growth cycles, whereas *C. immitis* (which causes most cases in California) undergoes just one.

Fewer epidemiologic studies have assessed associations between soil conditions resulting from observed meteorological events with coccidioidomycosis outcomes, limiting a mechanistic understanding of how climate and meteorological events influence the saprobic life cycle of *Coccidioides* and subsequent human risk for infection. Coopersmith et al. (2017) attempted to investigate this mechanism by assessing relationships between coccidioidomycosis incidence and data on soil moisture and precipitation simultaneously [85]. Using *in situ* soil moisture measurements collected across the Southwestern United States by the U.S. Climate Reference Network, Coopersmith et al. (2017) found that in both California and Arizona, coccidioidomycosis incidence was associated with soil moisture conditions in the previous summers and falls[85], suggesting that the impact of precipitation on fungal growth and subsequent human risk may be mediated by soil moisture.

Caution should be exercised when drawing upon epidemiologic evidence to characterize the climatic niche of *Coccidioides* in soil. Finding associations between climate and meteorological conditions and coccidioidomycosis incidence does not confirm the realized niche of the fungal pathogen for several reasons. First, incidence of coccidioidomycosis may not be spatially correlated with the presence of the fungus in soils because infectious arthroconidia are airborne and can be dispersed in the wind during dust generation. Thus, the soil source of an infection may be miles away from the place where a person acquires an infection or from where a diagnosis ultimately takes place. What is more, people are highly mobile, leading to potential exposures occurring far from where incident cases are ultimately diagnosed and reported. Cohort studies that follow individuals over time may help clarify the location of exposure, but identifying specific sources of dust exposures is generally not possible even within these study designs. Moreover, individuals may be susceptible to infection based on race, ethnicity, and pre-existing conditions [90,91] as well as engagement in certain occupational sectors [92,93]. Spatial aggregation of vulnerable populations may further confound estimates of pathogen location or relative density. Last, soils may support *Coccidioides*, but if there is little soil disturbance or fugitive dust emissions resulting in infection amongst the local population, a correlation between climate conditions and epidemiologic outcomes may not be observed. Altogether, associations between climatic factors and coccidioidomycosis incidence reveal important patterns for public health messaging but may not yield reliable inference on the pathogen's soil niche.

Edaphic Properties

Even within localized geographic areas that experience the same climate and meteorological fluctuations, the distribution of soil-dwelling *Coccidioides* is highly heterogeneous. Clusters of detection range on the scale of tens of meters, and appear widely scattered and uneven [29,32,46,94].

While reasons for this sporadic nature remain unclear [13], there are several shared edaphic characteristics across many *Coccidioides* detection sites. In this next section, we review the evidence for common edaphic properties that describe soil environments where *Coccidioides* has been found, including soil depth, texture and porosity, alkalinity and salinity, and nutrients. We also discuss potential roles of small burrowing mammals, like wild rodents, influencing edaphic properties related to the *Coccidioides* soil niche.

Soil depth

Soil depth mediates several soil properties that may influence fungal presence, including soil moisture, temperature, bulk density, aeration, hydraulic conductivity, organic matter content, pH, and nutrient content [45]. Germination of *Coccidioides* spores and mycelial development has been found to occur at soil depths ranging from 2 to 31 centimeters [50]. This range generally aligns with the depth of the surface horizon (the "topsoil") [95], and *Coccidioides* is most frequently isolated from surface soils at depths between 2 and 20 cm [50]. The surface horizon usually constitutes the soil stratum with the highest concentration of organic matter and microorganisms, as it accumulates surface litter [95,96]. As such, it is also where biological activity is the highest [97].

Soil texture and porosity

Soil consists of sand-, silt-, and clay-sized particles, with sand particles being the largest (0.5 to 2 mm diameter) ad clay particles being the smallest (0.002 to 0.05 mm). Soil texture is determined by the proportion of those sand-, silt-, and clay-size particles and plays a key role in fungal growth *via* its influence on soil porosity, pore size distribution, water holding capacity, and aeration [45]. Soil porosity refers to the interstitial space between soil particles that is filled by either water or air. Coarser-grained soils have large pores but low porosity [45,98]. Soils with smaller pores have lower infiltration, allowing water to be held more tightly. Therefore, soils with a relatively higher percentage of clay particles retain more water than soils with a higher percentage of sand particles [45,98], which could lead to the development of anoxic conditions. Detection of *Coccidioides* in field studies has commonly occurred in soils with sandy or sandy loam textures [50,51], which contain a high proportion of large-grained sand and smaller proportions of both medium-grained silt and fine-grained clay. Sandy loam soils may offer several advantages to *Coccidioides.* First, the coarse sand grains create medium to large pores to accommodate hyphal expansion and motility [99,100] while providing adequate water infiltration and drainage. At the same time, smaller clay particles aid in meeting a minimum threshold of water and nutrient retention [50]. This combination may help achieve the required balance between water and nutrients for growth, and pore space for mycelia to extend their networks. In general, organisms that can grow as filamentous hyphae are better equipped to reach water pockets in coarse, dry soils, suggesting that *Coccidioides* is well-suited to coarse-textured soils in relatively dry regions because the mycelium can effectively forage for moisture and nutrients [50,101,102].
As soil pore spaces are occupied by either water or air, the spatial architecture of pores and the distribution of water within this architecture can influence the flow of gases, such as oxygen and carbon dioxide [103]. Coarse-textured soils, including sandy loam soils, allow for increased aeration and a supply of oxygen within the soil needed for fungal growth [104]. During its saprobic life cycle in soil, *Coccidioides* are obligate aerobes, and greater oxygen availability has been shown to increase the growth rate of mycelia [105]. For well-aerated soils, oxygen availability is unlikely to be a limiting factor for *Coccidioides* growth near the surface, but can become a limiting factor at lower depths where anoxic conditions may exist [50]. In an *in vitro* study,

mycelium cellular protein growth and viable *Coccidioides* spore counts increased along increasing aeration rates up to a maximum oxygen flux tested (approximately 1 mM O_2 L^{-1} min^{-1}) [106]. At low aeration rates, oxygen was the limiting factor for *Coccidioides* mycelium growth, whereas at higher aeration rates, nutrients in the growth media became the limiting growth factor [68].

Alkalinity and Salinity

Salinity, electrical conductivity, and soil cation exchange capacity can either promote or inhibit fungal growth. Together, these factors influence soil alkalinity. *Coccidioides* presence in soils has been associated with high levels of alkalizing ions and compounds, including magnesium, calcium, potassium, bicarbonates [50,107], and dissolved salts [25,34,44,51,57,108].

A positive association has been observed between *C. immitis* detection and soil salinity [108], which suggests that *Coccidioides* is a halotolerant microorganism [51]. Over an 8-year period, Elconin et al. (1964) collected roughly 5,000 soil surface samples in the San Joaquin Valley of California [108]. *C. immitis* was isolated during the years where the chemical composition of the surface soils showed elevated soluble salts including sodium, calcium, sulfates, and chlorides. The reported salinity, measured in terms of saturation extract conductivity (EC_e), ranged from 11 to 27 EC_e/ 10^3 when *C. immitis* was detected, but from 3.5 to 8.8 $EC_e/10^3$ when *C. immitis* was not detected [108]. In Washington state, the presence of *Coccidioides* DNA was statistically associated with elevated concentrations of calcium and sodium, as well as boron, magnesium, and silicon in soil leachates [79]. Soils positive for *Coccidioides* had a median concentration of sodium and calcium of 496 ug/L and 4,460 ug/L, respectively, compared to 293 and 3,130 ug/L in soils negative for *Coccidioides* DNA [79]. A common pattern for *Coccidioides* detection includes areas that can be flooded for a portion of the year and dried out at other times which may be particularly suitable for *Coccidioides* (e.g., soils adjacent to arroyos, dry washes, or drainage channels) [47,108–110]. In addition to providing favorable moisture conditions, these locales may serve to concentrate salt in surface soils due to evaporation of surface water.
Tolerance to high saline soils may influence *Coccidioides* presence and abundance by providing yet another competitive advantage over other soil microorganisms in a given habitat [50]. It is hypothesized that salts may inhibit antagonistic or competitive microbial species [50]. In a study by Egeberg et al., two microbial antagonists of *C. immitis* were isolated and their radial colony growth examined under a range of salinity conditions between 0 and 8 percent [57]. One antagonist, the soil fungus *Penicillium janthinellum*, did not grow in the presence of sodium chloride (NaCl) and calcium chloride ($CaCl_2$). Another antagonist, the gram-positive soil bacterium *Bacillus subtilis*, showed decreasing growth along increasing salt concentrations. *C. immitis,* on the other hand, was able to grow at all salt concentrations challenged with, with peak growth occurring at 2 percent both for both NaCl and $CaCl_2$ [57].

A key unknown is why *Coccidioides* appears to be halotolerant, while its soil competitors are not. Pérez-Llano et al. (2020) found that halotolerant and halophilic fungi experience physiological changes, such as an increase in the thickness of the cell wall, in response to the ionic stress induced by high salinity [111]. These responses help fungi tolerate more extreme conditions, even beyond high salinity, compared to co-occurring microbes within the same soil niche. Additionally, climate change may lead to increases in soil salinity broadly which in turn could expand suitable habitats for *Coccidioides* [112–114], highlighting the need to understand the

metabolic and physiological effects of salinity on the saprobic stages of the *Coccidioides* life cycle in order to anticipate how *Coccidioides* populations may respond to future soil salinization.
Macro- and micronutrients

Fungi rely on carbohydrates, proteins, and minerals for growth [99,100]. Cultivation experiments have illuminated some basic nutritional requirements for *Coccidioides* growth, including adequate concentrations of soil carbon, nitrogen, potassium, iron, phosphorus, and magnesium [68,106,115–117]. In the absence of competition, *Coccidioides* grew well in solutions containing amino acids, sugars (glucose), ammonium lactate, and inorganic salts, e.g., phosphate, sulfate (potassium sulfate), metallic cations (potassium, iron, magnesium, zinc) [68,106,115–117], while no significant effects on growth were noted for micronutrients such as manganese, calcium, copper, molybdenum, cobalt, or boron salts [68]. In the laboratory environment, simple sugars like glucose were found to be suitable sources of carbon for *Coccidioides,* whereas more complex amino acids were effective sources of nitrogen [117,118]. Recent work about the growth rate of *Uncinocarpus*, a non-pathogenic close relative of *Coccidioides*, on more complex molecules may thus help us speculate about what *Coccidioides* likely metabolizes in nature [119]. *U. reesii* showed growth on a limited range of carbohydrates, primarily basic plant sugars and cell wall components, along with growth on gelatin and a wide range of dipeptides and amino acids [120]. This suggests that Onygenales, including dimorphic fungi, can degrade cellulosic plant material in the soil, but may prefer proteinaceous growth substrates, including animal biomass, over carbohydrates [120].

In the soil, carbon and nitrogen are derived from both plant, microbial and animal origins. Many fungal species primarily gain nutrients from the breakdown of plant residues, and gain energy from cellulose derived from plant cell walls [45]. In contrast, *Coccidioides* appears to be specialized for growth on substrates containing proteins derived from mammalian hosts, like that in keratin. Comparative genomic analyses have revealed that, compared to closely related species in the Onygenaceae family, there have been significant deviations in the *Coccidioides* genome that code for enzymatic activity related to the breakdown of plant and animal substrates, whereby gene families coding for enzymes that breakdown plant-based cellulose have been reduced and those coding for enzymes that break down keratin (keratinase) have enlarged [8,9,12]. Laboratory studies have shown that *Coccidioides* is able to grow on keratinized tissues from animal hair [121], confirming classification of *Coccidioides* as keratinolytic fungi capable of decomposing keratinized structures and colonizing keratinous materials [122]. This further suggests that *Coccidioides* species have evolved specialization to derive nutrients from keratin—which is the main structural constituent of mammalian hair and nails[8]. This specialization may provide a competitive advantage over cohabitating fungus, [118,123–128] or bacteria with antifungal properties [78], whereby *Coccidioides* can gain nutrients from animal matter in desert environments where plant-derived nutrients can be scarce [12]. In these environments, small burrowing mammals may provide a consistent source of keratin. Moreover, many rodent species have been shown to be susceptible to asymptomatic *Coccidioides* infection [129,130], leading to an active debate over whether deceased rodents merely serve as an important nutrient source, or also serve as important reservoir hosts for *Coccidioides* in maintaining its parasitic life cycle. Consolidated argument for the essential role that rodents play in supporting *Coccidioides* populations have been summarized as the “endozoan, small-mammal reservoir hypothesis” [83], discussed in more detail in the next section.

While genetic analysis indicates that gene families coding for use of plant-derived cellulose have reduced over time, plant-derived nutrients likely remain an important soil nutrient source in the *Coccidioides* saprobic life cycle. Which plant species provide essential soil nutrients for *Coccidioides* growth remains unclear. Studies have found positive associations between *Coccidioides* presence and specific salt tolerant plants native to the southwestern United States, notably creosote bush (*Larrea tridentata)* and salt bush (*Atriplex spp.)* [18,131]. However, these plant species may not be a direct source of nutrients for *Coccidioides*. Rather, they may be a nutritious foraging source for small burrowing mammals in these arid environments; for example, salt bush has been associated with wildlife habitat, including for Kangaroo rats [132]. Alternatively, these plants may serve as indicators for other physical and chemical soil conditions that *Coccidioides* requires. Moving forward, field and laboratory studies to elucidate the relative contributions of plant and animal-derived nutrients to *Coccidioides* growth, as well as to elucidate the role of small burrowing mammals as growth substrates and/or important disease reservoirs, are needed. The evolution of *Coccidioides* to utilize animal fibers and protein in addition to plant-derived nutrients may have occurred in order to compensate for the extreme environmental conditions that otherwise define its niche, including the scarcity of nutrients in desert soil communities [12]. In the next section, we discuss the potential role that rodent burrows play as microhabitats within soil ecosystems conducive to *Coccidioides* growth.

Influence of rodent burrows on the soil niche

Rodents have been known to be asymptomatic hosts for *Coccidioides* since the 1940's [129,130]. An early hypothesis that they could serve as reservoir hosts as opposed to merely incidental hosts was introduced by Emmons in the 1940s [130,133,134]. This hypothesis fell out of favor in the late 1950's, but has recently surfaced [83] given genomic data indicating evolution of *Coccidioides* towards reliance on organic material derived from small mammals [8,9] along with field sampling data demonstrating higher concentration of *Coccidioides* within burrows. Studies generally report as much as four times or higher probability of *Coccidioides* detection in rodent burrows compared to other soils [44,51,121]. There is active debate over the mechanism behind this strong association. Research is needed to ascertain the specific role that mammals play – as reservoir hosts, as nutrient sources, or as ecosystem engineers (i.e., burrow creation) – and their relative importance in the *Coccidioides* life cycle [22,83].

Parasitism of small mammals building and using burrows may concentrate *Coccidioides* within and near burrow soils. Under the "endozoan, small-mammal reservoir hypothesis", fungi are released from granulomas in infected hosts upon death, releasing endospores that utilize the keratin of the dead host as a substrate to convert to hyphae and propagate [83]. Furthermore, research has shown that presence of colloidal (e.g., rabbit's blood) material protects both *Coccidioides* spherules and mycelia from destruction when subjected to dry season environmental stresses such as high temperatures and low soil moisture [135]. This protective association with mammalian blood may explain observations that the fungus can remain viable in desert soils for years [79]. Moreover, after burying infected canine, murine, and bovine tissues in soil [136], researchers found that the fungus proliferated in the immediate vicinity of the burial site over seven years [136].

Through creation of microhabitats within their burrows, rodents may indirectly support *Coccidioides* by providing special loci with more nutrients or favorable soil conditions. *Coccidioides* are keratinolytic fungi, and burrows likely accumulate higher concentrations of keratin from burrowing mammal hair and nails. Additionally, rodent burrows experience fewer fluctuations in temperature than would be experienced in the ambient air or at the soil surface [137]. Burrows typically have higher porosity compared to surrounding soil, which may lead to faster water infiltration and lower overall soil moisture [138–140]. In some cases, burrows may promote the growth of vegetation [141], potentially allowing higher retention of moisture. Additionally, animal host environments are often enriched with organic material [83,121,142] and are typically higher in nutrients like total nitrogen and nitrates [139–143]. By concentrating nutrients, burrows may act as "islands of fertility" that support fauna [141].

Beyond changing soil conditions, burrows may provide a suitable microhabitat in the soil which allows the fungus to develop specific microbiota associations and symbioses. Vargas-Gastélum (2015) observed a higher rate of detection of not just *Coccidioides* in burrow samples taken from a semi-arid ecosystem in Mexico, but also a fungal community consisting of species belonging to the phyla Basidiomycota, Glomeromycota and Chytridiomycota and the sub-phylum Mucoromycotina. Overall, the microhabitat was dominated by Ascomycota and Basidiomycota [144]; however these fungi are commonly found in soils both positive and negative for *Coccidioides* [79]. However, as there is limited research on the soil microbial community specific to *Coccidioides*, further investigation into the biotic environment associated with animal burrows may provide information on the soil microbial community associated with the fungi during its mycelial phase.

Discussion and Future Research

Many of the results and syntheses presented here are based on non-replicated or non-replicable studies and are therefore not considered conclusive. This is in part because *in situ* study of *Coccidioides* is laborious owing to the fungus' sporadic and clustered distribution in space, and subsequent detection challenges. In the laboratory, *Coccidioides* cultures and samples can be dangerous to researchers and must be handled under strict biosafety precautions that introduces barriers to performing laboratory work. However, field and laboratory research has identified a range of features that help define the *Coccidioides* soil niche, including locales in regions with alternating cool/wet and warm/dry seasons; sandy loam soil textures; alkaline soils; soils with high salinity and conductivity; and soils with adequate nutrient availability largely sourced from animal-derived keratin. Some of these features are considered harsh relative to the niches of other soil microbes, suggesting that *Coccidioides* may possess a competitive advantage in extreme conditions.

The *Coccidioides* life cycle relies on complex interactions between soil physical, chemical, and biological properties, as well the larger abiotic and biotic components of the ecosystems which it inhabits. Differentiating between which soil properties are associated with different stages of the saprobic life cycle also remains unclear, in part because *in situ* molecular detection methods for *Coccidioides* cannot currently distinguish between detection of mycelia versus spores in *Coccidioides*-positive soil samples. What is more, it remains unclear whether certain soil properties are universal requirements for different *Coccidioides* species. Spatially explicit, randomized sampling methods repeated in space and time are needed generate reproducible and comparable data on both *Coccidioides* presence and associated environmental parameters. *In silico* assessments via modeled computer simulations of *Coccidioides* interactions with the environment may also help us better understand the soil niche and important factors for fungal growth and regulation.

Below we discuss two key areas of emerging investigation related to the *Coccidioides* soil niche, occurring at different scales: fine-scale interactions between *Coccidioides* and other microbes in the soil, and large-scale shifts in the geographic distribution of the fungus.

Effects of soil biodiversity on *Coccidioides* presence and abundance

Interactions between *Coccidioides* and its surrounding soil microbiota are not well understood. Comprehensive analysis of soil microbial communities in endemic areas where *Coccidioides* is and is not consistently found is badly needed to better understand the microbial community dynamics that influence *Coccidioides* presence. In general, *Coccidioides* has been characterized as a poor competitor for which long-term survival may benefit from an ability to withstand harsh conditions rather than an ability to directly compete with other microorganisms resources [56]. Identifying specific microbes or groups of microbes that do serve as effective antagonists against *Coccidioides* under "normal" conditions could help us to identify natural biocontrol agents against the fungus. Currently, however, there are few studies that directly assess community-level microbial diversity in relation to *Coccidioides* presence or absence, leaving any understanding of potential beneficial or antagonistic symbioses in natural settings lacking. Bivariate analysis of soil collected from a site in Washington State found that the identified that a soil saprotroph, *Aureobasidium*, was positively associated with the presence of *Coccidioides* species DNA in soil, while a plant endophyte, *Phialocephala*, was negatively associated with *Coccidioides* [79]. However, these bivariate analyses may be confounded by associations with other soil conditions, and associations cannot be interpreted as being causally associated. One promising approach to begin to understand this complex soil community is the nascent field of network analysis, through which it may be possible to infer the degree to which *Coccidioides* is interacting with its surrounding microbial community [145,146].

A major challenge to conduct *Coccidioides* microbial community analyses is targeting *Coccidioides*-positive soils for sample collection. Targeting rodent burrows, where *Coccidioides* is commonly successfully collected from, could help overcome this challenge. Currently, the characterization of the fungal community associated with rodent burrows is already actively investigated [147–149].

Another challenge to understand natural interactions between *Coccidioides* and its surrounding microbial community is disentangling the impact of anthropogenic influences on *Coccidioides* from naturally occurring community dynamics. Human land use and land use change has wide-ranging impacts on soil microbial communities. Across altered landscapes, human activity could support or suppress *Coccidioides* presence and growth via impacts on the soil niche and subsequent microbial community. As coccidioidomycosis cases continue to rise across the southwestern United States, large-scale and thoughtful soil sampling is badly needed to determine the impact of human-driven landscape change on *Coccidioides* in the context of its broader microbial community.

Expansion of the *Coccidioides* geographic distribution

There is evidence that *Coccidioides* is expanding beyond the range previously considered endemic and becoming more prevalent in areas with historically lower human disease burdens. Between 2000 and 2018, there was a 15-fold increase in incidence in people residing in counties in the central and southern coast and northern San Joaquin Valley in California, where incidence was previously low [6]. Outside the southwestern United States, *C. immitis* has now been isolated from soil as far north as Washington State, a location with no history of autochthonous coccidioidomycosis[150].

Anthropogenic climate change may lead to increased mobilization of spores and subsequent geographic range expansion of *Coccidioides*. Studies have found that areas endemic to *Coccidioides* typically have warmer air temperatures and drier soils, conditions that are likely to become more common in the western United States due to climate change [38,151]. In California, average precipitation over winter months is projected to see a modest increase [152], precipitation in autumn and spring is projected to decrease [153], and the duration, intensity, and frequency of temperature-driven drought is expected to increase [153,154]. These changes may enhance conditions favorable for *Coccidioides* wet growth period, dry dispersion period, and competitive advantages. One study predicts that by 2050, nearly the entire western United States could contain suitable habitat for *Coccidioides* [31]. Within endemic regions, projected intensification of drought conditions [153] could facilitate the dispersion of *Coccidioides* spores via an increase in dust and wind events [155]. Already there is evidence for increasing dust storms across the western United States [86] from which we may expect an increase in disease burden in already established hotspots or an increase in disease incidence in new regions as more naïve hosts are exposed to spores. At the same time, drought conditions in already very arid, endemic regions may reduce cases overall [87], by limiting the moisture available for the fungus to grow. While most changes are expected to be gradual shifts in the range of *Coccidioides*, regime shifts, and tipping points are being increasingly examined in the ecological sciences to describe abrupt ecological transitions under changing climate [156] and have yet to be reviewed with respect to *Coccidioides*.

Anthropogenic land use change may also change patterns of *Coccidioides* presence in endemic areas or facilitate range expansion. For example, in California, the Sustainable Groundwater Management Act (SGMA) plans to cycle lands out of agricultural production to reduce overdraw of irrigation water from overstressed groundwater basins [157]. This may result in the fallowing of cultivated lands that were previously unsuitable to *Coccidioides* growth due to intensive cultivation practices. Absent intensive agriculture, fallowed land may also become more populated or re-populated with rodents. Long-term, transforming agricultural land for alternative, less water-intensive uses such as for solar farms may result in new areas of favorable habitat for *Coccidioides*. There may be opportunity to anticipate some land-use change impacts on *Coccidioides* by studying soil microbial and rodent communities of previously fallowed lands that have already been taken out of production or transformed into new land uses in endemic areas.

Conclusion

Coccidioidomycosis is an emerging infectious disease caused by a soil fungus with a largely understudied environmental niche. *Coccidioides* has generally been associated with arid and semi-arid environments with characteristic climate patterns of alternating wet and dry seasons. In the soil, *Coccidioides* has been associated with porous, sandy-loam soil, with high alkalinity and pH and high levels of organic matter, including from animal-derived keratin. Beyond this, there is limited understanding of the specific soil conditions that encourage or inhibit fungal growth, spore development, and spore dispersal. This limits our ability to establish strong inference on the spatio-temporal distribution of the fungus across landscapes and regions and hinders pathogen surveillance and control strategies for coccidioidomycosis. Several critical gaps in our understanding of the *Coccidioides* soil niche remain, including the role of small mammals as potential reservoir hosts of the fungus; a broader understanding of the microbial community within which *Coccidioides* is found; and how climate and land-use change may drive shifts in the *Coccidioides* endemic range. Future field, laboratory, and *in silico* research is recommended in these areas.

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Figures

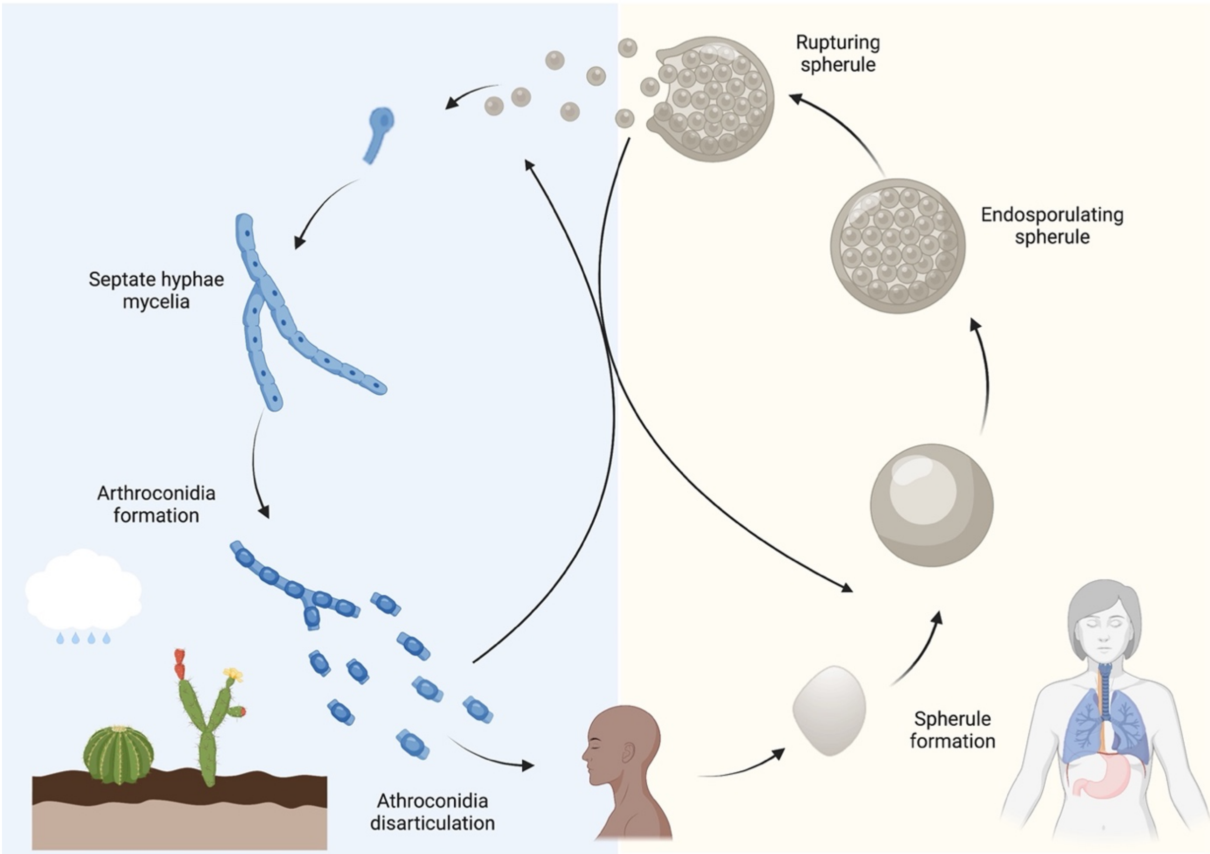

Figure 1. Saprobic **(left panel)** and parasitic **(right panel)** life cycle of *Coccidioides*. In the saprobic lifecycle, spores in the soil develop threadlike chains, called hyphae, which branch and fuse to form a dense network of filaments called the mycelium Arthroconidia form as alternating cells on mycelia, which are released during lyses of the empty intermediate cell. These spores can settle on soil, allowing for continuation of the saprobic lifecycle. Inhalation of infectious arthroconidia by a host initiates the parasitic cycle. Within the host, endospores develop within a spherule. Rupture of the spherule can lead to dissemination of endospores throughout the body, causing disseminated disease within the host.

References

1. Chiller TM, Galgiani JN, Stevens DA. Coccidioidomycosis. *Infect Dis Clin North Am*. 2003;17(1):41-57. doi:10.1016/S0891-5520(02)00040-5
2. Brown J, Benedict K, Park BJ, Thompson GR. Coccidioidomycosis: Epidemiology. *Clin Epidemiol*. 2013;5(1):185-197. doi:10.2147/CLEP.S34434
3. Pappagianis D. Epidemiology of Coccidioidomycosis. In: *Coccidioidomycosis*. Boston, MA: Springer US; 1980:63-85. doi:10.1007/978-1-4757-1712-9_4
4. Viriyakosol S, Singhania A, Fierer J, Goldberg J, Kirkland TN, Woelk CH. Gene expression in human fungal pathogen *Coccidioides immitis* changes as arthroconidia differentiate into spherules and mature. *BMC Microbiol*. 2013;13(1). doi:10.1186/1471-2180-13-121
5. Galgiani JN, Ampel NM, Blair JE, et al. Coccidioidomycosis. 2005;85723:1217-1223.
6. Sondermeyer Cooksey GL, Nguyen A, Vugia D, Jain S. Regional Analysis of Coccidioidomycosis Incidence — California, 2000–2018. *MMWR Morb Mortal Wkly Rep*. 2020;69(48). doi:10.15585/mmwr.mm6948a4
7. McCotter OZ, Benedict K, Engelthaler DM, et al. Update on the Epidemiology of coccidioidomycosis in the United States. *Med Mycol*. 2019;57. doi:10.1093/mmy/myy095
8. Sharpton TJ, Stajich JE, Rounsley SD, et al. Comparative genomic analyses of the human fungal pathogens *Coccidioides* and their relatives. *Genome Res*. 2009;19(10):1722-1731. doi:10.1101/gr.087551.108
9. Whiston E, Taylor JW. Comparative phylogenomics of pathogenic and nonpathogenic species. *G3 Genes, Genomes, Genet*. 2016;6(2):235-244. doi:10.1534/g3.115.022806
10. Scott JA, Untereiner WA. Determination of keratin degradation by fungi using keratin azure. *Med Mycol*. 2004;42(3). doi:10.1080/13693780310001644680
11. Stevens DA. Coccidioidomycosis. *N Engl J Med*. 1995;332(16):1077-1082. doi:10.1056/NEJM199504203321607
12. Kollath DR, Miller KJ, Barker BM. The mysterious desert dwellers: *Coccidioides immitis* and *Coccidioides posadasii*, causative fungal agents of coccidioidomycosis. *Virulence*. 2019;10(1):222-233. doi:10.1080/21505594.2019.1589363
13. Kirkland TN, Fierer J. *Coccidioides immitis and posadasii*; a review of their biology, genomics, pathogenesis, and host immunity. *Virulence*. 2018;9(1):1426-1435. doi:10.1080/21505594.2018.1509667
14. Freedman M, Jackson BR, McCotter O, Benedict K. Coccidioidomycosis outbreaks, United States and worldwide, 1940–2015. *Emerg Infect Dis*. 2018;24(3). doi:10.3201/eid2403.170623
15. Schneider E, Hajjeh RA, Spiegel RA, et al. A coccidioidomycosis outbreak following the Northridge, Calif, earthquake. *J Am Med Assoc*. 1997;277(11):904-908. doi:10.1001/jama.277.11.904
16. Jibson RW, Harp EL, Schneider E, Hajjeh RA, Spiegel RA. An outbreak of coccidioidomycosis (valley fever) caused by landslides triggered by the 1994 Northridge, California, earthquake. *GSA Rev Eng Geol*. 1998;12:53-61. doi:10.1130/REG12-p53
17. Jibson RW. A public health issue related to collateral seismic hazards: The valley fever outbreak triggered by the 1994 Northridge, California earthquake. *Surv Geophys*. 2002;23(6). doi:10.1023/A:1021226827679
18. Lauer A, Lopez J, Abarca S, Bains J. Earthquake-Ridden Area in USA Contains *Coccidioides*, the Valley Fever Pathogen. *Ecohealth*. 2020;17(2). doi:10.1007/s10393-

020-01485-w
19. Harp EL, Jibson RW. Landslides triggered by the 1994 Northridge, California, earthquake. *Bull Seismol Soc Am*. 1996;86(1 SUPPL. B).
20. Oltean HN, Etienne KA, Roe CC, et al. Utility of whole-genome sequencing to ascertain locally acquired cases of coccidioidomycosis, Washington, USA. *Emerg Infect Dis*. 2019;25(3). doi:10.3201/eid2503.181155
21. Marsden-Haug N, Goldoft M, Ralston C, et al. Coccidioidomycosis acquired in Washington State. *Clin Infect Dis*. 2013;56(6). doi:10.1093/cid/cis1028
22. del Rocío Reyes-Montes M, Pérez-Huitrón MA, Ocaña-Monroy JL, et al. The habitat of *Coccidioides* spp. and the role of animals as reservoirs and disseminators in nature. *BMC Infect Dis*. 2016;16(1). doi:10.1186/s12879-016-1902-7
23. Egeberg RO. Factors Influencing The Distribution Of *Coccidioides Immitis* In Soil. In: *Recent Progress in Microbiology VIII*. ; 2019. doi:10.3138/9781487595807-083
24. Maddy KT. Ecological factors of the geographic distribution of *Coccidioides immitis*. *J Am Vet Med Assoc*. 1957;130(11):475-476.
25. Swatek FE. *Ecology of Coccidioides Immitis*. Vol 40.; 1970.
26. Werner SB, Pappagianis D, Heindl I, Mickel A. An Epidemic of Coccidioidomycosis among Archeology Students in Northern California. *N Engl J Med*. 1972;286(10). doi:10.1056/nejm197203092861003
27. Werner SB, Pappagianis D. Coccidioidomycosis in Northern California: an outbreak among archeology students near Red Bluff. *CALIFMED*. 1973;119(3).
28. Kafka JA, Catanzaro A. Disseminated coccidioidomycosis in children. *J Pediatr*. 1981;98(3). doi:10.1016/S0022-3476(81)80695-6
29. Barker BM, Tabor JA, Shubitz LF, Perrill R, Orbach MJ, Fisher M. Detection and phylogenetic analysis of *Coccidioides posadasii* in Arizona soil samples. *Fungal Ecol*. 2012;5(2):163-176. doi:10.1016/j.funeco.2011.07.010
30. Mead HL, Hamm PS, Shaffer IN, et al. Differential thermotolerance adaptation between species of *coccidioides*. *J Fungi*. 2020;6(4). doi:10.3390/jof6040366
31. Gorris ME, Treseder KK, Zender CS, Randerson JT. Expansion of Coccidioidomycosis Endemic Regions in the United States in Response to Climate Change. *GeoHealth*. 2019;3(10):308-327. doi:10.1029/2019GH000209
32. Nguyen C, Barker BM, Hoover S, et al. Recent advances in our understanding of the environmental, epidemiological, immunological, and clinical dimensions of Coccidioidomycosis. *Clin Microbiol Rev*. 2013;26(3):505-525. doi:10.1128/CMR.00005-13
33. Swatek FE, Omieczynski DT. Isolation and identification of *Coccidioides immitis* from natural sources. *Mycopathol Mycol Appl*. 1970;41(1-2):155-166. doi:10.1007/BF02051491
34. Greene DR, Koenig G, Fisher MC, Taylor JW. Soil isolation and molecular identification of *Coccidioides immitis*. *Mycologia*. 2000;92(3):406-410. doi:10.2307/3761498
35. Kolivras KN, Comrie AC. Modeling valley fever (coccidioidomycosis) incidence on the basis of climate conditions. *Int J Biometeorol*. 2003;47(2):87-101. doi:10.1007/s00484-002-0155-x
36. Tamerius JD, Comrie AC. Coccidioidomycosis incidence in Arizona predicted by seasonal precipitation. *PLoS One*. 2011;6(6). doi:10.1371/journal.pone.0021009
37. Weaver EA, Kolivras KN. Investigating the Relationship Between Climate and Valley

Fever (Coccidioidomycosis). *Ecohealth*. 2018;15(4):840-852. doi:10.1007/s10393-018-1375-9
38. Gorris ME, Cat LA, Zender CS, Treseder KK, Randerson JT. Coccidioidomycosis Dynamics in Relation to Climate in the Southwestern United States. *GeoHealth*. 2018;2(1):6-24. doi:10.1002/2017GH000095
39. Comrie AC. Climate factors influencing coccidioidomycosis seasonality and outbreaks. *Environ Health Perspect*. 2005;113(6):688-692. doi:10.1289/ehp.7786
40. Smith CE, Beard RR, Rosenberger HG, Whiting EG. Effect of season and dust control on coccidioidomycosis. *J Am Med Assoc*. 1946;132(14):833-838. doi:10.1001/jama.1946.02870490011003
41. The University of Arizona, Southwest CA for the. Temperature and Precipitation | CLIMAS. 2017:Temperature. https://climas.arizona.edu/sw-climate/temperature-and-precipitation. Accessed March 26, 2022.
42. US Department of Commerce, NOAA NWS. Northern Arizona Monsoon Season. https://www.weather.gov/fgz/Monsoon. Accessed March 26, 2022.
43. Sehler R, Li J, Reager J, Ye H. Investigating Relationship Between Soil Moisture and Precipitation Globally Using Remote Sensing Observations. *J Contemp Water Res Educ*. 2019;168(1):106-118. doi:10.1111/j.1936-704x.2019.03324.x
44. Egeberg RO, Ely AF. *Coccidioides immitis* in the soil of the southern San Joaquin Valley. *Am J Med Sci*. 1956;231(2):151-154. doi:10.1097/00000441-195602000-00005
45. Brady NC, Weil RR. Nature and Properties of Soils, The 15th Edition. *Pearson Educ*. 2016:1104.
46. Maddy KT. Observations on *Coccidioides immitis* Found Growing Naturally in Soil. *Ariz Med*. 1965;22:281-288.
47. Swatek FE, Omieczynski DT, Plunkett OA. *Coccidioides immitis* in California. In: *Coccidioidomycosis: Papers from the Second Symposium on Coccidioidomycosis*. Tucson; 1967:255-265.
48. Chow NA, Griffin D, Barker B, Loparev VN, Litvintseva AP. Molecular detection of airborne *coccidioides* in tucson, arizona. *Med Mycol*. 2016;54(6). doi:10.1093/mmy/myw022
49. Ajello L, Maddy K, Crecelius G, Hugenholtz PG, Hall LB. Recovery of *coccidioides immitis* from the air. *Med Mycol*. 1965;4(2):92-95. doi:10.1080/00362176685190231
50. Fisher FS, Bultman MW, Johnson SM, Pappagianis D, Zaborsky E. *Coccidioides* niches and habitat parameters in the southwestern United States: A matter of scale. In: *Annals of the New York Academy of Sciences*. Vol 1111. Blackwell Publishing Inc.; 2007:47-72. doi:10.1196/annals.1406.031
51. Lacy GH, Swatek FE. Soil Ecology of *Coccidioides immitis* at Amerindian Middens in California. *Appl Microbiol*. 1974;27(2):379-388. doi:10.1128/aem.27.2.379-388.1974
52. Dobos RR, Benedict Id K, Jackson BR, Mccotter OZ. Using soil survey data to model potential *Coccidioides* soil habitat and inform Valley fever epidemiology. doi:10.1371/journal.pone.0247263
53. Friedman L, Smith CE, Pappagianis D, Berman RJ. Survival of *Coccidioides immitis* under controlled conditions of temperature and humidity. *Am J Public Health*. 1956;46(10):1317-1324. doi:10.2105/ajph.46.10.1317
54. Kolivras KN, Johnson PS, Comrie AC, Yool SR. Environmental variability and coccidioidomycosis (valley fever). *Aerobiologia (Bologna)*. 2001;17(1):31-42.

doi:10.1023/A:1007619813435
55. Zender CS, Talamantes J. Climate controls on valley fever incidence in Kern County, California. *Int J Biometeorol*. 2006;50(3):174-182. doi:10.1007/s00484-005-0007-6
56. Baptista-Rosas RC, Hinojosa A, Riquelme M. Ecological niche modeling of *Coccidioides* spp. in western North American deserts. In: *Annals of the New York Academy of Sciences*. Vol 1111. Blackwell Publishing Inc.; 2007:35-46. doi:10.1196/annals.1406.003
57. Egeberg RO, Elconin AE, Egeberg MC. Effect of Salinity and Temperature on *Coccidioides immitis* and three Antagonistic Soil Saprophytes. *J Bacteriol*. 1964;88(2). doi:10.1128/jb.88.2.473-476.1964
58. Rogers HJ, Perkins HR, Ward JB. Cell walls of filamentous fungi. In: *Microbial Cell Walls and Membranes*. ; 1980. doi:10.1007/978-94-011-6014-8_13
59. Barrera CR, Szaniszlo PJ. Formation and germination of fungal arthroconidia. *Crit Rev Microbiol*. 1985;12(4):271-292. doi:10.3109/10408418509104431
60. Mahmood R, Littell A, Hubbard KG, You J. Observed data-based assessment of relationships among soil moisture at various depths, precipitation, and temperature. *Appl Geogr*. 2012;34. doi:10.1016/j.apgeog.2011.11.009
61. Seneviratne SI, Corti T, Davin EL, et al. Investigating soil moisture-climate interactions in a changing climate: A review. *Earth-Science Rev*. 2010;99(3-4). doi:10.1016/j.earscirev.2010.02.004
62. Greer A, Ng V, Fisman D. Climate change and infectious diseases in North America: The road ahead. *C Can Med Assoc J*. 2008;178(6).
63. Comrie AC, Glueck MF. Assessment of climate-coccidioidomycosis model: Model sensitivity for assessing climatologic effects on the risk of acquiring coccidioidomycosis. In: *Annals of the New York Academy of Sciences*. Vol 1111. ; 2007. doi:10.1196/annals.1406.024
64. Griffin DM. Effect of Soil Moisture and Aeration on Fungal Activity: an Introduction. In: *Root Diseases and Soil-Borne Pathogens*. ; 2021:77-80. doi:10.1525/9780520339941-018
65. Baptista-rosas RC, Catalán-dibene J, Romero-olivares AL, Hinojosa A, Cavazos T, Riquelme M. Molecular detection of *Coccidioides* spp. from environmental samples in Baja California: Linking Valley Fever to soil and climate conditions. *Fungal Ecol*. 2012;5(2). doi:10.1016/j.funeco.2011.08.004
66. Luard EJ. Effect of osmotic shock on some intracellular solutes in two filamentous fungi. *J Gen Microbiol*. 1982;128(11). doi:10.1099/00221287-128-11-2575
67. Duran R, Cary JW, Calvo AM. Role of the osmotic stress regulatory pathway in morphogenesis and secondary metabolism in filamentous fungi. *Toxins (Basel)*. 2010;2(4). doi:10.3390/toxins2040367
68. Goldschmidt EP, Taylor GW. Nutritional requirements for the growth and arthrospore formation of *Coccidioides immitis*. *J Bacteriol*. 1958;75(3):265-271. doi:10.1128/jb.75.3.265-271.1958
69. USGS. California Drought Information | USGS California Water Science Center. https://ca.water.usgs.gov/california-drought/what-is-drought.html. Published 2017. Accessed March 26, 2022.
70. Weiss JL, Castro CL, Overpeck JT. Distinguishing pronounced droughts in the southwestern united states: Seasonality and effects of warmer temperatures. *J Clim*. 2009;22(22):5918-5932. doi:10.1175/2009JCLI2905.1
71. Seager R, Ting M, Held I, et al. Model projections of an imminent transition to a more

arid climate in southwestern North America. *Science (80-)*. 2007;316(5828). doi:10.1126/science.1139601
72. Griffin D, Anchukaitis KJ. How unusual is the 2012-2014 California drought? *Geophys Res Lett*. 2014;41(24):9017-9023. doi:10.1002/2014GL062433
73. Mao Y, Nijssen B, Lettenmaier DP. Is climate change implicated in the 2013-2014 California drought? A hydrologic perspective. *Geophys Res Lett*. 2015;42(8). doi:10.1002/2015GL063456
74. Williams AP, Cook BI, Smerdon JE. Rapid intensification of the emerging southwestern North American megadrought in 2020–2021. *Nat Clim Chang 2022 123*. 2022;12(3):232-234. doi:10.1038/s41558-022-01290-z
75. Brown HE, Comrie AC, Tamerius J, Khan M, Tabor JA, Galgiani JN. Climate, wind storms, and the risk of valley fever (coccidioidomycosis). *Bronx Environ Res Bull World Heal Organ*. 1988;4766(1).
76. Metcalf JL, Xu ZZ, Weiss S, et al. Microbial community assembly and metabolic function during mammalian corpse decomposition. *Science (80-)*. 2016;351(6269):158-162. doi:10.1126/science.aad2646
77. Elconin AF, Egeberg MD, Lubarsky R. *Growth Patterns of Coccidioides Immitis*. Proceedings of Symposium on Coccidioidomycosis: Held at Phoenix, Arizona; 1957.
78. Lauer A, Baal JD, Mendes SD, et al. Valley fever on the rise—searching for microbial antagonists to the fungal pathogen *coccidioides immitis*. *Microorganisms*. 2019;7(2):1-16. doi:10.3390/microorganisms7020031
79. Chow NA, Kangiser D, Gade L, et al. Factors Influencing Distribution of *Coccidioides immitis* in Soil, Washington State, 2016. *mSphere*. 2021;6(6). doi:10.1128/msphere.00598-21
80. Weaver E, Kolivras KN, Thomas RQ, Thomas VA, Abbas KM. Environmental factors affecting ecological niche of *Coccidioides* species and spatial dynamics of valley fever in the United States. *Spat Spatiotemporal Epidemiol*. 2020;32. doi:10.1016/j.sste.2019.100317
81. Prugh LR, Deguines N, Grinath JB, et al. Ecological winners and losers of extreme drought in California. *Nat Clim Chang*. 2018;8(9). doi:10.1038/s41558-018-0255-1
82. Galgiani JN, Hayden R, Payne CM. Leukocyte effects on the dimorphism of *coccidioides immitis*. *J Infect Dis*. 1982;146(1). doi:10.1093/infdis/146.1.56
83. Taylor JW, Barker BM. The endozoan, small-mammal reservoir hypothesis and the life cycle of *Coccidioides* species. *Med Mycol*. 2019;57(Supplement_1):S16-S20. doi:10.1093/mmy/myy039
84. Shriber J, Conlon KC, Benedict K, McCotter OZ, Bell JE. Assessment of vulnerability to coccidioidomycosis in Arizona and California. *Int J Environ Res Public Health*. 2017;14(7). doi:10.3390/ijerph14070680
85. Coopersmith EJ, Bell JE, Benedict K, Shriber J, McCotter O, Cosh MH. Relating coccidioidomycosis (valley fever) incidence to soil moisture conditions. *GeoHealth*. 2017;1(1):51-63. doi:10.1002/2016GH000033
86. Tong DQ, Wang JXL, Gill TE, Lei H, Wang B. Intensified dust storm activity and Valley fever infection in the southwestern United States. *Geophys Res Lett*. 2017;44(9):4304-4312. doi:10.1002/2017GL073524
87. Head JR, Sondermeyer-Cooksey G, Heaney AK, et al. Effects of precipitation, heat, and drought on incidence and expansion of coccidioidomycosis in western USA: a

longitudinal surveillance study. *Lancet Planet Heal*. 2022;6(10):e793-e803. doi:10.1016/S2542-5196(22)00202-9
88. Pappagianis D. Marked increase in cases of coccidioidomycosis in california: 1991, 1992, and 1993. *Clin Infect Dis*. 1994;19:S14-S18. doi:10.1093/clinids/19.Supplement_1.14
89. Benedict K, McCotter OZ, Brady S, et al. Surveillance for Coccidioidomycosis - United States, 2011-2017. *MMWR Surveill Summ*. 2019;68(7). doi:10.15585/mmwr.ss6807a1
90. Sondermeyer GL, Lee LA, Gilliss D, Vugia DJ. Coccidioidomycosis-associated deaths in California, 2000-2013. *Public Health Rep*. 2016;131(4):531-535. doi:10.1177/0033354916662210
91. Rosenstein NE, Emery KW, Werner S Ben, et al. *Risk Factors for Severe Pulmonary and Disseminated Coccidioidomycosis: Kern County, California, 1995–1996*. Vol 32.; 2001. https://academic.oup.com/cid/article/32/5/708/358336.
92. De Perio MA, Materna BL, Sondermeyer Cooksey GL, et al. Occupational coccidioidomycosis surveillance and recent outbreaks in California. *Med Mycol*. 2019;57(Supplement_1):S41-S45. doi:10.1093/MMY/MYY031
93. Das R, McNary J, Fitzsimmons K, et al. Occupational coccidioidomycosis in California: outbreak investigation, respirator recommendations, and surveillance findings. *J Occup Environ Med*. 2012;54(5):564-571. doi:10.1097/JOM.0B013E3182480556
94. Bowers JR, Parise KL, Kelley EJ, et al. Direct detection of *Coccidioides* from Arizona soils using CocciENV, a highly sensitive and specific real-time PCR assay. *Med Mycol*. 2019;57(2):246-255. doi:10.1093/mmy/myy007
95. Delgado-Baquerizo M, Powell JR, Hamonts K, et al. Circular linkages between soil biodiversity, fertility and plant productivity are limited to topsoil at the continental scale. *New Phytol*. 2017;215(3):1186-1196. doi:10.1111/nph.14634
96. Power JF, Sandoval FM, Ries RE, Merrill SD. Effects of Topsoil and Subsoil Thickness on Soil Water Content and Crop Production on a Disturbed Soil1. *Soil Sci Soc Am J*. 1981;45(1):124. doi:10.2136/sssaj1981.03615995004500010027x
97. Rivera D, Mejías V, Jáuregui BM, Costa-Tenorio M, López-Archilla AI, Peco B. Spreading topsoil encourages ecological restoration on embankments: Soil fertility, microbial activity and vegetation cover. *PLoS One*. 2014;9(7). doi:10.1371/journal.pone.0101413
98. Ball J. Soil and Water Relationships. *Ag News Views*. 2001:2014. http://www.noble.org/ag/Soils/SoilWaterRelationships/Index.htm.
99. Walker GM, White NA. Introduction to Fungal Physiology. In: *Fungi: Biology and Applications, Third Edition*. John Wiley & Sons, Inc.; 2017:1-35. doi:10.1002/9781119374312.ch1
100. Jennings DH. *The Physiology of Fungal Nutrition*.; 1995. doi:10.1017/cbo9780511525421
101. Otto S, Bruni EP, Harms H, Wick LY. Catch me if you can: Dispersal and foraging of Bdellovibrio bacteriovorus 109J along mycelia. *ISME J*. 2017;11(2):386-393. doi:10.1038/ismej.2016.135
102. Fricker MD, Heaton LLM, Jones NS, Boddy L. The Mycelium as a Network. *Microbiol Spectr*. 2017;5(3). doi:10.1128/microbiolspec.funk-0033-2017
103. Harris K, Young IM, Gilligan CA, Otten W, Ritz K. Effect of bulk density on the spatial organisation of the fungus Rhizoctonia solani in soil. *FEMS Microbiol Ecol*. 2003;44(1):45-56. doi:10.1016/S0168-6496(02)00459-2
104. Sarojini TS, Yogeswari L. Aeration affecting growth and sporulation of some soil Fusaria

in liquid cultures. *Proc Indian Acad Sci - Sect B*. 1947;26(2):69-76. doi:10.1007/BF03048154
105. Bump WS. Observations on growth of *coccidioides immitis*. *J Infect Dis*. 1925;36(6):561-565. doi:10.1093/infdis/36.6.561
106. Goldschmidt EP, Taylor GW, Demetroulakos LJ. Biochemical changes occurring during growth of *Coccidioides immitis* in a defined medium. *J Bacteriol*. 1958;75(6):702-706. doi:10.1128/jb.75.6.702-706.1958
107. Merriam CH. *Life Zones and Crop Zones of the United States.*; 2011. doi:10.5962/bhl.title.35423
108. Elconin AF, Egeberg RO, Egeberg MC. Significance of Soil Salinity on the Ecology of *Coccidioides Immitis*. *J Bacteriol*. 1964;87:500-503. doi:10.1128/jb.87.3.500-503.1964
109. Duran F, Robertstad GW, Donowho E. The distribution of *coccidioides immitis* in the soil in el paso, texas. *Med Mycol*. 1973;11(2):143-148. doi:10.1080/00362177385190301
110. Hoggan MD RJPDDGBA. Isolation of *Coccidioides immitis* from the air. Stanford Medical Bulletin. https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=Isolation+of+Coccidioides+immitis+from+the+air&btnG=. Published 1956. Accessed March 6, 2023.
111. Pérez-Llano Y, Rodríguez-Pupo EC, Druzhinina IS, et al. Stress Reshapes the Physiological Response of Halophile Fungi to Salinity. *Cells*. 2020;9(3):1-21. doi:10.3390/cells9030525
112. Eswar D, Karuppusamy R, Chellamuthu S. Drivers of soil salinity and their correlation with climate change. *Curr Opin Environ Sustain*. 2021;50. doi:10.1016/j.cosust.2020.10.015
113. Butcher K, Wick AF, Desutter T, Chatterjee A, Harmon J. Soil salinity: A threat to global food security. *Agron J*. 2016;108(6). doi:10.2134/agronj2016.06.0368
114. Hassani A, Azapagic A, Shokri N. Global predictions of primary soil salinization under changing climate in the 21st century. *Nat Commun 2021 121*. 2021;12(1):1-17. doi:10.1038/s41467-021-26907-3
115. Roessler WG, Herbst EJ, Mccullough WG, Mills RC, Brewer CR. Studies with *Coccidioides Immitis*: I. Submerged Growth in Liquid Mediums. *J Infect Dis*. 1946;79(1). doi:10.1093/infdis/79.1.12
116. Northey WT, Brooks LD. Studies on *Coccidioides immitis*. I. A simple medium for in vitro spherulation. *J Bacteriol*. 1962;84. doi:10.1128/JB.84.4.742-746.1962
117. Sippel JE, Levine HB. Sugars and Amino Acids as Carbon, Nitrogen, or Energy Sources for *Coccidioides immitis* Spherules and Endospores. *Appl Microbiol*. 1969;18(3). doi:10.1128/am.18.3.522-524.1969
118. Baker EE, Smith CE. Utilization of carbon and nitrogen compounds by *coccidioides immitis* (Rixford and Gilchrist, 1896). *J Infect Dis*. 1942;70(1). doi:10.1093/infdis/70.1.51
119. Martinez DA, Oliver BG, Gräser Y, et al. Comparative genome analysis of Trichophyton rubrum and related dermatophytes reveals candidate genes involved in infection. *MBio*. 2012;3(5). doi:10.1128/mBio.00259-12
120. Desjardins CA, Champion MD, Holder JW, et al. Comparative genomic analysis of human fungal pathogens causing paracoccidioidomycosis. *PLoS Genet*. 2011;7(10). doi:10.1371/journal.pgen.1002345
121. Kollath DR, Teixeira MM, Funke A, Miller KJ, Barker BM. Investigating the Role of Animal Burrows on the Ecology and Distribution of *Coccidioides* spp. in Arizona Soils.

Mycopathologia. 2020;185(1):145-159. doi:10.1007/s11046-019-00391-2
122. Garg AP, Gandotra S, Mukerji KG, Pugh GJF. Ecology of keratinophilic fungi. *Proc Plant Sci*. 1985;94(2-3):149-163. doi:10.1007/BF03053134
123. Gilardi GL. Nutrition of systemic and subcutaneous pathogenic fungi. *Bacteriol Rev*. 1965;29(3). doi:10.1128/br.29.3.406-424.1965
124. Kuznetsova TA, Kam M, Khokhlova IS, et al. Desert Gerbils Affect Bacterial Composition of Soil. *Microb Ecol*. 2013;66(4):940-949. doi:10.1007/s00248-013-0263-7
125. Kunert J. Physiology of keratinophilic fungi. *Rev Iberoam Micol*. 2000;17(SUPPL.).
126. Raudabaugh DB, Miller AN. Nutritional Capability of and Substrate Suitability for Pseudogymnoascus destructans, the Causal Agent of Bat White-Nose Syndrome. *PLoS One*. 2013;8(10). doi:10.1371/journal.pone.0078300
127. Huang Y, Busk PK, Herbst FA, Lange L. Genome and secretome analyses provide insights into keratin decomposition by novel proteases from the non-pathogenic fungus Onygena corvina. *Appl Microbiol Biotechnol*. 2015;99(22). doi:10.1007/s00253-015-6805-9
128. Burmester A, Shelest E, Glöckner G, et al. Comparative and functional genomics provide insights into the pathogenicity of dermatophytic fungi. *Genome Biol*. 2011;12(1). doi:10.1186/gb-2011-12-1-r7
129. Emmons CW, Ashburn LL. The Isolation of Haplosporangium parvum n. sp. and *Coccidioides immitis* from Wild Rodents. Their Relationship to Coccidioidomycosis. *Public Heal Reports*. 1942;57(46):1715. doi:10.2307/4584276
130. Emmons CW. Coccidioidomycosis in Wild Rodents. A Method of Determining the Extent of Endemic Areas. *Public Heal Reports*. 1943;58(1):1. doi:10.2307/4584326
131. Colson AJ, Vredenburgh L, Guevara RE, Rangel NP, Kloock CT, Lauer A. Large-Scale Land Development, Fugitive Dust, and Increased Coccidioidomycosis Incidence in the Antelope Valley of California, 1999–2014. *Mycopathologia*. 2017;182(5-6):439-458. doi:10.1007/s11046-016-0105-5
132. Walsberg GE. Small mammals in hot deserts: Some generalizations revisited. *Bioscience*. 2000;50(2):109-120. doi:10.1641/0006-3568(2000)050[0109:SMIHDS]2.3.CO;2
133. Emmons CW. Isolation of *Coccidioides* from Soil and Rodents. *Public Heal Reports*. 1942;57(4). doi:10.2307/4583988
134. Ashburn L, Emmons C. Spontaneous coccidioidal granuloma in the lungs of wild rodents. *Arch Pathol*. 1942;34:791-800.
135. Sorenson RH. Survival characteristics of mycelia and spherules of *Coccidioides immitis* in a simulated natural environment. *Am J Epidemiol*. 1964;80(3):275-285. doi:10.1093/oxfordjournals.aje.a120476
136. Maddy KT, Crecelius HG. Establishment of Coccidiodies immitis in negative soil following burial of infected animal tissues. In: *Second Symposium on Coccidioidomycosis1965*. ; 1965.
137. Studier EH, Baca TP. Atmospheric Conditions in Artificial Rodent Burrows. *Southwest Nat*. 1968;13(4). doi:10.2307/3668907
138. Whitford WG, Kay FR. Biopedturbation by mammals in deserts: A review. *J Arid Environ*. 1999;41(2). doi:10.1006/jare.1998.0482
139. Hyeong-Tae Mun, Whitford WG. Factors affecting annual plants assemblages on banner-tailed kangaroo rat mounds. *J Arid Environ*. 1990;18(2). doi:10.1016/s0140-1963(18)30850-4

140. Gurney CM, Prugh LR, Brashares JS. Restoration of Native Plants is Reduced by Rodent-Caused Soil Disturbance and Seed Removal. *Rangel Ecol Manag*. 2015;68(4). doi:10.1016/j.rama.2015.05.001
141. Miranda V, Rothen C, Yela N, et al. Subterranean Desert Rodents (Genus Ctenomys) Create Soil Patches Enriched in Root Endophytic Fungal Propagules. *Microb Ecol*. 2019;77(2). doi:10.1007/s00248-018-1227-8
142. Clark KL, Branch LC, Hierro JL, Villarreal D. Burrowing herbivores alter soil carbon and nitrogen dynamics in a semi-arid ecosystem, Argentina. *Soil Biol Biochem*. 2016;103:253-261. doi:10.1016/j.soilbio.2016.08.027
143. Hawkins LK, Nicoletto PF. Kangaroo rat burrows structure the spatial organisation of ground- dwelling animals in a semiarid grassland. *J Arid Environ*. 1992;23(2):199-208. doi:10.1016/s0140-1963(18)30531-7
144. Vargas-Gastélum L, Romero-Olivares AL, Escalante AE, Rocha-Olivares A, Brizuela C, Riquelme M. Impact of seasonal changes on fungal diversity of a semi-arid ecosystem revealed by 454 pyrosequencing. *FEMS Microbiol Ecol*. 2015;91(5). doi:10.1093/femsec/fiv044
145. Matchado MS, Lauber M, Reitmeier S, et al. Network analysis methods for studying microbial communities: A mini review. *Comput Struct Biotechnol J*. 2021;19:2687-2698. doi:10.1016/J.CSBJ.2021.05.001
146. Knight R, Vrbanac A, Taylor BC, et al. Best practices for analysing microbiomes. *Nat Rev Microbiol*. 2018;16(7). doi:10.1038/s41579-018-0029-9
147. Hawkins LK. Burrows of kangaroo rats are hotspots for desert soil fungi. *J Arid Environ*. 1996;32(3). doi:10.1006/jare.1996.0020
148. Hawkins LK. Microfungi associated with the banner-tailed kangaroo rat, Dipodomys spectabilis. *Mycologia*. 1999;91(5). doi:10.2307/3761526
149. Herrera J, Kramer CL, Reichman OJ. Microfungal community changes in rodent food stores over space and time. *Microb Ecol*. 1999;38(1). doi:10.1007/s002489900156
150. Litvintseva AP, Marsden-Haug N, Hurst S, et al. Valley fever: Finding new places for an old disease: *Coccidioides immitis* found in Washington state soil associated with recent human infection. *Clin Infect Dis*. 2015;60(1):e1-e3. doi:10.1093/cid/ciu681
151. Garfin G, Franco G, Blanco H, et al. *Ch. 20: Southwest. The Third National Climate Assessment*. (Melillo JM, Richmond T (T. C., Yohe GW, eds.). Washington, DC: U.S. Global Change Research Program; 2014. doi:10.7930/J08G8HMN
152. Neelin JD, Langenbrunner B, Meyerson JE, Hall A, Berg N. California Winter Precipitation Change under Global Warming in the Coupled Model Intercomparison Project Phase 5 Ensemble. *J Clim*. 2013;26(17):6238-6256. doi:10.1175/JCLI-D-12-00514.1
153. Diffenbaugh NS, Swain DL, Touma D, Lubchenco J. Anthropogenic warming has increased drought risk in California. *Proc Natl Acad Sci U S A*. 2015;112(13):3931-3936. doi:10.1073/pnas.1422385112
154. Bedsworth L, Cayan D, Franco G. California's Fourth Climate Change Assessment. www.ClimateAssessment.ca.gov. Accessed March 27, 2022.
155. Pu B, Ginoux P. Projection of American dustiness in the late 21st century due to climate change. *Sci Rep*. 2017;7(1). doi:10.1038/s41598-017-05431-9
156. Dakos V. *Ecological Transitions: Regime Shifts, Thresholds and Tipping Points. Oxford Bibliographies in Environmental Science*.; 2019.

157. Hanak E, Escriva-Bou A, Gray B, et al. *Water and the Future of the San Joaquin Valley*.; 2019. doi:10.13140/RG.2.2.24360.83208

Chapter 1 & 2 Transition

Coccidioidomycosis is a fungal infection that affects the respiratory system. The two recognized fungal species in the genus *Coccidioides*, *C. immitis* and *C. posadasii,* have been identified as the etiological agents for coccidioidomycosis. Once the infective arthroconidia are inhaled, infection begins. In Chapter 1, I review environmental factors associated with the soil niche for *C. immitis* and *C. posadasii* to illuminate the current understanding of the pathogen's ecology and life history. Chapter 1 focuses on pathogen biology to address gaps in our understanding of the soil dwelling *Coccidioides* species for disease management strategies that may target the pathogen directly.

Coronavirus disease (COVID-19) is an infectious, respiratory disease caused by the SARS-CoV-2 virus. There are multiple routes of transmission including droplet transmission at conversation distances, long-range aerosol or long-range airborne transmission typically in poorly ventilated and/or crowded indoor settings, and fomite transmission (inanimate objects that can carry and spread disease and infectious agents). In Chapter 2, I quantify the relationship between per capita COVID-19 outcomes and various county-level factors across the United States including, physical and mental health, environmental pollution, access to health care, demographic characteristics, and vulnerable population scores. By pursuing the gaps in our understanding of county-level features related to COVID-19 incidence and mortality, the goal for Chapter 2 is to offer population-level insights that can inform control strategies for managing the spread of COVID-19.

Chapter 2 | Ensemble machine learning of factors influencing COVID-19 across US counties

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Included as a dissertation chapter with permission from co-authors.

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Abstract

Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) the causal agent for COVID-19, is a communicable disease spread through close contact. It is known to disproportionately impact certain communities due to both biological susceptibility and inequitable exposure. In this study, we investigate the most important health, social, and environmental factors impacting the early phases (before July 2020) of per capita COVID-19 transmission and per capita all-cause mortality in US counties. We aggregate county-level physical and mental health, environmental pollution, access to health care, demographic characteristics, vulnerable population scores, and other epidemiological data to create a large feature set to analyze per capita COVID-19 outcomes. Because of the high dimensionality, multicollinearity, and unknown interactions of the data, we use ensemble machine learning and marginal prediction methods to identify the most salient factors associated with several COVID-19 outbreak measure. Our variable importance results show that measures of ethnicity, public transportation and preventable diseases are the strongest predictors for both per capita COVID-19 incidence and mortality. Specifically, the CDC measures for minority populations, CDC measures for limited English, and proportion of Black- and/or African-American individuals in a county were the most important features for per capita COVID-19 cases within a month after the pandemic started in a county and also at the latest date examined. For per capita all-cause mortality at day 100 and total to date, we find that public transportation use and proportion of Black- and/or African-American individuals in a county are the strongest predictors. The methods predict that, keeping all other factors fixed, a 10% increase in public transportation use, all other factors remaining fixed at the observed values, is associated with increases mortality at day 100 of 2012 individuals (95% CI [1972, 2356]) and likewise a 10% increase in the proportion of Black- and/or African-American individuals in a county is associated with increases total deaths at end of study of 2067 (95% CI [1189, 2654]). Using data until the end of study, the same metric suggests ethnicity has double the association as the next most important factors, which are location, disease prevalence, and transit factors. Our findings shed light on societal patterns that have been reported and experienced in the U.S. by using robust methods to understand the features most responsible for transmission and sectors of society most vulnerable to infection and mortality. In particular, our results provide evidence of the disproportionate impact of the COVID-19 pandemic on minority populations. Our results suggest that mitigation measures, including how vaccines are distributed, could have the greatest impact if they are given with priority to the highest risk communities.

Introduction

COVID-19 background. Coronavirus disease 2019 (COVID-19), caused by the novel severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), spread rapidly around the world[1–6]. Within a month of discovering the first cluster of cases in Wuhan, China[1,3,6], 18 additional countries had reported a case of COVID-19[7]. The World Health Organization declared the resulting outbreaks a Public Health Emergency of International Concern by January 30, 2020 and a pandemic by March 11, 2020 [7,8].

There are a few consistent observations regarding the epidemiology of the COVID-19 pandemic in the US. Most prominent is the relatively high infection and death rates of minority populations, particularly Black- and/ or African-Americans[9,10], a disparity researcher have noted occurred in previous pandemics, such as HIV [11]. This disparity has been observed in both adults and children [12]. There is much previous work on the causes of health disparities among Black- and/or African-Americans, and others have speculated on which of these causes are related to the differential impact of COVID-19[13,14]. Thus, to tease out the impact on vulnerable groups, one needs data on other baseline health factors, such as obesity [15,16], co-morbidities, age [17,18] environmental exposures, transportation use and employment factors, including types of occupations [10,19].

US health response and forecasting. At the point our analysis was conducted, the US had implemented complex and regionally uneven community-level, non-pharmaceutical interventions, including travel restrictions, social distancing, and stay-at-home orders. Although these interventions have shown to mitigate the community spread in certain communities, the trend did not hold for all communities. Many counties experienced an uptick in cases after an initial decline. There are several reasons why certain communities experienced a growing number of cases, including: (1) lifting shelter-in-place or other social distancing restrictions earlier than advised; (2) lax controls on gatherings that resulted in super-spreader events[20], and; (3) unknown affects of plausible seasonality that impacts viral transmission[21]. As such, early in the pandemic, complex epidemiological contexts have emerged in US communities. The complexity is a result of dynamic environmental factors constituting social and physical environments for US populations that impact an individual's risk for contracting COVID-19. Thus, to adequately control the spread of COVID-19, it is important to identify early in the pandemic the most salient social and physical environmental factors within US communities, driving transmission and and effecting susceptibility.

Though models accounting for the specific vulnerabilities of local populations have been proposed, only a few models exist that assess the importance county-level variation of such variables in fueling COVID-19 outbreaks[22,23]. Altieri et al.[22], for example, use county-level data from similar sources to this paper, to create an ensemble forecasting model, dubbed "Combined Linear and Exponential Predictors" to predict death counts from COVID-19. Their goal is to curate a data repository that can be used to forecast exponential and sub-exponential cases weeks in advance in order to help nonprofit organization disseminate much needed personal protective devices and respirators to areas projected to have higher mortality rates.

In our study, we use overlapping data sources to model cross-sectional COVID-19 outcomes. Our goal, rather than prediction, is to explore the relative importance of different types of social, physical and environmental factors on COVID-19 transmission and mortality. Hospital case and mortality data, and seropositive surveillance studies have shown there are subgroups of the population that are more susceptible to higher cases of morbidity and mortality. These include people older than 65 and and communities affected by racial disparities. We attempt in this paper to expand on previous studies (as of July 2020) of county level variation in COVID-19 (e.g., see[24]) by evaluating additional socio-environmental data to understand if these disparities have direct effects on COVID-19 outcomes or are indirect through additional risk factors, such as diabetes, food security, air pollution or access to health care. Likewise, no study has been carried out to determine which of these factors are most associated with COVID-19 outcomes while still controlling non-parametrically for high dimensional covariates.

Our data set is not comprised of individual-level data but includes a large number of predictor variables with the potential for complicated interactions between sets of risk factors, e.g. the intersection between race/ ethnicity, environmental exposures and underlying health on COVID-19 outcomes. To avoid as much as possible model misspecification, we fit a prediction model for each outcome using SuperLearner [25], an ensemble of machine learning algorithms, which relied on cross-validation across many algorithms to derive an optimal combination of such algorithms. Using this approach, one can derive an improved fit to the data than an arbitrary linear regression model or any one machine learning algorithm. This is important because, in the current study, accurate estimates for our parameters of interest (variable importance and expected COVID-19 cases and/or mortality given a shift in these important variables) is contingent on a good fit to the actual prediction function. Additionally, we are guaranteed to get estimates that are less biased compared to a single pre-specified algorithm because SuperLearner is guaranteed to perform asymptotically as well as the best performing algorithm included in the candidate set of algorithms.

Added value of this study. We aggregate 5 types of COVID-19 outcomes, (1) day of the first case in a county relative to the first known case reported in the U.S. (Snohomish County, Washington, USA), (2) number of cases 25 days after the initial case in a county, (3) number of all-cause deaths 100 days after the first case in a county, (4) total number of cases in a county to-date after initial case and (5) total number of all-cause deaths in a county to-date after first case in a county. From many sources including the CDC, U.S. Census Bureau, USA facts, google mobility data, and others, we collect a large number of pertinent variables for COVID-19. Using ensemble machine learning (ML) we create models that make no assumptions on the distributions of the data, these models are thereby non-parametric and allow all degrees of interactions and distributions in order to make the best fit.

In each of these models we identify the most important variables in the model by removing the variable and measuring the difference in model risk (model error). Based upon the SuperLearner fits, we make marginal predictions for the number of cases and mortalities from COVID-19 when increasing or decreasing these top variables while controlling for all other factors (i.e., keeping all other predictors fixed at the original values). Confidence intervals (CIs), significance and robustness of findings are measured via bootstrapping the model. Additionally, we investigate the predicted number of cases and mortalities from our model when controlling for only variables outside the target variable category (i.e., ethnicity, public transportation subcategories) and univariate predictions (not controlling for other variables). Given this approach, our contributions are, rather than predictive forecasting the number of cases, an approach to measure the relative importance of risk factors for COVID-19 from a county-level perspective.

There are many known risk factors measured from case hospitalization data, including diabetes and heart disease. As such, we hypothesize these factors will show high variable importance, specifically for case mortality. Additionally, we hypothesize that environmental dynamics, which increase exposure time to the virus (i.e., number of occupations in a county, public transit use), will also be strongly associated with COVID-19 cases early in the pandemic. When such factors are identified, this information could also be used to update or improve the public health response to specifically target factors related to high case counts in order to further mitigate new cases or prevent a resurgence of cases. We estimate variable importance of the high dimensional assembled county features without constraints (which induces bias), using a combination of machine learning and intuitive substitution estimators. Lastly, we make both the data and methods used in this paper accessible to others, thereby providing open source access and enhancing the utility of our results. All code, data, and county variables used are available and outcome data are updated daily on GitHub (See Code Availability section).

Methods

Data sources. For all outcomes and predictors we compiled publicly available data for US jurisdictions reported at the state-level (e.g. Google Mobility Data) and county-level, excluding Alaska, Hawaii, and Puerto Rico. Our final dataset includes county-level case counts, death counts and a wide variety of county-level demographic, epidemiological, health, and environmental data used as predictors in our analysis. Our analysis was based on the cumulative confirmed cases and deaths of COVID-19 in US counties, starting on January 22, 2020 (referred to as Day 1) until July 14, 2020 (USA Facts). The sources for our county-level features were: USA Facts, Bureau of Economic Analysis, American Community Survey, Tiger/Line GeoDatabase, CDC Interactive Atlas of Heart Disease and Stroke, County Health Rankings, Centers of Medicare and Medicaid Services, National Centers for Environmental Information, CDC Vulnerability Index, Bureau of Labor Statistics, MIT Election Lab, Google Community Mobility Reports; a total of 12 different sources which were joined on county FIPS codes.

Outcomes. We use five COVID-19 outcome scenarios: (1) we transformed the case data into day of the first case after the first confirmed case on January 21 2020; (2) we determined the number of cumulative cases on the 25 days after the day of the first case within each county (i.e., day 25 of the outbreak in each county); (3) we used the number of all-cause deaths on day 100 after the day of the first case of the outbreak for each respective county up to July 14 2020; (4) we determine the total number of cases to date after the day of the first case for each county and likewise scenario five is the total number of all-cause mortalities to-date after the day of the first case for each county.

For each outcome variable excluding number of cases at day 25, we divide the counts by population size for each county to create a per capita COVID-19 case or per capita all-cause mortality outcome. Likewise, all predictor variables measured in counts were also standardized by population size. All-cause deaths were used rather than reported fatalities due to COVID-19 for several reasons related to unreliable case data, differences in testing, and co-morbidities between COVID-19 and other fatal acute diseases. By using all-cause deaths measured since day of first case reported in a county, we hope to get a better estimate on the impact of COVID-19 on mortality. As discussed, our predictors cover a wide scope, Table 1 gives a review of the data sources and variables collected from each source. Table S1 in the supplementary section gives more details of this process.

Predictors. Data on our predictor variables include demographics, health resource availability, health risk factors, social vulnerability, and other COVID-19-related information. The predictor variables used are collected from different sources which have also been used in Altieri et al.[26] and Killeen et al.[27]. Because the aims of this paper are not purely predictive, but focus on understanding the relative impact each variable has on COVID-19 outcomes, our data curation process is different when compared to these two papers. We aggregate data from different stratified variables to create an overall public transportation use feature. Likewise for social vulnerability scores, we attempt to include core variable that represent a specific type of risk feature. For example, given our interest are variable importance measures and marginal predictions, if we included both the aggregated CDC vulnerability index with many features collected from other sources that are proxy measures for this index (percent non-English speaking, poverty levels etc.) then findings for aggregate vulnerability index would be conservative given these other variables are also included in the model. That being said, given the large overlap and interactions of all variables collected, it it likely that all variable importance estimates are conservative. In our curation process, only unstratified variables are used (not stratified by age or sex), we also create sub-categories for variables (ethnicity, geography, disease prevention, etc.) These sub-categories we use in later analysis to explore possible over correction of the model for a respective target variable.

Briefly, some predictor variables include proportions of individuals by poverty level, gender, age distribution, race distribution, household income, healthcare access, occupation type, and so on, these were collected from USA Facts and the Census Bureau. Airport data, including, distance from county polygon centroid to airports were calculated from the Federal Aviation Administration. The 2020 county health rankings and Center for Medicaid and Medicare services were used to gather information on a range of health data including smoking, diabetes, obesity, air pollution and many other physical and mental health metrics. Precipitation by month was gathered from the National Oceanic and Atmospheric Association. Vulnerability index scores from each theme (described in Table S1) were aggregated from the Center of Disease Control. In total, over 150 predictor variables were gathered before curation. This curated data along with all relevant code, documentation and results are provided on our GitHub page.

Data cleaning and curation. The data curation process is described in more detail in the supplementary information alongside the data dictionary. All resulting data was numerical (no factor variables). In addition, we screen out any variables with more than 70% missing values. Similarly, we removed variables with close to zero variance. For variables that were nearly perfectly correlated (Pearson correlation = 0.95) we selected one for the analysis. Missing data in this cleaned dataset were imputed with the mean. For Google mobility data, we scraped data from the published mobility trend reports from February 16, 2020 to March 29, 2020. These data represent the general increase or decrease in movement to the respective destination (grocery stores, parks etc.) compared to baseline (pre-pandemic period). To create an aggregate score representing the mobility trend for each movement category for each county, we use the slope from linear regression to measure this trend over time. The slope for each movement category was included in our SuperLearner models.

Exploratory analysis. To graphically represent how our feature data are related to one another, and likewise how counties are related to one another through these variables, we use unsupervised hierarchical agglomerative clustering of both county features and counties. We present the results of this clustering as a heatmap using the pheatmap package in R [28]. Our first goal of this method is to understand if there are counties that have a trend for early first case reported, high COVID-19 case rates at day 25, and COVID-19 case rates to-date, as well as high all-cause mortalities at day 100 and to-date. If this trend was seen, we next wanted to investigate what variables were 'highly expressed' in these counties. As such, all feature data was z-score standardized. We then took the quantiles of each outcome to create factor dummy variables that can be plotted alongside clustering of counties. Clustering was done for both counties and county features and reordered accordingly using Euclidean distances. As this is an unsupervised approach, outcome data are not included in this machine learning method but are simply plotted alongside the clustering results to visually identify correspondences. Groups of county features that were found to be associated with groups of COVID-19 outcomes are presented.

Machine learning pipeline. Although our ultimate goal is not to use our final models for forecasting and prediction, one still needs to estimate a regression model in order to determine our measures of variable importance. By estimating this model as accurately as possible, one can better estimate the variable importance measures that rely on the prediction model. As such, instead of choosing one machine learning (ML) algorithm to model county features for each outcome, we used an ensemble approach (SuperLearner) to fit a prediction function for each of our outcomes. The SuperLearner combines the predictive probabilities of COVID-19 outcomes across many ML algorithms. The SuperLearner finds the optimal combination of a collection of algorithms by minimizing the cross-validated risk [25,29]. This method is an improvement over methods using only one ML algorithm because no one algorithm is universally optimal. The SuperLearner has been shown in theory to be at least as good as the best performing algorithm in the ensemble and often times performs considerably better [30]. Given the high-dimensionality and complex relationships of the county data, we chose a wide range of algorithms for the ensemble in order to optimize performance. For COVID-19 cases at day 25 and to-date per capita rates and all-cause mortalities at day 100 and total to-date per capita, we use a large number of linear Gaussian based algorithms including conditional mean (control algorithm) simple generalized linear model, a series of penalized regressions setting alpha at levels to create ridge regression, lasso regression, and elastic net regression [31]. Similarly, we use a number of gradient boosted decision trees that differed in depth [32]. Because these algorithms require hyper-parameter tuning for optimal performance, we create a grid of all possible hyper-parameters and choose algorithms across this grid for inclusion in the ensemble. For example, for xgboost models we create a grid of all combinations for max depth (2, 4, 6, 8, 10, 12), eta (0.001, 0.01, 0.1, 0.2, 0.3), and nround (20,50) and use models with these hyper-parameters at intervals across the grid. Likewise for decision trees [33] we select models with max number of trees (10, 50, 100). For elastic net we set alpha to 1 for lasso regression, 0 for ridge and also for alpha set to 0.25, 0.50 and 0.75. Overall, 19 algorithms were used in our Super Leaner library. The same procedure was applied for day-of-first-case in a county relative to-day-of-first case in the U.S. Instead of using Gaussian algorithms, however, custom learners were made for the SuperLearner environment that model Poisson outcome data. The same parameters were chosen for this set of learners to create the Poisson ensemble. To address possible over-fitting and to get cross-validated risks for each algorithm in the ensemble sets, five-fold cross-validation was used for internal SL cross-validation both to build optimal models with each classifier and to determine optimal weighting across classifiers in the ensemble.

Unpacking the black box. The algorithm used to create our predictor given covariates has desirable optimality properties, being asymptotically guaranteed to have a fit as good as any of the candidate members (the "oracle property"), with no risk of over-fitting. If a library of both smooth (e.g., parametric models) and flexible, non-parametric learners, then one can find it hard to outperform [25,34]. However, the result is a black box that creates predictions as a complex ensemble of different learners, some having their own internal variable selection process and model selection framework. Thus, the resulting black-box needs to be intelligently queried to estimate the independent impact of the various predictors used in the model. We do so in two ways. One, is using a straightforward leave-one-variable out method and re-examining the change in prediction accuracy. However, this provides no information about the direction of the impact, which is why we follow with a query inspired by causal inference methods. In that case, we use the model to forward model situations where we change the distribution of predictors across the counties in sequential fashion and then calculate the marginal predicted counts (so called substitution estimators, or G-computation [35,36]). The combination of these two versions of nonparametric variable importance measures provide both the importance of the variable (or sub-category of variable) to the resulting predictor as well as an intuitive measure of the adjusted association of single variables.

Variable importance. We built SuperLearners from the same county-level data for each of the COVID-19 outcomes. To measure variable importance in each model, we take the fitted model and make predictions using all county features and measure the model risk (average in squared differences in model prediction versus truth, or mean-squared error). We then scramble individual variables and sets (all variable in a category) and re-do the prediction and derive the new MSE. The plots (Figures 2 and 3) show the resulting ranked list of variables (most to least change in the MSE by scrambling). We use a risk-ratio (MSE-ratio) for each variable to measure its relative importance in the model for each outcome. The risk-ratio is the risk in the model without the respective variable (numerator) over the risk when the variable is included in the model (denominator). As such, a risk-ratio of 1.5 indicates that the model MSE rises by 50% when the variable is scrambled while controlling for all other variable affects. We use a similar approach to measure the variable sub-category importance on each outcome. Each variable was given a sub-category (described in supplementary material) resulting in a total of 15 categories. Blocks of variables in each category were scrambled and the model risk-ratio measured to attain information on category importance.

Marginal predictions. Given that we fit a black-box to derive our prediction models, we have to unpack the black-box to understand what it implies about the adjusted relationship of the important variables to the outcomes. We thus use substitution methods to evaluate the predicted change in the mean if county characteristics are changed. We examine how the mean outcomes would be predicted to change if the inputs of the specific variable of interest are modified, such as reducing a variable in some equivalent way across counties. Other modifications of the inputs could be used to examine these variable importance plots, but we looked at % changes in the variable across counties. Using these models we then make marginal predictions on the predicted number of COVID-19 cases and all-cause mortalities when increasing (or decreasing) the top variables found by the variable importance procedure. For example, if heart disease were to be identified as a significant predictor for COVID-19 mortality, the question our forward modeling approach answers is, "What are the expected number of COVID-19 deaths if we were to reduce the number of people with heart disease by 25% across all counties in the U.S.?". Similarly, another question is, "What is the trend in expected COVID-19 cases given a incremental decreases in heart disease, say a decrease by 10%, 20% ...90%, is this trend linear or nonlinear?". And furthermore, "If the trend is linear, what is the average decrease in expected COVID-19 deaths for a 10% reduction in heart disease?". The non-parametric, forward modeling approach detailed below aims to answer these questions.

Suppose a particular observation $O_i = (W_i, A_i, Y_i)$ in county ^{i}, $^i = 1, \ldots, ^n$, depends on explanatory variable A_i , other adjustment covariates W_i , and outcome Y_i , all in county *i*. If we wish to generate an estimate that characterizes the association of Y across all counties with A adjusting for W, but does not rely on a linear approximation, then we do this through plotting the estimate

$$\varphi(\pi) = E\{E(Y|A = \max(A_{min}, (1 - \pi) * A), W)\} \qquad (1)$$

as a function of π, where A_{min} is the minimum observed value of A across all counties in the data and π is interpreted as the proportional reduction in the county-specific value of the variable. To avoid extrapolation, we truncate A at the minimum observed value for the variable among counties. In essence, we exam the resulting predicted mean outcome across all counties as though the particular variable were reduced by π % in all counties, and all other covariates remain fixed at their observed values. This plot then provides a relevant function of the importance of the variable to the outcome.

Under several strong assumptions, including that the other covariates (the W, being either all other predictors or all but the ones in same sub-category) contain all the confounding information, sufficient experimentation (no positivity violations [36,37]), and independence of outcomes across counties, one could interpret (1) as identifying the marginal mean had, contrary to fact, all counties been set at the stochastic value, $\max(A_{min}, (1 - \pi) * A)$. We do not have information to impose a time-ordering among the covariates, so we treat these plots as a nonparametric form of association measure.

To derive inference, we use the non-parametric bootstrap (randomly sampling counties with replacement) for each π reduced mean. The procedure is as follows: (1) fit each outcome using the aforementioned set of learners, (2) iteratively remove variables and determine risk-ratios, (3) set the variable with the highest risk-ratio as the target variable for marginal predictions, (4) for each percentage from 0 to 1.0 at 0.10 intervals (a) resample the county data with replacement, (b) refit the SuperLearner with this resampled data, (c) reduce or increase the target variable for the respective percentage, and (d) predict the expected number of cases or mortalities with this new fit. Here, in step (4) we bootstrap this procedure 1000 times by resampling, refitting, and making marginal predictions, in order to create confidence intervals (CI) at each percent change to the target variable.

Note that we use three different models to estimate the regression $E(Y|A, W)$ depicted in (1): fully adjusted, adjusted only variables not in the sub-category of the variable of interest, and unadjusted. To evaluate the performance of our model, we compare each marginal prediction to that of a univariate model of the target variable (found by variable importance) for each outcome. Here, a generalized additive model (GAM[38]) was retrained at each iteration of the bootstrap for each reduction in the target variable and cases/mortalities were predicted through this univariate model. Likewise, to investigate possible over-corrections of our SuperLearners, we also remove similar variables that may have strong multi-collinearity with the target variable. This was done by removing variables in the target variable sub-category and training a SuperLearner on this set of covariates through the bootstrap. Results are presented as line plots and the actual observed average or sum for each outcome are plotted as horizontal lines for comparing actual outcomes to model predictions.

All data aggregation, curation, cleaning, exploratory analysis, ML pipleine, and marginal predictions were performed in R [39]. All coding scripts are available on our GitHub page for open-access and use. See Code Availability section for more details.

Results

COVID-19 outcomes and county feature distributions. There are 3142 counties in the U.S. After our data cleaning and curation process, there were 2620 counties included in the analysis and 101 county-level features. As such, our analysis covers 83% of the U.S. population as represented by counties. In these counties, as of July 15, 2020 there were 243,065 cases at day 25, 2,531,134 cases to-date, 53,018 all-cause deaths at day 100, 111,991 all-cause deaths to-date, and the average number of days to the first case in a county relative to the first case in Snohomish County, Washington was 68 days. A description of the variables used and their sources are given in supplementary materials (Table S1). A breakdown of these features with the respective mean, standard deviation, and range of values are also given in the supplementary materials (Table S2).

Exploratory. The heatmap for exploring the patterns in these data are given in Figure 1. The marked section of the heatmap show an outcome trend for (1) first quantile of day of first case (Q1 = earlier days of first case): (2) highest total deaths to-date (Q4): (3) highest deaths at day 100 (Q3): (4) highest total COVID-19 cases to date (Q4): and (5) highest COVID-19 cases at day 25 (Q4). The distribution of the outcome quantiles across the county dendrogram groups are provided in the supplementary materials (Table S8). The cluster of counties with most severe outcomes is marked on the left in Figure 1. These patterns indicate there are counties that cluster together based on similar characteristics and these counties correspond with an earlier first case in the county and higher COVID-19 case and mortality rates. For a breakdown of the number of counties in each state in this cluster see the supplementary material; briefly, however, the states with the highest number of counties in this cluster with highest outcomes are 1. Virginia (36), 2. Florida (33), and 3. Texas (30). The highest column values (red and orange pixels in the heat map) in this highest county row cluster occur in branches 3–16 and branches 46–53 of the column-wise dendrogram. A full list for each cluster is given in the plot but the highest county features for this subset were: 1—obesity, 2—sexually transmitted diseases, 3—income inequality, 4—food environment index, 5—CDC limited English scores, 6—latitude, 7—poverty income ratio, 8—GDP, 9—preventable hospital stays, 10—arthritis, 11—asthma, and 12—ischemic heart disease.

SuperLearner. As discussed, we use cross-validation to generate a coefficient that defines the weight for a respective learner in the ensemble. This procedure is done for each outcome and the same learners are used for each outcome (outside of day of first case where Poisson outcomes were defined). Tables S3–S7 in supplementary give a detailed breakdown of how each algorithm was used in the SuperLearner, the risk of the respective algorithm and the overall risk of the SuperLearner. Overall, our SuperLearners were able to achieve good fits by utilizing multiple algorithms. Results show that for each outcome the SuperLearners were largely built from multiple elastic net models, multiple xgboost models, and random forest. Table 2 shows resulting risk for each SuperLearner for each outcome. Because the learners were fit to the per capita standardized outcome data, we multiply each risk (mean squared error or MSE) by the total population in the dataset to get absolute error based on total numbers of cases or mortalities. We also calculate the r-squared for each SuperLearner to show variance explained by each model.

Variable importance. The top variable categories for each outcome were: (1) day of first case in a county: demography; (2) COVID-19 cases at day 25: ethnicity, transit and preventable disease; (3) total COVID-19 cases to-date: ethnicity and preventable disease; (4) mortalities at day 100: transit and ethnicity; (5) total mortalities to-date: ethnicity and transit. The top individual variables across all the models were: overall population of a county, CDC vulnerability scores for minority and limited English, public transportation use, and proportion of Black- and/or African-American individuals in a county. To visualize results, we present the risk-ratio (RR) results for each COVID-19 outcome collectively in Figures 2 and 3 as a series of dot-plots (RR threshold at 1.01). Based on these figures, it can be seen that for day of the first case in a county the total population (RR: 1.38) was the most important variable. For per capita COVID-19 cases at day 25, the top variable is the CDC minority score (RR: 1.04). For per capita COVID-19 cases to-date, the CDC's score for limited English speaking (1.40) the CDC's score for minority populations (1.17) and proportion Black- and/or African-American individuals in a county (RR: 1.12) were the top variables. For per capita all-cause mortalities at day 100, proportion taking public transportation (RR: 1.14) and proportion Black- and/or African-American individuals (RR: 1.07) were the top variables. For per capita all-cause mortalities to-date, proportion Black- and/or African-American individuals (RR: 1.08) and proportion taking public transportation (RR: 1.03) were the top county features.

Marginal prediction results. For the day of first case, population size was clearly most important predictor. For examining the association of cases and deaths of COVID-19 we choose two outcomes (total deaths and cases by July 14, 2020) and three of the most consistently important variables: two related to demographic features of the population (CDC Minority Score and Proportion of Black- and/or African-American individuals) and one related to transportation (metric of public transportation use). We estimate the relationship of proportional reductions in each of the predictor variables on the marginal outcome (using the substitution estimator of (1)) based upon a machine learning fit when controlling for: (1) all other variables (including possibly strongly collinear variables within the same sub-category), (2) only variables outside the target variable sub-category, and (3) nothing (unadjusted). The latter estimator of $E(Y|A)$ is based upon a smooth regression of the outcome versus the continuous covariates, specifically using general additive model with identify link (GAM [38]).

Figure 4 shows the predicted average day of first case across all counties for each proportion of population size reduced across the counties. Generally, smaller county populations are predicted to have a delay relative to counties with higher population sizes, *all other factors in the model staying constant* (the current average being 68 days after the initial U.S. case in Washington) for all three estimators, with somewhat larger effects in the adjusted models. For all models, a 0.50 proportional reduction in population size across the counties suggest a delay of around 2–3 days from the onset of the COVID-19 in the county.

Figure 5 shows plotted results for two outcomes (total counts and deaths), both versus proportion reductions in the three predictor variables. Proportional decreases in CDC Minority Score is associated with a decrease in COVID-19 cases and death. The large attenuation of the relationship in the adjusted models suggest strong confounding by the other covariates, where in the fully adjusted (and perhaps over-adjusted) curve approaches the null line. Using the curves not adjusting for other variables in the sub-category, the association suggest a 0.5 proportional reduction in the score would predict a reduction of 750,000 cases (out of around 2,400,000 total number by July 14) and approximately 10,000 deaths (out of around 115,000). Note that, particularly with deaths, the unadjusted curve is quite different from the actual number (pink line is substantially below the horizontal black line at the point of no intervention), this should be equal to that value if the model fits the data well. This is due to a few counties with extreme large counts (of both death and cases), which are poorly predicted by the bivariate smooths resulting in large positive residuals. Thus, when one estimates counts based upon reductions in the variable of interest (CDC Minority Score in this case), you get a prediction of the count that underestimates the true count. Note, by substantially reducing residual variation, the adjusted curves tend to be much closer to the observed count at 0 reduction.

Reducing public transportation suggests significant reduction in deaths, but little impact on case counts. For cases, we again have a poor fit of the bivariate smooth (unadjusted), along with the suggestion of significant confounding by other covariates. For deaths, a reduction of 50% suggest a reduction in deaths of 10,000, but the fact that the intercept for both adjusted curves (and unadjusted) is less than the observed count suggest again the influence of outliers. Bootstrapped linear regression of the marginal predictions showed that for a 10% reduction in public transit use, total deaths reduce by 2012 (95% CI [1972, 2356]).

Finally, for reductions in the proportion of Black- and/or African-American populations, there appears to be quite different estimates between the adjusted curves of COVID-19 counts, suggesting that variables in the sub-category of this variable create the possibility of over-adjustment in the full model. For deaths, the curves are nearly identical and imply that a reduction of the disparity between Black- and/or African-Americans and White-Americans in 50% of the population (one way to interpret an actual reduction in this variable) suggest a reduction of about 9000 total deaths. Likewise bootstrapped linear regression of these predictions are associated with a 10% increase in the proportion of Black and/or African-American individuals in a county increases total deaths to date by 2067 (95% CI [1189, 2654]). For total cases, although the expected COVID-19 cases was not perfectly linear given a shift in CDC minority index score, a 10% increase in CDC minority index score was associated with 111,006 additional cases (95% CI [91,991, 127,684]), using the model that adjust for variables outside of ethnicity.

Discussion

In this paper, we took a semi-parametric (machine learning) approach to evaluating a wide range of county-level features which may impact the spread, number of cases, and deaths of COVID-19 in the U.S. Our contributions are the following: (1) curating an open-source data repository that includes variables from many sources, categorized into sub-groups and filtered such that strongly collinear variables are removed for statistical analysis; (2) demonstrating the use of these variables in ensemble machine learning to build 5 SuperLearners for each COVID-19 outcome measure; (3) evaluating the features to identify the top variables that influence each outcome; (4) adjusting the top variables in our model to make marginal predictions for each COVID-19 outcome, while controlling for all other factors to establish the strength and directionality of the relationships; (5) constructing confidence intervals around all effects via bootstrapping to evaluate significant trends from baseline and between modeling approaches. Overall, using 101 county-level features our models show very good fits to the outcomes (all observed outcomes were within model confidence intervals apart from mortality which were slightly outside our CIs at baseline).

These fits establish that our models are able to accurately predict each outcome given the county-level feature variables. Our variable importance measures for each model fit generally show a trend that the total population size drives day of first case in a county and the proportion of Black- and/or African-American individuals in a county and CDC minority scores are most important independent contributions of COVID-19 cases and deaths as of mid July.

Causal inference pertaining to the individual relationships of these variables to each outcome is speculative at best given that these study variables are ecological and also are a static snap-shot of county variables collected before the pandemic hit the U.S. However, the general trend in these results seem to represent what has been reported as the U.S. faces this continuing pandemic. That is, for day of first case in a county, the total population as the most important variable makes sense given the larger the population the higher the probability of someone being infected traveling to the respective county. Likewise, CDC minority scores and Black- and/or African-American individuals are correlated with reports that suggest that minority populations and People of Color are disproportionately impacted by COVID-19 [10,12]. In addition, we also show a significant potential impact of baseline public transportation use and mortality [24,40,41]. This could indicate that there is higher probability of exposure early in the pandemic in counties where travel on public transportation leads longer and closer duration contains. This may also lead to higher infectious doses that may possibly increase severity of infection and consequent mortality, a phenomenon thought to be the case for influenza [42].

Our finding that counties with larger CDC minority population measures have higher COVID-19 outcomes, even when controlling for 100 other county-level variables (Table 1, Table S1), show the value of such measures when trying to determine the impact of risk level based on social factors for those disproportionately impacted by COVID-19. Additional measures, however, are necessary to understand the reasons for this. For instance, although our models adjust for income, access to health, and occupation types, our data are limited to reported factors that may not account for systematic or institutional levels of cultural/societal factors placing individuals at risk. Such factors may confound or modify others for which have been adjusted and may place certain individuals at greater risk for SARS-CoV-2 infection. Our future work will integrate additional data on environmental exposures and calculate racial dissimilarity scores to further investigate findings found in this study. The main difference between our findings and those reported to date is that our analysis controls for many other possible mediating factors (e,g., access to health-care, smoking, diabetes, heart-disease, and food security).

Conclusion

The goal of our study is to identify, early in the COVID-19 pandemic, the most salient factors that put populations at risk for COVID-19, thereby providing some guidance to individuals making difficult policy decisions at this critical time to quell the evolving pandemic. Specifically, racial composition of counties and intensity of public transportation use therein seem to be the most important risks factors for both the initial rapid growth and subsequent high incidence, and also help explain variations in mortality rates across counties. More work, however, is needed to establish causal rather than purely statistical relationships. Future work with detailed individual data will be important for getting more robust estimates of the individual impact of the factors examined. Whether causal or statistical, these results should be taken into account when developing policies for lifting restrictions. Additionally, as efforts continue to disseminate services and funding, and to roll out vaccination programs, once effective vaccines have been developed, consideration of these factors will facilitate the efficacious allocation of resources to the benefit of the US population as a whole.

Code Availability

All code for collecting data, collected data, statistical scripts, up-to-date outcome data, visualizations, and statistical results are available on GitHub: https://github.com/blind-contours/Getz_Hubbard_Covid_Ensemble_ML_Public \

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Figures

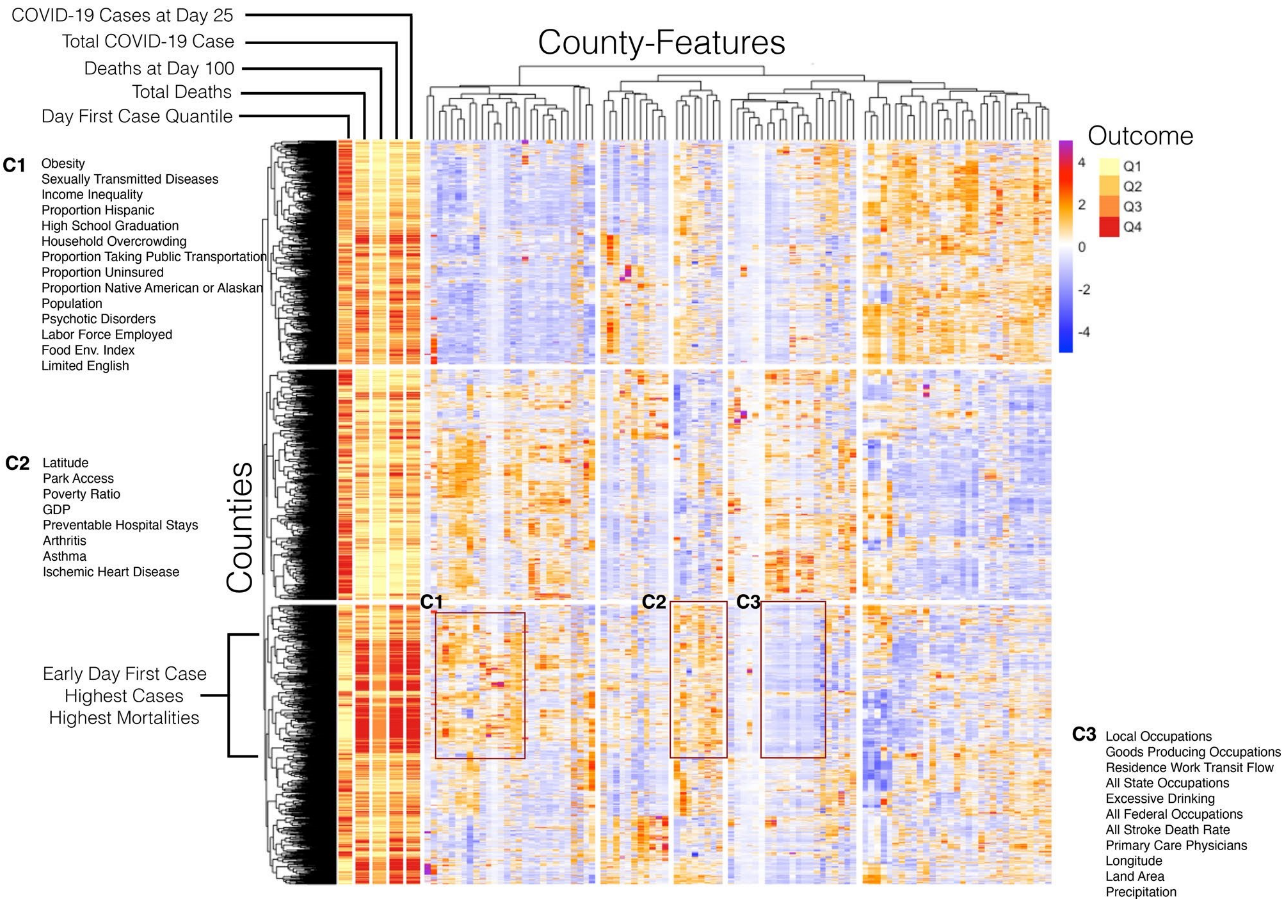

Figure 1. COVID-19 heatmap visualization of the distribution of county-level data. The rows represent counties clustered by the dendrogram and the columns are features of the counties which are also clustered by similarity. Red coloration indicates higher values (up to a z-score of 4) and blue coloration indicates lower values (− 4). The column bars on the left are outcomes, categorized by quantiles. The sections marked by C1, C2, and C3 show similar high or low features of counties in this region which have early COVID-19 appearance and high transmission and mortalities. Figure was created using pheatmap version 1.0.12 [28].

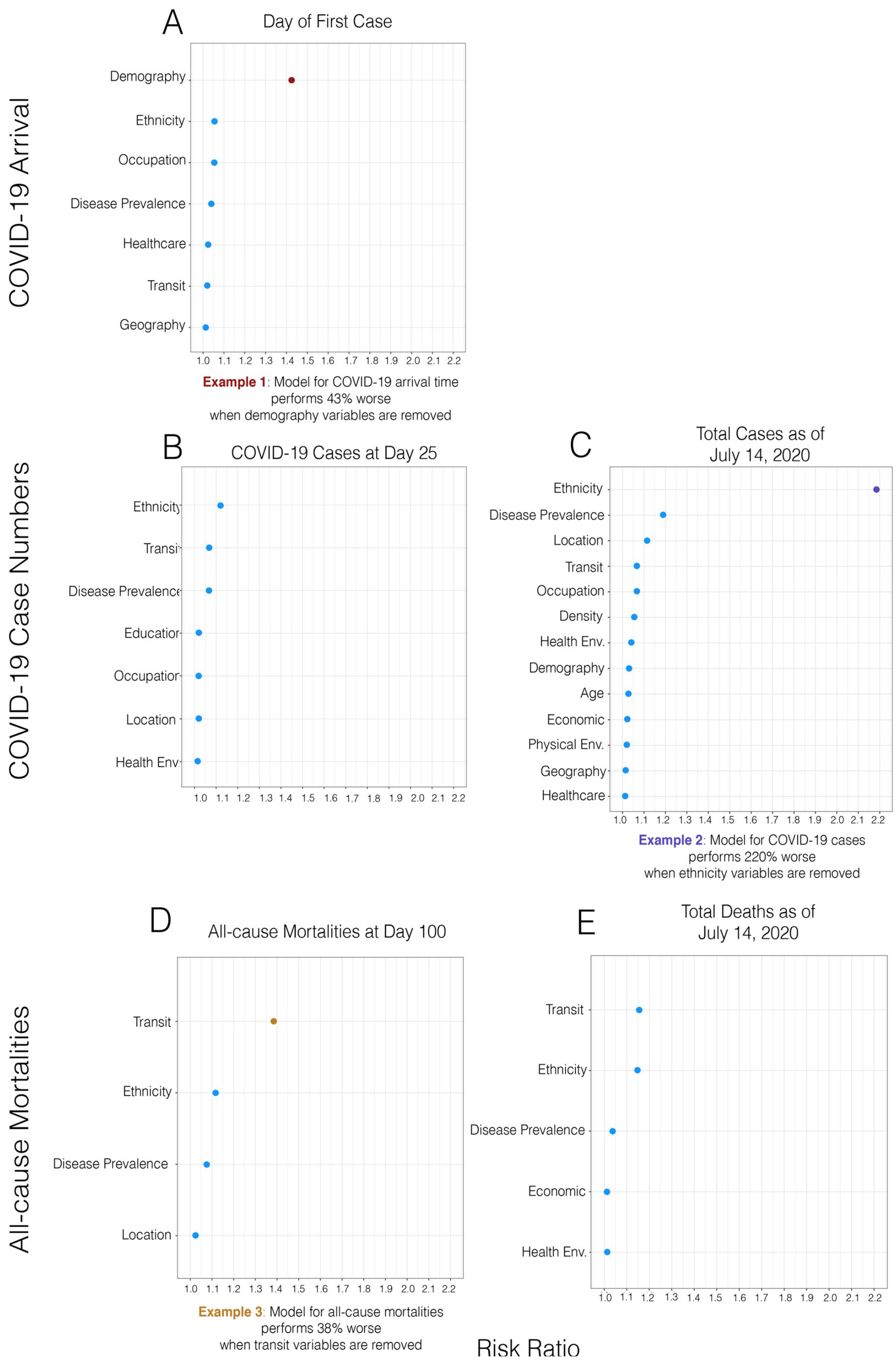

Figure 2. Variable importance as indicated by the relative increase of mean-squared error when the block of variables is permuted.

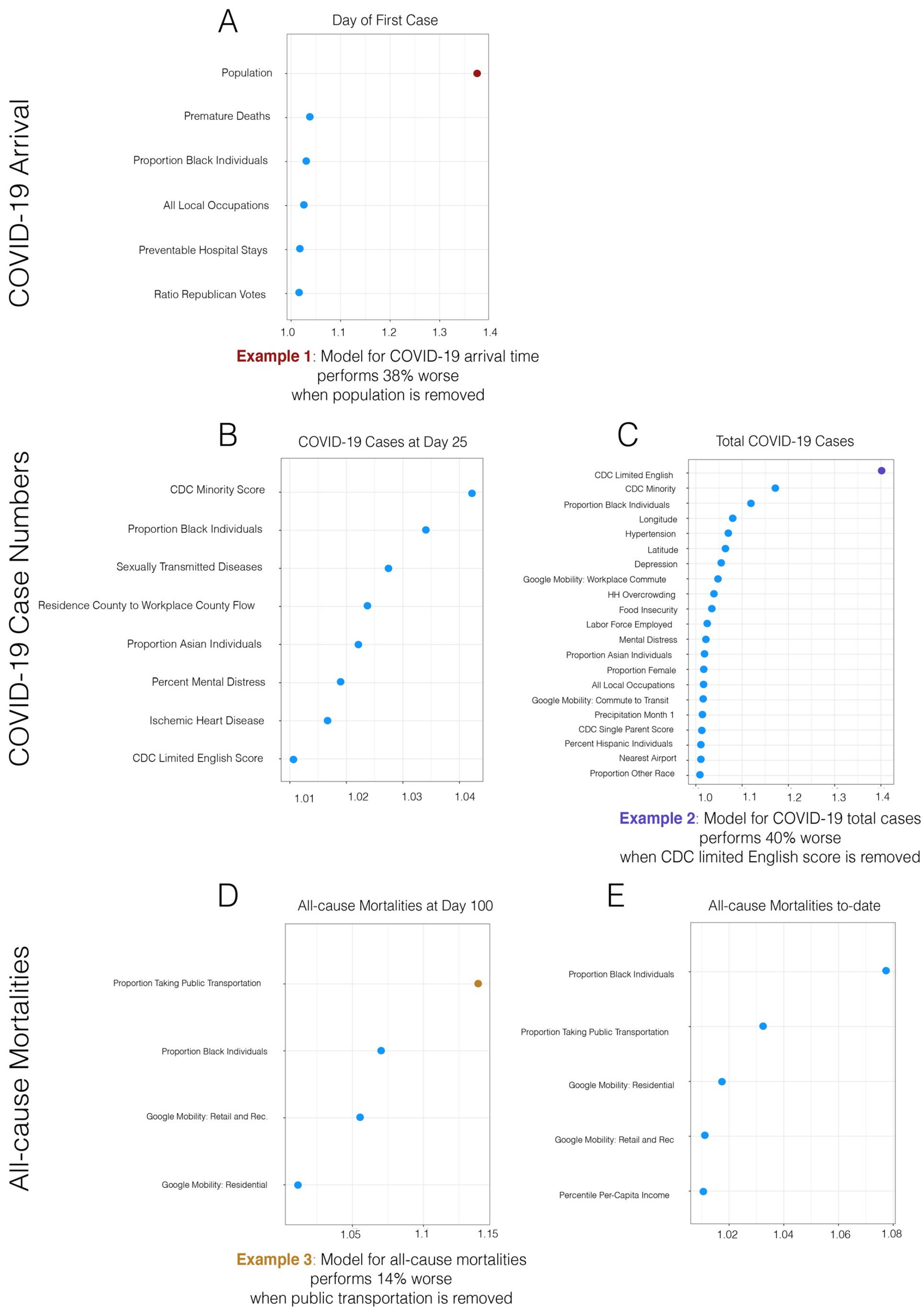

Figure 3. Variable importance as indicated by the relative increase of mean-squared error when a single variable is permuted.

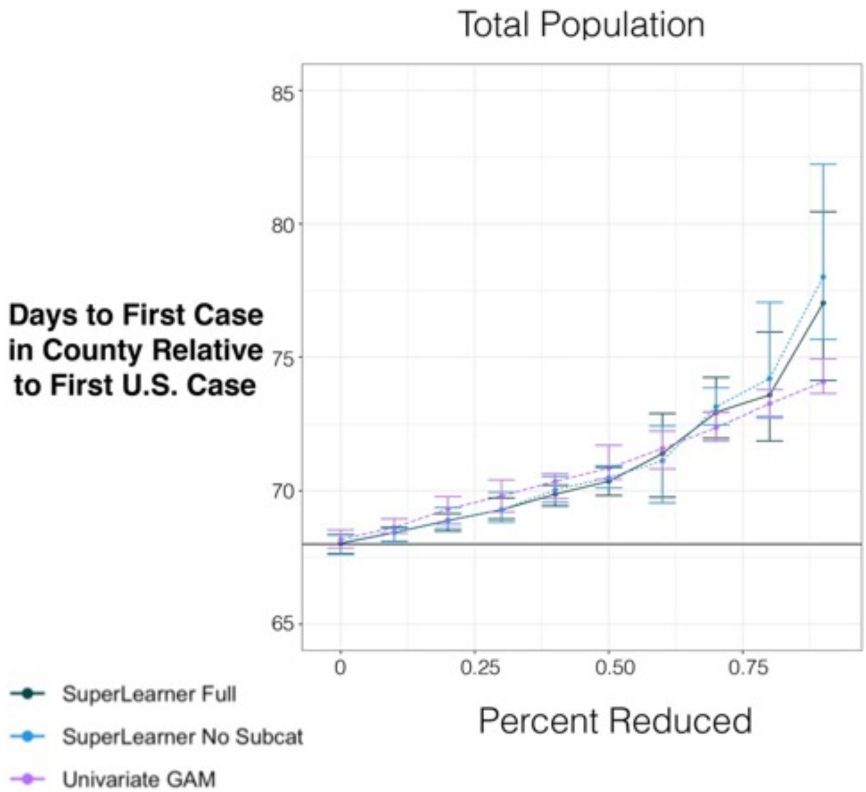

Figure 4. Marginal predictions of day of first case (relative to index time) for different proportional reductions of total population size for models adjusting for all other covariates, only covariates not in sub-category (see supplement Table S1) and unadjusted.

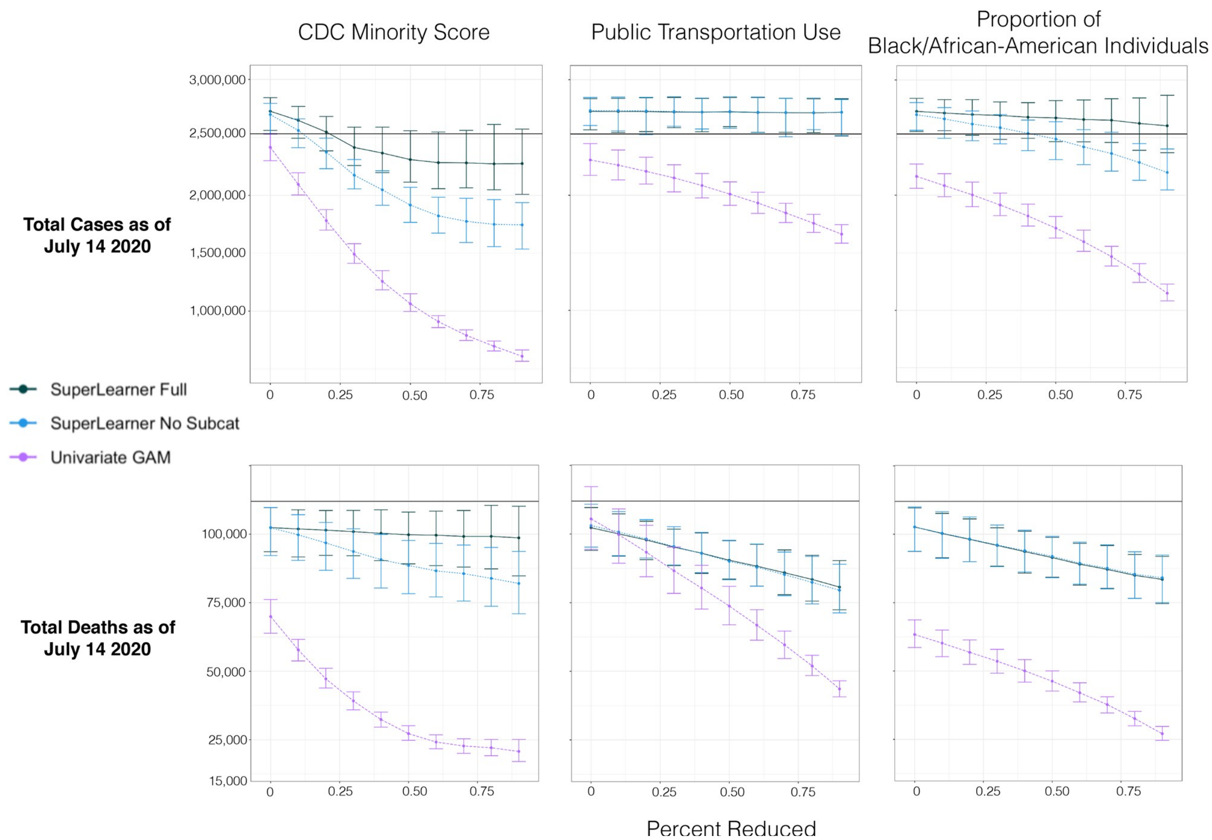

Figure 5. Marginal predictions of total cases and deaths by July 14, 2020) for three of the most consistently important variables in predicting the count outcomes: CDC minority score, proportion of Black- and/or African-Americans and a metric of public transportation use. X-axis is different proportional reductions of each of the three predictors, the Y-axis is the marginal predicted total counts for models adjusting for all other covariates, only covariates not in sub-category (see supplement table S1) and unadjusted. Black lines indicate actual total number of COVID-19 cases and mortalities.

Tables

Table 1. Number of variables used from respective sources with some examples given, complete list with distributions given in supplementary material.

SOURCE	N VAR.	VAR. EXAMPLES
USAFACTS	6	COVID-19 outcome data, population
BUREAU OF ECONOMIC ANALYSIS (BEA)	1	GDP
5-YEAR AMERICAN COMMUNITY SURVEY (ACS), 2014–2018	14	County percentages by Sex and Ethnicity, Employment, Household Income, use of Public Transportation
TIGER/LINE GEODATABASES	7	Latitude, longtitude, land area
TIGER/LINE GEODATABASES; FEDERAL AVIATION ADMINISTRATION (FAA)		Distance to Airports
INTERACTIVE ATLAS OF HEART DISEASE AND STROKE (2014–2016)	4	Number of Hospitals, Stroke, Access to Parks
COUNTY HEALTH RANKINGS AND ROADMAPS	21	Life Expectancy, Smoking, Obesity, Food Access, Mental Health, Physicians, Houshold Overcrowding etc.
CENTERS FOR MEDICARE & MEDICAID SERVICES (CMS)	15	Druge Abuse, Hypertension, Hyperlipidemia, Osteoporosis, etc.
NATIONAL CENTERS FOR ENVIRONMENTAL INFORMATION	1	Precipitation
CDC'S SOCIAL VULNERABILITY INDEX (SVI)	11	Percentile over 65 or under 17, Minority Scores, Limited English, Low Income Housing Estimates, Number Institutionalized
QUARTERLY CENSUS OF EMPLOYMENT AND WAGES	14	Labor force types, farming/mining, private industry, education/healthcare etc.
MIT ELECTION LAB	1	Calculated Proportion Voted Republican 2016
GOOGLE	6	Google mobility to location type, Residence, Grocery etc.

Table 2. Cross validated SuperLearner risk across COVID-19 Outcomes.

COVID-19 OUTCOME	MODEL RISK (PER CAPITA)	MODEL RISK (COUNTS)	R-SQUARED
DAY OF FIRST CASE	NA	159.58	0.75
COVID-19 CASES AT DAY 25	4.22 e−05	10539.64	0.59
TOTAL COVID-19 CASES TO-DATE	5.22 e−05	13053.75	0.87
ALL-CAUSE DEATH AT DAY 100	2.80 e−08	7.00	0.57
ALL-CAUSE DEATH AT TO-DATE	1.42 e−07	35.52	0.59

References

1. Zhu, N. *et al.* A novel coronavirus from patients with pneumonia in China. *N. Engl. J. Med.* **20**, 20 (2019).
2. Wu, F. *et al.* A new coronavirus associated with human respiratory disease in China. *Nature* **579**(7798), 265–269 (2020).
3. Rothan, H. A. & Byrareddy, S. N. The epidemiology and pathogenesis of coronavirus disease (COVID-19) outbreak. *J. Autoimmunity* **102433**, 20 (2020).
4. Ye, Z.-W. *et al.* Zoonotic origins of human coronaviruses. *Int. J. Biol. Sci.* **16**(10), 1686 (2020).
5. Zhou, P. *et al.* A pneumonia outbreak associated with a new coronavirus of probable bat origin. *Nature* **579**(7798), 270–273 (2020).
6. Lu, R. *et al.* Genomic characterisation and epidemiology of 2019 novel coronavirus: Implications for virus origins and receptor binding. *Lancet* **395**(10224), 565–574 (2020).
7. WHO, Who timeline—COVID-19. http://precog . iiitd. edu. in/ people/ anupa ma (2020).
8. CDC, Coronavirus (COVID-19). https:// www. cdc. gov/ coron avirus/ 2019- ncov/ index. html (2020).
9. Yancy, C. W. Covid-19 and African Americans. *JAMA* (Published online).
10. Coughlin, S. S., Moore, J. X., George, V., Johnson, J. A. & Hobbs, J. Covid-19 among African Americans: From preliminary epidemiological surveillance data to public health action. *Am. J. Public Health* **20**, 1157–1159 (2020).
11. Kodidela, S., Kumar, A., Gerth, K., Kumar, S. & Walker, C. Lessons learned from health disparities among African Americans in the HIV epidemic: What to expect for COVID-19 and potential approaches to mitigate health disparity. *Emerg. Infect. Dis. Diag. J.* **2**(03), 1 (2020).
12. Bandi, S., Nevid, M. Z. & Mahdavinia, M. African American children are at higher risk for COVID-19 infection. *Pediatr. Allergy Immunol.* **31**(7), 861–4 (2020).
13. Tai, D. B. G., Shah, A., Doubeni, C. A., Sia, I. G. & Wieland, M. L. The disproportionate impact of COVID-19 on racial and ethnic minorities in the United States. *Clin. Infect. Dis.* **72**(4), 703–6 (2021).
14. Wiemers, E. E., Abrahams, S., AlFakhri, M., Hotz, V. J., Schoeni, R. F., & Seltzer, J. A. Disparities in vulnerability to severe complications from COVID-19 in the United States. Tech. rep., National Bureau of Economic Research (2020).
15. Pettit, N. N. *et al.* Obesity is associated with increased risk for mortality among hospitalized patients with COVID-19. *Obesity* **28**(10), 1806–10 (2020).
16. Lighter, J. *et al.* Obesity in patients younger than 60 years is a risk factor for COVID-19 hospital admission. *Clin. Infect. Dis.* **71**(15), 896–7 (2020).
17. Covid, C., COVID, C., COVID, C., Chow, N., Fleming-Dutra, K., Gierke, R., Hall, A., Hughes, M., Pilishvili, T. & Ritchey, M.
18. et al., Preliminary estimates of the prevalence of selected underlying health conditions among patients with coronavirus disease 2019—United States, February 12–March 28, 2020. Morbidity Mortality Wkly Rep. **69**(13), 382 (2020).
19. Lipsitch, M., Swerdlow, D. L. & Finelli, L. Defining the epidemiology of COVID-19—studies needed. *N. Engl. J. Med.* **382**(13), 1194–1196 (2020).

20. Baker, M. G., Peckham, T. K. & Seixas, N. S. Estimating the burden of United States workers exposed to infection or disease: A key factor in containing risk of COVID-19 infection. *PLoS One* **15**(4), e0232452 (2020).
21. Lloyd-Smith, J. O., Schreiber, S. J., Kopp, P. E. & Getz, W. M. Superspreading and the effect of individual variation on disease emergence. *Nature* **438**(7066), 355 (2005).
22. Sajadi, M. M., Habibzadeh, P., Vintzileos, A., Shokouhi, S., Miralles-Wilhelm, F. & Amoroso, A. Temperature and latitude analysis to predict potential spread and seasonality for COVID-19. Available at SSRN 3550308.
23. Altieri, N., Barter, R. L., Duncan, J., Dwivedi, R., Kumbier, K., Li, X., Netzorg, R., Park, B., Singh, C. & Tan, Y. S. et al., Curating a COVID-19 data repository and forecasting county-level death counts in the United States. arXiv:2005 . 07882 (arXiv preprint).
24. Ferstad, J. O., Gu, A. J., Lee, R. Y., Thapa, I., Shin, A. Y., Salomon, J. A., Glynn, P., Shah, N. H., Milstein, A. & Schulman, K. et al., A model to forecast regional demand for COVID-19 related hospital beds. *medRxiv*.
25. Desmet, K. & Wacziarg, R. Understanding spatial variation in COVID-19 across the United States. Tech. rep., National Bureau of Economic Research (2020).
26. VanDer Laan, M. J., Polley, E. C. & Hubbard, A. E. Super learner. *Stat. Appl. Genet. Mol. Biol.* **6**, 1. https:// doi. org/ 10. 2202/ 1544- 6115. 1309 (2007).
27. Altieri, N., Barter, R. L., Duncan, J., Dwivedi, R., Kumbier, K., Li, X., Netzorg, R., Park, B., Singh, C., Tan, Y. S., Tang, T., Wang, Y. & Yu, B. Curating a COVID-19 data repository and forecasting county-level death counts in the United States. arXiv:2005 .0788 2.
28. Killeen, B. D., Wu, J. Y., Shah, K., Zapaishchykova, A., Nikutta, P., Tamhane, A., Chakraborty, S., Wei, J., Gao, T., Thies, M. & Unberath, M. A county-level dataset for informing the United States' response to COVID-19. arXiv: 2004. 00756.
29. Kolde, R. pheatmap: Pretty Heatmaps, r package version 1.0.12 (2019). https:// CRAN.R-project . org/ packa ge= pheat map.
30. Polley, E. C. & van der Laan, M. J. Super Learner in Prediction, U.C. Berkeley Division of Biostatistics Working Paper (2010) 1–19. http://bios t ats. bepre ss. com/ ucbbi ostat/pape r266 /.
31. LeDell, E., Van Der Laan, M. J. & Peterson, M. AUC-maximizing ensembles through metalearning. *Int. J. Biostat.* **12**(1), 203–218.
32. https:// doi.org /10 . 1515/ijb -2015 -003 5 (2016).
33. Zou, H. & Hastie, T. Regularization and variable selection via the elastic net. *J. R. Stat. Soc. Ser. B* **67**, 301–320 (2005).
34. Chen, T. & Guestrin, C. XGBoost: A scalable tree boosting system. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '16, ACM, New York, NY, USA, 2016, pp. 785–794. https://doi . org/10 . 1145/ 29396 72. 29397 85.
35. Liaw, A. & Wiener, M. Classification and regression by randomforest, R News 2 (3) 18–22. (2002).https:// CRAN.R- proje ct. org/ doc/Rnews /.
36. Dudoit, S. & Laan, M. J. V. D. Asymptotics of cross-validated risk estimation in estimator selection and performance assessment asymptotics of cross-validated risk estimation in estimator selection and performance assessment. U.C. Berkeley Division of Biostatistics Working Paper Series Year.

37. Hernán, M. A. & Robins, J. M. Estimating causal effects from epidemiological data. *J. Epidemiol. Community Health* **60**(7), 578–586. https:// doi. org/10 .1136 /jech . 2004.02949 6 (2006).
38. Robins, J. M. Addendum To "a New Approach To Causal Inference in Mortality Studies With a Sustained Exposure Period— Application To Control of the Healthy Worker Survivor Effect''. *Comput. Math. Appl.* **14**(912), 923–945. https://doi . org/ 10. 1016/ 0898- 1221(87) 90238-0 (1987).
39. Petersen, M. L., Porter, K. E., Gruber, S., Wang, Y. & van der Laan, M. J. Diagnosing and responding to violations in the positivity assumption. *Stat. Methods Med. Res.* **21**(1), 1–13. https:// doi.org / 10.4018 / 978-1- 4666- 2661-4. ch001 (2012).
40. Hastie, T. J. & Tibshirani, R. J. *Generalized Additive Models* (Chapman and Hall, 1990).
41. R Core Team, R: *A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria (2013). http:// www.R-proj e ct.org /.
42. Loomba, R. S., Aggarwal, G., Aggarwal, S., Flores, S., Villarreal, E. G., Farias, J. S. & Lavie, C. J. Disparities in case frequency and mortality of coronavirus disease 2019 (COVID-19) among various states in the United States. *medRxiv*.
43. Tenforde, M. W. *et al.* Characteristics of adult outpatients and inpatients with COVID-19–11 academic medical centers, United States, march-may 2020. *Morbid. Mortality Wkly Rep.* **69**(26), 841 (2020).
44. Paulo, A. C., Correia-Neves, M., Domingos, T., Murta, A. G. & Pedrosa, J. Influenza infectious dose may explain the high mortality of the second and third wave of 1918–1919 influenza pandemic. *PLoS One* **5**(7), e11655 (2010).

Chapter 2 & 3 Transition

There is a substantial need for change across academic departments to build belonging and inclusivity for racially-marginalized students, as is the need to create a community of scholars with a shared language and commitment to advance justice, equity, diversity, and inclusion (JEDI). For the past two years, the Department of Environmental Science, Policy, and Management (ESPM) at the University of California, Berkeley, held a course titled "Critical Engagements in Anti-Racist Environmental Scholarship." The course was developed and co-taught by a team of graduate students in direct response to the nationwide protests following a slew of violent acts against Black men and women in 2020. The structure and curriculum of the course was designed to facilitate ***actionable change*** in teaching, research, and departmental culture among faculty, staff, graduate students, and postdoctoral scholars. Ultimately, we aimed to create a community of scholars with a commitment to advancing JEDI in academic departments and beyond.

My final chapter uses the course I co-developed/taught, *ESPM 290: Critical Engagements in Anti-Racist Environmental Scholarship*, as an exemplary framework for anti-racist pedagogy.

Chapter 3 | Cultivating Anti-Racism in the Classroom and Beyond through Collaborative Learning in the Environmental Sciences

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Included as a dissertation chapter with permission from co-authors.

Abstract

Spurred by nationwide protests against anti-Black violence in the summer of 2020, academic departments across the United States saw an uptick in efforts to integrate belonging, diversity, equity, justice, and inclusion initiatives into their programs. In this vein, graduate students in the Department of Environmental Science, Policy, and Management at the University of California, Berkeley, developed and led a semester-long course, "Critical Engagements in Anti-Racist Environmental Scholarship." The course cultivated anti-racist mindsets across scales through collaborative learning and action projects. We designed and taught the class as a team of doctoral students, and course participants consisted of faculty, staff, postdoctoral scholars, and other graduate students, thus disrupting traditional academic power structures. In this article, we draw on our experiences from two years of developing and teaching this course. We first outline our theory of change, envisioned as a tree—rooted in our pedagogical approach with a multi-layered trunk composed of interacting individual, organizational, and institutional layers of the tree trunk's structure—that ultimately bears fruit of anti-racist action. We then provide an overview of our pedagogical approach, which includes attending to the roots of curriculum, classroom structures, and teaching practices. To conclude, we highlight the five key branches of the course's success: **(1) Centering Black voices and experiences, (2) Flattening academic hierarchies, (3) Fostering a community of learners, (4) Developing action-oriented mindsets, and (5) Sustaining long-term anti-racist praxis.** Overall, this article offers a model for any department seeking to implement anti-racist praxis through coursework and long-form professional development training for academics.

Introduction

In 2020, the deaths of George Floyd, Breonna Taylor, Ahmaud Arbery, and Jacob Blake challenged higher education to reckon with racist organizational structures. Inspired by Black Lives Matter protests and decades of student-led organizing at the University of California, Berkeley, a diverse collective of graduate student leaders in the Department of Environmental Science, Policy and Management (ESPM) came together to challenge what they felt to be insufficient departmental and campuswide responses to national calls for change *and* ongoing instances of overt racism and anti-Black violence at UC Berkeley (Chancellor's Independent Advisory Board on Police Accountability and Community Safety, 2020; Roberts-Gregory, 2020; Rodríguez, 2012; UC Berkeley Office of the Chancellor, 2019; Watanabe, 2020). This effort was led by the ESPM Graduate Diversity Council, a graduate student organization, and took two primary forms. First, Graduate Diversity Council members wrote a letter to faculty detailing a list of demands for departmental anti-racist action (ESPM Graduate Diversity Council, 2020). Second, five Graduate Diversity Council members, all authors on this article (see Table 1), developed a 16-week course entitled "Critical Engagements in Anti-Racist Environmental Scholarship" (hereafter called the Course) for faculty, staff, graduate students, postdoctoral scholars, and cooperative extension specialists in ESPM[1]. In creating this class, we moved beyond the limitations of one-time, mandatory anti-bias/diversity trainings (Devine & Ash, 2022; Dobbin & Kalev, 2016; Pendry et al., 2007) to foster meaningful learning across multiple professional positions and personal identities. We worked toward anti-racist praxis in our department by interrogating how anti-Black racism and intersecting oppressions structure academia, specifically in the environmental sciences (e.g., Dancy et al., 2018; Marín-Spiotta et al, 2020; Miriti et al., 2020; Mustaffa, 2017; Schell et al., 2020). We first held the Course in fall 2020, followed by a second iteration in fall 2021,[2] which expanded to include the Department of Plant and Microbial Biology.[3]

In creating the Course, our working definition of anti-racism was the active, non-neutral confrontation of racial inequities via design, practice, and application of the following: lifelong learning, action, and critical self-reflection on racism; recognizing and challenging white supremacy in interpersonal and organizational-level interactions; and community accountability for racial equity and justice in micro, meso, and macro practices and outcomes (after Chavez, 2012; Kendi, 2019; Welton et al., 2018). Guided by this definition, our work with the Course built on a rich tradition of graduate student-led anti-racist organizing (e.g., Chu et al., 2022, Lantz et al., 2016; Museus & Sifuentez, 2021; Rhoads, 2016), faculty-student-staff partnerships (Kezar, 2010), and decades of scholarship on enacting long-lasting anti-racist change in academia (reviewed in Welton et al., 2018).

In this article, we describe and reflect upon the development and implementation of the Course. Using a tree-based metaphor, we first outline our theory of change and then provide an overview of our theory of change and pedagogical approach, which includes attending to curriculum, classroom structures, and teaching practices. Finally, we summarize **five key lessons for implementing similar courses: (1) Centering Black voices and experiences, (2) Flattening academic hierarchies, (3) Fostering a community of learners, (4) Developing action-oriented mindsets, and (5) Sustaining long-term anti-racist praxis** (see Figure 1)**.** We believe

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[1]Across the 2020 and 2021 iterations of the course there were 71 participants, including the teaching team: 42 PhD students, 2 masters students, 7 postdocs, 15 faculty, 2 cooperative extension specialists, and 2 professional staff.
[2] This article speaks to the first two iterations of the Course. In spring 2023, a "Deeper Dive" version of the Course is being offered for alumni of the first two course iterations, and a third iteration of the original course will be taught again in fall 2023.
[3] Lorenzo Washington, an author on this article, a 2020 course participant, and member of the 2021 teaching team, was instrumental in expanding the course to include his home Department of Plant and Microbial Biology.

the Course functions as a model for the environmental science community and higher education at large. In this article, our broader aim is to provide documentation for others interested in implementing similar anti-racism courses and long-form professional development training for academics.

Theory of Change

Our initial pedagogical decision-making drew on our various racialized identities and experiences as teaching team members[4] with the racist, violent academic structures we wished to disrupt. We primarily draw from the rich scholarly traditions of critical race theory, critical pedagogy, and social movement and organizational theory to understand and illustrate which course components were most successful in fostering anti-racist change and why. Drawing on our lived experiences and collective dialogue as a teaching team, participant feedback, and theory-oriented reflection, we distill our theory of change for the Course into five key lessons (see Figure 1).

In our theory of change, we envision these lessons in anti-racist change-making as branches emerging from a tree trunk comprised of three concentric rings (Figure 1) representing: the ***individual level*** (e.g. course participants in community with each other; the "heartwood"), the ***organizational level*** (e.g. ESPM and Plant and Microbial Biology departments, specific lab groups; the "sapwood"), and the ***institutional level*** (e.g. UC Berkeley, environmental science and academia at large; the "bark"). Much like the layers of a tree trunk, all layers are interdependent and anti-racist change occurring at one level is intricately connected to and feeds back to anti-racist change between and across all other levels. While the Course primarily operated at the organizational and individual levels, by examining the structures and processes of our department and cultivating "internal change agents" (Cox, 2001; Hartley et al., 1997; Patrick & Fletcher, 1998), these orientations fed into our goal of anti-racist institutional-level change.

In our tree metaphor, heartwood is at the center of our theory of change and represents individual course participants coming together in a community of learners. From this community, "radical change in how members perceive, think, and behave at work" (Henderson, 2002) emerges and starts the process of anti-racist development to provide the necessary ideation, support, and structure for change at the organizational and institutional levels. Importantly, the heartwood also supports the branches—the key takeaways in our metaphor—that emerge from our theory of change. Much like the photosynthetic products from leaves on the branches of a tree, the knowledge gained from our key takeaways provide the energy necessary for continued growth. By focusing on heartwood-level anti-racist changes to attitudes/core belief systems in individuals and how they interact with organizational policy, we hope to in turn influence anti-racist changes in the sapwood: that is, the organizational level (Kezar, 2001). The sapwood layers represent the many organizational structures within departments and lab groups that comprise the day-to-day implementation of policies, practices, and decision-making procedures. Extending our metaphor even further, the sapwood is marked by past growth (tree rings) and carries the histories of

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[4] See Table 1 for a description of author/teaching team positionalities.

individual, organizational, and institutional efforts. The final, outermost layer in our theory of change is the bark, representing the level of institutions. As ESPM is UC Berkeley's third largest department and among the top-ranked environmental science programs in the U.S., we hope that our individual- and organizational-level work can, in fact, contribute to institutional-level change. Similar to a tree trunk, all layers influence each other, and their interactions facilitate growth and change in the right conditions.

The Course's pedagogical approach, made up of curriculum, teaching practices, and classroom structures, serves as the roots of the tree, providing nutrients and water to grow our anti-racist community. Finally, the Course's Collaborative Action Projects (see Classroom Structures, below) are represented as the fruits and seeds of this anti-racist work. We hope that these fruits and seeds can serve to inspire and catalyze change in other departments, colleges, and institutions.

Pedagogical Approach

In applying our change-making approach to an academic setting, we looked to the field of critical pedagogy, which attempts to "understand how power works through the production, distribution, and consumption of knowledge within particular institutional contexts and seeks to constitute students as informed subjects and social agents" (Giroux, 2010, p. 717). ***Anti-racist*** critical pedagogy explicitly serves as "a method for addressing race, ethnicity, power, and class" (Blakeney, 2005, p. 121). For our course, we worked to examine and challenge these power dynamics through three key components of pedagogy: ***curriculum, classroom structures, and teaching practices*** (Morales-Doyle, 2017). We see these pedagogical components as foundational roots for change-making across all three levels (individual, organizational, institutional). Here we define and briefly outline our curriculum, classroom structures, and teaching practices. For more detailed explanations of each of these three components, please see Supplementary Materials 1.

Curriculum

We define curriculum as the organization of course topics and materials. In our course, the curriculum consisted of six course modules, outlined below. In choosing topics and designing the syllabus, we sought specifically to interrogate the hidden curriculum that ideologically informs academic culture in environmental sciences (Bang et al., 2012; Hansson, 2018; Kelly, 2009). Each module included learning objectives that built upon knowledge developed in prior modules and topically-relevant guest speakers (see Table 2 for a summary of all modules and Chapter 3 Appendix 1 for further in-depth descriptions).

Course Modules

We began first with a module on "Framing the Conversation," which aimed to lay community foundations of mutual trust and develop a shared working language around anti-racism, structural and institutional racism, and intersecting oppressions. The second module, "Centering Black, Indigenous, and other People of Color's (BIPOC) Voices," worked to decenter whiteness in environmental scholarship through a theoretical exploration of the centering concept (e.g., Price et al., 2020) and by uplifting the lived experiences and scholarship of minoritized environmental scientists. While the module title used the term “BIPOC” to allow future course iterations to highlight a diverse set of voices, in the 2020 and 2021 course, we specifically sought out Black speakers to counter anti-Black racism given events at the time of course conception (Dancy et al., 2018; Fasching-Varner et al., 2015; Mustaffa, 2017; Smith et al., 2006).

After rooting the course in the development of a shared (if by definition never “finished”) understanding of anti-racist principles and the centering of Black voices, we then spent the next three modules drilling down into specific structures and processes within academia. For each of these modules, we aimed to expose and untangle harmful power dynamics and engage in alternative anti-racist praxis. We began with Module 3 on mentorship , as mentorship is a throughline that influences every aspect of one’s experience in academia—it can be a site of generative affirmation or harm, or often an ambiguous mix of the two (Estrada et al., 2018a), with worse outcomes for racially minoritized individuals[5] (Estrada et al., 2018b; Griffin et al., 2020; Martinez-Cola, 2020; McCoy et al., 2015; McCoy et al., 2017;). We offered tools for creating collaborative, multi-directional relationships between mentees and mentors (Estrada et al., 2018a; Montgomery 2017). In Module 4, we honed in on key organizational structures and practices with academia: inclusion and belonging in lab culture (Berkeley Agroecology Lab, 2020; Chaudhary & Berhe 2020; CLEAR, 2021), power dynamics in author order (Liboiron et al. 2017), racially minoritized faculty recruitment and retention (e.g., Fasching-Varner et al., 2015; Harley, 2008; Harris, 2017; Stanley, 2006), and disability justice in the classroom (Garcia, 2020; Karpicz, 2020; Shelton, 2020). Module 5 focused on colonialism in the research process, particularly the colonial origins and imperialist deployment of environmental science subdisciplines (Gray & Sheikh, 2021; Raby, 2017; Roy, 2018) and how scientific training in the United States has perpetuated the logics of both settler and exploitation colonialism (Bang et al., 2012; Nejadmehr, 2020; Smith, 2012). Readings and activities emphasized the inherently political nature of science and the research process, encouraging participants to consider how both their fields’ colonial orientations and their own identities impact how they conduct their research, from research questions to research methods (i.e., data evaluated) to manners of engagement with landscapes and communities (Free Radicals 2020).

The sixth and final module, “Scaling Out,” expanded beyond academia to discuss racism and anti-Blackness in the environmental movement writ large. Topics for readings and discussions included the racist foundations of majority-white, eugenics-affiliated conservation movements (Brune, 2020; Purdy, 2015) and the continuing lack of diversity in leadership of mainstream environmental organizations (Taylor, 2014), despite increased attention to environmental racism and social equity (Jennings & Osborne Jelks, 2020). We emphasized the importance of pursuing anti-racist action beyond the ivory tower, which is particularly vital in departments such as ESPM, where a large proportion of graduate students go on to seek careers outside of academia.

[5] Estrada’s emphasis on micro- and macro-affirmations in addition to the more commonly addressed micro- and macro-aggressions (Estrada et al., 2018a) was particularly impactful for the class, as expressed in course evaluations (see Chapter 3 Appendix 2).

Classroom Structures

In addition to carefully crafting course curriculum, we also fostered sustained engagement through intentional classroom structures, which included interdependent components of sharing authority, designing tasks, and evaluating students (Ames, 1992). To allow participants to grapple with the material through cycles of inquiry (Engeström, 2001), we sought to flatten academic hierarchies, hold all participants accountable to learning, and promote active learning. We provide an overview of our approach here (see Chapter 3 Appendix 1 for more detail.)

Reframing Authority

Academic hierarchies, which often threaten classroom participants' sense of safety, drastically exacerbate the type of discomfort that accompanies anti-racism work (Esmonde & Booker, 2017; Freire, 2018; hooks, 1994). We created two intentional structures to foster "classroom counterspaces" (Masta, 2021) that attempted to ameliorate these harmful academic hierarchies. First, the Course was co-taught by a five-graduate student teaching team rather than a single faculty member,[6] and participants included faculty, staff, postdocs, and graduate students. Second, from the beginning, we framed the teaching team as non-experts' intent on learning alongside course participants. Each session was developed and collaboratively co-led by rotating members of the full teaching team, and our intersectional identities and diverse disciplinary backgrounds informed how each of us "showed up" in the space. By modeling the active questioning of an "inquiry stance" (Cochran-Smith & Lytle 2009) and designing and delivering highly participatory course content and classroom tasks, we aimed to create an overarching ethos of a "community of learners" (Brown & Campione, 1994; Matusov, 2001; Rogoff et al., 1998).

Designing Tasks for Active Learning

As we designed this course during the early stages of the COVID-19 pandemic when in-person classes were not possible, we sought to incorporate online classroom tasks that would foster active learning (Harris et al, 2020). We enhanced the intimacy and accessibility of the remote learning environment through use of Zoom chat features, professional captioning, live-time polls, and frequent use of breakout rooms. We also created action-oriented classroom assignments designed to facilitate applied learning in addition to reading and discussion (see Teaching Practices below for more detail).

Participant Evaluation and Accountability

Our method for participant evaluation also intentionally disrupted academic hierarchies. We took an "ungrading" approach (Kohn & Blum, 2020): graduate students received a "credit/no credit" rather than a letter grade, with engaged participation—understood as a shared commitment to the community and learning goals—as the evaluation criteria. While course participants of all positions were considered student peers, technically only graduate student members of the class were enrolled in official course units. The teaching team was concerned that faculty and staff members in particular would attrit as the semester progressed. To counter this risk, each faculty

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[6] One faculty member worked with the teaching team to navigate administrative requirements and provide input on course development but entered the classroom as a co-learner.

and staff participant signed an agreement to commit to full participation in the course at the same level of credit-receiving graduate students: attending all course sessions, active engagement in the classroom, and completing all assignments. This strategy was effective in 2020, but less so in 2021, likely due to greater commitments faculty faced with the return to in-person activities.

Teaching Practices

Here, we provide examples of specific practices and assignments we used to foster dialogue and collaborative learning between all course participants regardless of formal academic position. In designing our teaching practices, we relied on Freire (1994, 2018), Hooks (1994, 2003), and other critical pedagogical visionaries to disrupt "banking models" of curriculum delivery that view learners as empty boxes to be filled by instructor expertise. Rather than this one-way approach, we favored multi-directional, community-based learning. See Supplementary Materials 1 for more detailed descriptions of the practices we outline below.

Two-way Participant Interviews

One of the most effective teaching practices in the 2020 course was the use of "two-way interviews" to present curricular concepts through the lived experience of course participants. For these sessions, the two leads prepared a series of questions for each other in advance and then held a live, free-flowing conversation on these topics during class. All other course participants served as witnesses, respectfully holding the space for the two speakers. After 45 minutes of the two-way interview, we then opened the conversation up to all participants to ask follow-up questions of the speakers, contribute their own experiences on the same topics, and reflect on their reactions to their colleagues' stories. In 2020, we conducted two-way interviews between two graduate students and then two faculty members; in 2021, we had a faculty panel with a similar structure. This teaching practice was particularly powerful for community-building, because it allowed for participants to have intense emotional responses to their colleagues' vulnerable, resilient, and honest perspectives on navigating the department, academia at large, and environmentalist spaces. Inviting emotion into the classroom enhances intercultural learning (Jokikokko, 2016; Zembylas, 2008).

Inclusive Selection of Guest Speakers and Topics

Another core teaching practice was our inclusion of guest speakers as part of each module. Our desire to center Black scholars meant we wanted to provide a platform for them to share their expertise in environmental science. By engaging with Black scholars about their academic subjects and assigning their publications as required readings, the course worked to dismantle racist assumptions about Black intelligence (Evans-Winters, 2014) and position Black scholars as holders of knowledge (Leonardo & Grubb, 2019). Of note, to uphold our commitment to compensating Black scholars for their time and expertise, guest speakers, when possible,[7] were paid for their contribution to the course. As Berkeley courses are not given funding for such

[7] UC Berkeley College of Natural Resource's policy is that university funds cannot be used to pay honoraria to University of California employees, so we were unfortunately unable to pay honoraria to every single guest speaker, despite our best efforts.

expenses, the teaching team fundraised through the campus Office of Graduate Diversity for speaker honoraria.

Balancing Lecture and Dialogue

In addition to guest speakers, the teaching team often provided brief introductions or summaries of topics, readings, and modules. At the same time, we tried to minimize lectures and "sage on the stage" teaching models (King, 1993) to emphasize flattened classroom hierarchies. To maintain this balance, we interspersed lecture components with opportunities for class participants to share their understandings and learnings from readings through full group discussion, small group discussion, and pair-shares (see below).

Peer-to-Peer Learning

To forefront our "community of learners" ethos, in every session we balanced time spent as a whole class, in small group or pair discussions, and in individual reflection. Breakout rooms in Zoom facilitated this mix of practices. Small group activities provided the opportunity for exercising deep listening (Sangha & Bramesfeld, 2021), for which we provided explicit guidance. When placing course participants into small group breakout rooms, we were intentional that a mix of faculty, postdocs, professional staff, and graduate students were present. After breakout rooms, we held full group report backs. Keys to impactful report backs were: providing clear but participant-driven instructions on what to share back; having participants choose a group spokesperson in advance; and allocating adequate time for each group to share discussion highlights as well as time for full group conversations.

Course Assignments

Assignments served several key purposes: preparing participants for class discussion, providing an opportunity to reflect on learnings, and catalyzing Collaborative Action Projects (see below). Assignments included weekly readings and written reflections which included prompts about key takeaways from the previous week, lingering questions, and how participants might apply new learnings into their daily lives (e.g., in the lab, in the classroom, or beyond). We also held one online discussion forum per module.

Collaborative Action Projects

The closing course assignment was a Collaborative Action Project—the fruits of our theory of change tree (Figure 1)—where teams of mixed positions (faculty, students, postdocs, and staff together) developed action plans to extend beyond the end of the course. The projects, which received unanimous feedback as one of the most effective aspects of the Course, wove together pedagogy, participatory research, and activism (Freire, 2018; Hale, 2008) by enabling participants to practice change-making at the level(s) of individual labs, the department, and the college. Topics ranged from a disability justice guide to a lab-based anti-oppression plan to an anti-racist assessment of ESPM's undergraduate Food Systems Minor. (See Table 3 for all final projects from 2020 and 2021, and Box 1 for a more in-depth example). We invited groups to present in a public town hall meeting several months after the completion of the course as a way to create community accountability and check in about ongoing project progress.[8]

Iterative Course Changes

We view self-reflective iteration as fundamental to our pedagogical approach, in adherence to our view that anti-racism is a lifelong process of individual and organizational learning. During and after each semester of the Course, we committed to assessments and improvements to ensure that it was tailored to the specific needs of the class participants. As we worked through "improvement cycles" (Welton et al., 2018), we continued to evaluate how our curriculum, classroom structures, and teaching practices would best foster a non-hierarchical community of learners. We incorporated feedback from brief polls at the end of class sessions, a mid-semester evaluation, and an end-of-semester evaluation. For example, we modified reflection assignments mid-way through fall 2020 and shifted the course to a hybrid format mid-way through fall 2021, both in response to participant feedback. We also shifted the module organization and reading content for 2021 based on 2020 feedback. See Chapter 3 Appendix 1 for further details.

Discussion

The pedagogical approaches outlined above provide the roots for changemaking across multiple structural levels: from heartwood to sapwood to bark—individual to organization to institution. We understand the following five takeaways to be the key branches growing from both our pedagogical approaches and our theory of change: **(1) Centering Black voices and experiences, (2) Flattening academic hierarchies, (3) Fostering a community of learners, (4) Developing action-oriented mindsets, and (5) Sustaining long-term anti-racist praxis.** These lessons reflect not only the teaching team's own analysis, but also the feedback of participants about what they found most valuable about the course (see Supplementary Material 2 for a selection of participant comments). These five branches were essential to the Course's success, and much like we see the Collaborative Action Projects as seeding new trees of change, we believe these takeaways can also bear fruit—they can be applied to the development of similar anti-racism courses.

Centering Black Voices and Experiences

Courses on anti-racism must embed racially minoritized—especially Black—perspectives throughout the curriculum, inside classroom structures, and within teaching practices. All too often, anti-racism training seeks to appease and uplift white experiences, rather than centering racially minoritized experiences, consequently reinforcing white supremacy (Ikeda et al. 2021). For example, in the same manner that environmental racism (particularly in the United States)

[8] The first town hall, in April 2021, was attended by 75 people—the majority of the 2020 course participants, as well as other department members, Berkeley administrative leadership, and visitors from multiple environmental science departments at other universities. We also hosted a second town hall in April 2022, which featured final action projects from the 2021 course as well as follow-up presentations from groups first formed in the 2020 course.

excludes Black and other communities of color from accessing clean water, clean air, and outdoor recreation, the professional sphere of environmental sciences also excludes Black and other Scholars of Color from educational, research, and job opportunities (Masta, 2021; Tuitt et al, 2018).

When developing our anti-racist critical pedagogy, we embedded perspectives of racially minoritized scholars across guest lectures, assigned readings, and in-class activities. We dedicated an early module ("Centering BIPOC Voices," see Table 2) to centering and uplifting the knowledge and scholarship of Black environmental scientists, whose research ranged from inequities in urban green spaces to Black feminist environmentalisms. We centered Black scholars in particular to combat the anti-Black sentiments prevalent in the U.S. that violently flared up in the 2020. As whiteness is too often the norm in our academic spaces, we found this centering important to critical learning in anti-racism.

The 2020 two-way interview addressing the racialized atmosphere in academic departments was especially impactful because it centered the lived experiences of Black and Latinx scientists on our teaching team. Similarly, the two-way interview between two faculty participants, who are both first generation college students and respectively identify as Mexican American and queer, revealed how insidiously racism and the intersecting oppressions of classism and homophobia affect each aspect of the faculty experience (Stanley, 2006).

Flattening Academic Hierarchies

Our pedagogical strategies created a learning space for graduate students, faculty, postdocs, and professional staff alike. This approach recognized that any course participant, regardless of their position, can provide new and crucial insights into course topics and concepts. Graduate students, who, due to shifting demographics in graduate admissions, are more likely to embody minoritized identities than faculty members (Arbeit & Yamaner, 2021), bring valuable lived experiences and fresh perspectives. Staff bring their professional expertise as programmatic enactors of university policies and may also manage faculty-student relationships. Postdocs, who are at a crucial transitional stage between student and faculty (or other professional positions), have distinct expertise in shifting academic priorities. Lastly, faculty can contribute their in-depth knowledge of teaching, research, and power structure nuances derived from their experiences at university decision-making tables.

The mentorship module illustrated the importance of these varied perspectives. Activities in this module facilitated cross-dialogue between graduate students, postdocs, and faculty around their approaches to mentorship as well as their lived experiences and needs as mentors and mentees. Staff added a valuable birds-eye view of departmental mentorship policies and practices. These multi-positional, multi-directional dialogues between co-teacher-learners increased the Course's potential to actualize change (Jones, 2016; Posselt, 2020). This collective approach also worked to flatten hierarchies to mitigate the harm that graduate students may experience when engaging in departmental activism without access to the institutional power available to faculty (Perez et al., 2022).

Fostering a Community of Learners

Individual, organizational, and institutional change-making is an inherently relational process (Engeström, 2001; Phillips & Lawrence, 2019). Open dialogue must occur to effectively address racism, colonialism, and other intersecting forms of oppression and can only be achieved by developing a trusting community with a shared commitment to the work (hooks, 1994). Given how rarely faculty, staff, postdocs, and graduate students come together as co-learners in a classroom, our pedagogical approach sought to build relationships among course participants with varying identities and positions to subvert the power dynamics between them. To this end, we drew on community agreements and collective vulnerability to cultivate "brave" rather than "safe" spaces (Arao & Clemens, 2013), the latter of which often centers the safety of white people (Leonardo & Porter, 2010). We also employed intentional active-learning teaching methods to encourage participant interaction and collaboration. Participants frequently cited this opportunity for community-building as a major highlight of the course (see Supplementary Material 2).

Developing Action-Oriented Mindsets

All too often, a final lesson marks the end of anti-bias trainings or courses. In contrast, collective "action learning"—that is, learning-by-doing—encourages participants to apply anti-racist change mindsets beyond the classroom (Henderson, 2002). Action learning is key to broader systemic change because it combines the critical reflection of individual transformational learning with an organizational- and institutional-level focus of activity. In keeping with this learn-by-doing framework, our course featured long-term action plans as final deliverables. These projects were a major focal point of the course and provided opportunities for specific, action-oriented anti-racist interventions across multiple levels, from heartwood to sapwood to bark.

For both iterations of the Course, the Collaborative Action Projects were one of the most effective tools for change, as attested to by course participants (see Chapter 3 Appendix 2). Importantly, we emphasized that action plans developed during the semester were only the beginning; to advance their work, participants needed sustained and active engagement beyond the end of the course. To this end, we held space for concrete accountability with our town hall check-ins several months later. While some final action projects did not maintain momentum beyond the end of the course, many have continued more than two years out (see Table 3 and Supplementary Materials).

Sustaining Long-term Anti-racist Praxis

Racist ideologies are upheld by the discursive, relational, and material elements of universities as an organizational field (Phillips & Lawrence, 2019). As challengers to this dominant ideology (Fligstein and McAdam, 2012), internal change agents (Cox, 2001; Hartley et al., 1997; Patrick & Fletcher, 1998) work to cultivate a future that is more inclusive, creative, and anti-racist. This requires sustained, long-term engagement with anti-racist praxis. Academic communities are dynamic, where members range from semi-permanent (faculty and staff) to more ephemeral (graduate students and postdocs). One of the barriers to radical transformation in academia is a misalignment between the needs and timelines of different stakeholders (Jones, 2016; Kezar, 2010; Perez et al., 2022; Porter et al., 2018; Posselt, 2020). The Course created a space for these different stakeholders to come together, bond as a community, and deeply interrogate multiple interlocking academic values and structures. By cultivating community and shared action goals, we worked to realign the priorities of participants from different positions and foster collective buy-in to the anti-racist goals of the course. Together, we cultivated the tree that we hope will sustain long-term anti-racist praxis, provide the seeds for new anti-racist change efforts, and radically transform racially oppressive academic institutions. We recognize that it may take a long time for these seeds to grow into healthy ecosystems, but we are already seeing them take root.[9]

Summary

The 2020 national uprisings against anti-Black racism and police brutality highlighted the long-standing need for systemic anti-racist change, including in the academy and environmental organizations. Environmental science, as an interdisciplinary field that spans both academia and non-academic agencies and organizations, seeks solutions to environmental problems which are often racialized. However, as a discipline, environmental science largely eschews engaging with racial justice in research, education, and practice (Cronin et al., 2021; Marín-Spiotta et al, 2020; Miriti et al., 2020; Schell et al., 2020). Centering belonging, diversity, equity, justice, and inclusion in environmental research, education, and scholarship requires that current and future researchers, educators, and leaders be trained in anti-racist frameworks.

To cultivate this training, we developed a course, "Critical Engagements in Anti-racist Environmental Scholarship", that sought to advance anti-racist action in the environmental sciences, starting with our own departments. While universities maintain broad policies on diversity and inclusion—many adopted in response to the 2020 uprisings—follow-through by administration and support for faculty, staff, and students to implement these plans is opaque and often lacking (Ahmed, 2012; Berrey, 2015; Casellas Conners & McCoy, 2022; Tuitt, 2020). The goal of the Course was to move away from ad hoc efforts (e.g., one-off workshops) and instigate foundational individual (heartwood) learning and organizational (sapwood) shifts to build towards long-term institutional (bark) changes (see Figure 1).

Our goal in this article is to facilitate implementation of similar courses at other universities, which we see as one of the fruits of our tree of change. To this end, we outlined the theoretical underpinnings and pedagogical approaches of our course (the roots), including our curriculum, classroom structures, and teaching practices. To conclude, we summarized five key takeaways from the course (the branches in Figure 1)**.**

The Course clearly shaped many participants' attitudes, relationships, and commitments to anti-racist change (see Supplementary Material 2). We hope that our course incubated a community of "change agents" capable of working effectively both inside and outside of academia, at

[9] For example, by request, we have shared our syllabus for the Course over 80 times with departments across the United States and Canada and thus far have given four invited talks and workshops based on the Course.

different scales, for the long term (Cox, 2001; Hartley et al., 1997; Patrick & Fletcher, 1998). By necessity, anti-racism work is never finished, as racism and anti-Blackness are long-standing, insidious societal and structural harms. Nevertheless, through the experience of developing anti-racist praxis, our course participants are better equipped to make substantive changes at different scales and levels, including in the environmental sciences and academia.

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Figures

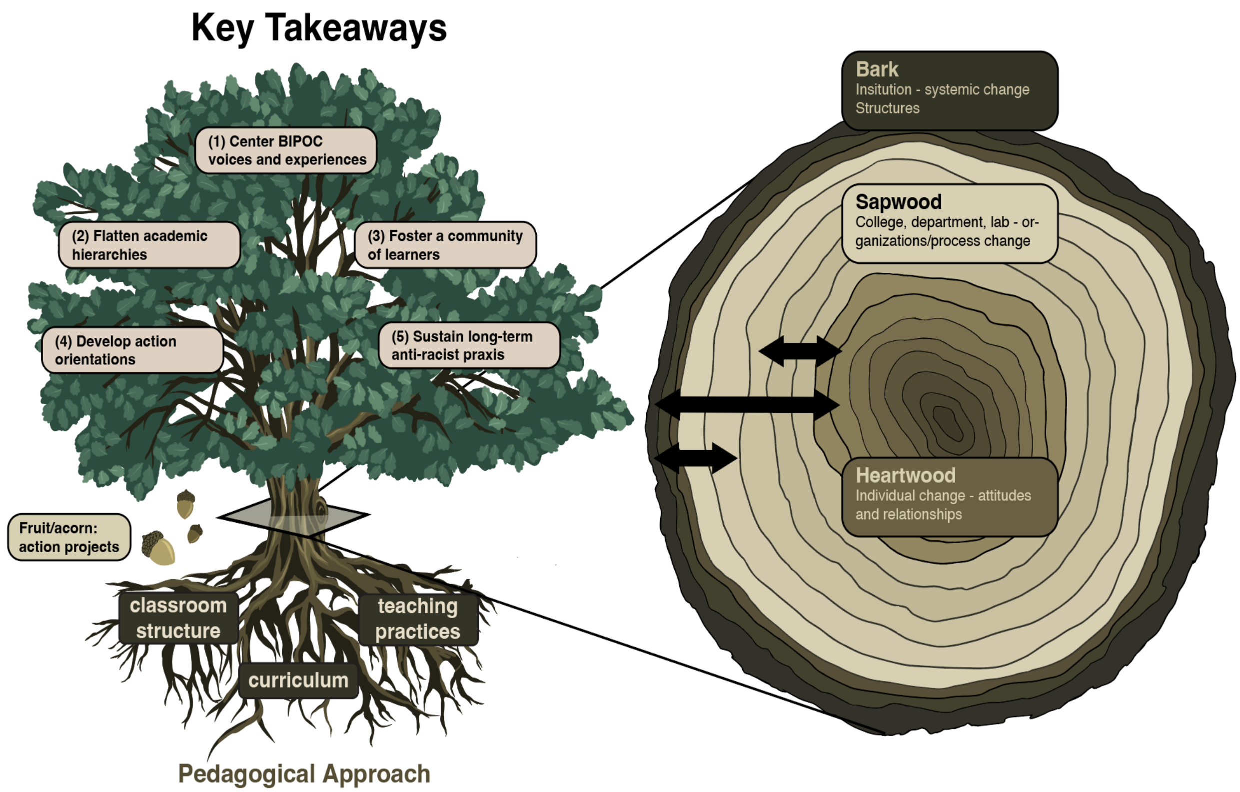

Figure 1. Theory of Change and Pedagogical Approach. We envision our anti-racist change-making as a tree. In our vision, change happens at three interdependent levels of the tree trunk's inner rings: the individual/heartwood, organizational/sapwood, and institutional/bark levels. The arrows represent flow between the levels of change. The pedagogical approach are the roots nourishing our change-making (i.e. the trunk of the tree), our key takeaways are the branches that emerge out of our change-making process, and our action (e.g., the Course's Collaborative Action Projects) are fruits and seeds of our work that may inspire more change.

Tables

Box 1. Advancing Inclusion and Anti-Racism in the College Classroom: A Rubric and Resource Guide for Instructors

In response to the 2020 graduate student letter calling for departmental action to address anti-Black racism (ESPM Graduate Diversity Council, 2020), an ESPM faculty-graduate student working group formed to create an anti-racist teaching tool entitled, "Advancing Inclusion and Anti-Racism in the College Classroom: A Rubric and Resource Guide for Instructors" (Blonder et al., 2022). The teaching tool developed in tandem with, and was informed by, the 2020 Course, with nine of the twelve tool authors participating in the Course. The tool authors also collaborated with staff at Berkeley's Center for Teaching and Learning and drew on curricular materials from the American Cultures Engaged Scholars Program.

In keeping with the Course's tenet that anti-racism is always an ongoing journey, the team designed the tool for iterative self-assessment over time. It contains sections on writing syllabi; exploring student and instructor positionality; rethinking assessments; cultivating inclusive learning environments; establishing and maintaining anti-racist norms and expectations; engaging with student feedback; and orienting curricular materials toward social justice, anti-racism and anti-colonialism. The team initially created the tool for environmental science courses, but it is widely applicable to other disciplines.

In 2021, a draft version of the teaching tool was piloted with two courses as part of another Course Collaborative Action Project, an anti-racist assessment of ESPM's undergraduate Food Systems Minor (see Table 3). In 2022, the project team received grant funding to hire several graduate students, who then worked with faculty to apply the tool to ten courses in ESPM and adjacent departments. Course changes included: creation of instructor positionality statements, new grading schemes, inclusion of more decolonial, justice-centered, and/or Indigenous perspectives in course materials, and an increase in centering of student experiences in course materials, among others.

As of February 23, 2023, this publicly-available resource has over 7,500 unique downloads. See the tool at: https://zenodo.org/record/5874656#.Y5thV-zMI6E.

Table 1: Author Positionalities
All authors are/were affiliated with the College of Natural Resources at the University of California, Berkeley. Salient identities are all in authors' own words.

Team Member	Institutional Position (Fall 2022; time of writing)	Institutional Position (Fall 2020; Y1)	Course Role (Fall 2020; Y1)	Course Role (Fall 2021; Y2)	Disciplines	Salient Identities
Whitney Mgbara	6th Year PhD Student[A]	4th Year PhD Student[A]	Teaching team / Course Development	Course development	Environmental Health and Epidemiology	Female, cis-gender, Nigerian-American
Rosalie Zdzienicka Fanshel	4th Year PhD Student[A]	2nd Year PhD Student[A]	Teaching team / Course Development	Student participant /research observer	Critical University Studies and Food Systems	Non-binary female, gay, white/Jewish, lower-working class background
Phoebe Parker-Shames	Postdoctoral Fellow[A]	5th Year PhD Student[A]	Teaching team / Course Development	Teaching team	Conservation Ecology	Female, cis-gender, queer, white/Jewish
Kenzo Esquivel	4th Year PhD Student[A]	2nd Year PhD Student[A]	Teaching team / Course Development	Teaching team	Agroecology	Male, cis-gender, queer, mixed-race (Mexican-Japanese)
Aidee Guzman	Postdoctoral Fellow[A,C]	6th Year PhD Student[A,C]	Teaching team/ Course Development / lead GSI	N/A	Agroecology	Female, cis-gender, Mexican-American, first generation
Lorenzo Washington	5th Year PhD Student[B]	3rd Year PhD Student[B]	Student participant	Course development	Plant Biology	Male, cis-gender, queer, Black mixed-race, first generation
Natasha Shannon	3rd Year PhD Student[A]	1st Year PhD Student[A]	Student participant	Course development / speaker support	Political Ecology and Critical Agrarian Studies	Female, cis-gender, white, low-income background
Damian O. Elias	Professor[A]	Associate Professor[A]	Student participant	Teaching Team	Animal Behavior and Evolutionary Biology	Male, cis-gender, Mexican-American,

						first generation

[A] Environmental Science, Policy and Management Department
[B] Plant and Microbial Biology Department
[C] Department of Ecology and Evolutionary Biology, University of California-Irvine, CA, USA

Table 2. Fall 2020 Course Modules. See Chapter 3 Appendix for Fall 2020 and 2021 syllabi.

Overall Course Vision and Learning Objectives	● Foster growth, both at the personal and community level within ESPM, in our understanding of the racist structures and cultures that exist in academia. ● Develop an anti-racist praxis around environmental scholarship. ● Uplift the voices and lived experiences of racially minoritized scholars in environmental science and adjacent fields represented in ESPM. ● Provide the tools necessary for faculty, postdocs, staff, and graduate students to act on anti-racist values to create tangible change in our community and beyond.
Module	Module Learning Objectives
1: Framing the Conversation	**Goal:** Begin building community, mutual trust, and a common working language. Get excited about learning together. Learning Objectives: ● What is the difference between an anti-racist and a non-racist? Why is it important to be an anti-racist? ● What steps can we take to practice (or learn more about) anti-racism? Preview of the work ahead. ● What is intersectionality? This class is framed around racism but recognizing how it relates to other forms of oppression.
2: Centering BIPOC Voices	**Goal:** Engage as anti-racists scholars by being open to people with different identities. Learning Objectives: ● What does it mean to center racially minoritized—specifically Black— voices? Why is it important? ● Recognize how socially constructed viewpoints of Black intelligence and competencies decenter them as learners in educational institutions. ● Describe, understand, listen to racially minoritized scholars' works, research, and/or lived experiences.
3: Advising and Mentoring	**Goal:** Identify common problems that racially minoritized (and all) graduate students encounter and provide guidelines for creating collaborative learning mentor-mentee relationships. Learning Objectives: ● How do student and faculty identities and lived experiences play out in the mentor-mentee relationship? ● Recognizing that mentees are not reservoirs for faculty ideas but rather younger colleagues.
4: Improving Academic Settings in Environmental Science A: The Lab B: Recruitment, Retention, and Department Culture C: The Classroom	**Goal:** Unpack the culture of ESPM as it relates to fostering inclusive spaces for faculty, staff, graduate and undergraduate students, and postdocs of color. Learning Objectives: ● How to create an intentionally anti-racist and inclusive culture in lab groups, department at large, and classroom.
5: Engaging in the Research Process in Environmental Science *A: Colonialism* B: Fieldwork	**Goal:** Examine how identity influences the research process and gain tools to decolonize the research process, particularly in fieldwork. Learning Objectives: ● How does the history and context of colonialism influence the goals and methods of research both in the United States and abroad? ● What role(s) do researchers play in perpetuating neo-colonialism and how do we decolonize our research? ● How is an individual's approach to fieldwork (including field safety) affected by different identities?
6: Scaling Out	**Goal:** Transgressions against racially minoritized scholars do not occur in a vacuum. Racially minoritized scholars are faced with challenging situations, ideals, and people beyond the campus and into their communities. We must address these issues within academia and beyond. How can we apply what we have learned in a broader context? Learning Objectives: ● Understand that anti-Black ideals are represented beyond academia in environmentalism and environmentalist spaces (NGOs, government agencies, industry). ● What is the importance of keeping track of the state of diversity in environmental organizations? ● How can we increase co-conspiratorship in these spaces?

Table 3. Collaborative Action Projects in 2020 and 2021

Year	Project Title	Publicly Available Link
2020	Improving Mentorship Practices module for required core graduate student class (ESPM 201A: Research Approaches in Environmental Science, Policy, and Management)	
	Berkeley Freshwater Labs Anti-Oppression Plan	https://www.youtube.com/watch?v=ByFOtru98sE
	Food Systems Minor Anti-racism Assessment	
	Interdisciplinary BIPOC Paper & Author Database (parallel project with POC In Wildlife Ecology Database)	https://docs.google.com/spreadsheets/d/14qyTDQNNnoQH6jZDwNfVePLYfaSdieTy4DZ7bQjiM4A/edit?usp=sharing
	Disability Justice Best Practices Guide	
	ESPM Graduate Student Exit Interviews	
	Indigenous Partnerships Project	
	Indigenous Science Book Club	
	Advancing Inclusion and Anti-Racism in the College Classroom	https://zenodo.org/record/5874656#.Y5uwGuzMI6E
2021	Providing Equitable Research Experience for Undergraduates	
	K-12 Outreach Project	
	Centering Equity in Plant and Microbial Biology Qualifying Exams	https://docs.google.com/document/d/1A_-7MVWf7oB0QioLbjPwcxDi7iJy8KoR/edit?usp%3Dsharing%26ouid%3D117680838385157441961%26rtpof%3Dtrue%26sd%3Dtrue
	Inclusion in Plant and Microbial Biology Seminar Series	
	Improving the Efficacy of ESPM's First Year Curriculum	
	Demystifying the Graduate School Process	https://esajournals.onlinelibrary.wiley.com/doi/full/10.1002/bes2.2029
	Assessing the Course as a Site of Organizational Change and Anti-Racist Meaning Making	

References

1. Ahmed, S. (2012). On being included: Racism and diversity in institutional life. Duke University Press.
2. Alderman, D., Narro Perez, R., Eaves, L. E., Klein, P., & Muñoz, S. (2021). Reflections on operationalizing an anti-racism pedagogy: Teaching as regional storytelling. *Journal of Geography in Higher Education*, *45*(2), 186–200. https://doi.org/10.1080/03098265.2019.1661367
3. Ames, C. (1992). Classrooms: Goals, structures, and student motivation. *Journal of Educational Psychology*, *84*(3), 261–271. https://doi.org/10.1037/0022-0663.84.3.261
4. Arao, B., & Clemens, K. (2013). From Safe Spaces to Brave Spaces. In L. M. Landreman (Ed.), *The art of effective facilitation: Reflections from social justice educators* (First edition.). Stylus Publishing.
5. Arbeit, C. A., & Yamaner, M. (2021). Trends for Graduate Student Enrollment and Postdoctoral Appointments in Science, Engineering, and Health Fields at U.S. Academic Institutions between 2017 and 2019. National Science Foundation. https://ncses.nsf.gov/pubs/nsf21317
6. Austin, A. E. (2002). Preparing the Next Generation of Faculty. *The Journal of Higher Education*, *73*(1), 94–122. https://doi.org/10.1080/00221546.2002.11777132
7. Avalos, N. (2020). Land-Based Ethics and Settler Solidarity in a Time of Corona and Revolution. *The Arrow*. https://arrow-journal.org/land-based-ethics-and-settler-solidarity-in-a-time-of-corona-and-revolution/
8. Baker, K., Eichhorn, M. P., & Griffiths, M. (2019). Decolonizing field ecology. *Biotropica*, *51*(3), 288–292. https://doi.org/10.1111/btp.12663
9. Balazs, C. L., & Morello-Frosch, R. (2013). The Three R's: How Community Based Participatory Research Strengthens the Rigor, Relevance and Reach of Science. *Environmental Justice (Print)*, *6*(1), 10.1089/env.2012.0017. https://doi.org/10.1089/env.2012.0017
10. Bang, M., Warren, B., Rosebery, A. S., & Medin, D. (2012). Desettling Expectations in Science Education. *Human Development*, *55*(5–6), 302–318. https://doi.org/10.1159/000345322
11. Barnes, B. J., & Austin, A. E. (2009). The role of doctoral advisors: A look at advising from the advisor's perspective. *Innovative Higher Education*, 297–315.
12. Berkeley Agroecology Lab. (2020, June 30). Berkeley Agroecology Lab. *Agroecology Lab*. https://nature.berkeley.edu/agroecologylab/anti-oppression/
13. Berrey, E. (2015). The Enigma of Diversity: The Language of Race and the Limits of Racial Justice. University of Chicago Press.
14. Blakeney, A. M. (2005). Antiracist Pedagogy: Definition, Theory, and Professional Development. *Journal of Curriculum and Pedagogy*, *2*(1), 119–132. https://doi.org/10.1080/15505170.2005.10411532
15. Blonder, B., Bowles, T., De Master, K., Fanshel, R. Z., Girotto, M., Kahn, A., Keenan, T., Mascarenhas, M., Mgbara, W., Pickett, S., Potts, M., & Rodriguez, M. (2022). *Advancing Inclusion and Anti-Racism in the College Classroom: A rubric and resource guide for instructors*. Zenodo. https://doi.org/10.5281/zenodo.5874656

16. Bratman, E. Z., & DeLince, W. P. (2022). Dismantling white supremacy in environmental studies and sciences: An argument for anti-racist and decolonizing pedagogies. *Journal of Environmental Studies and Sciences*. https://doi.org/10.1007/s13412-021-00739-5
17. Brown, A. L., & Campione, J. C. (1994). Guided discovery in a community of learners. In *Classroom lessons: Integrating cognitive theory and classroom practice* (pp. 229–270). The MIT Press.
18. Brune, M. (2020, July 22). *Pulling Down Our Monuments*. Sierra Club. https://www.sierraclub.org/michael-brune/2020/07/john-muir-early-history-sierra-club
19. Casellas Connors, I., & McCoy, H. (2022). Performing Anti-racism: Universities Respond to Anti-Black Violence. *Race and Justice,* 12(3), 588–613. https://doi.org/10.1177/21533687221101787
20. Chancellor's Independent Advisory Board on Police Accountability and Community Safety. (2020). *Annual Report (2019-2020)*. https://chancellor.berkeley.edu/sites/default/files/iab_annual_report_2019-20_final-2.pdf
21. Chaudhary, V. B., & Berhe, A. A. (2020). Ten simple rules for building an antiracist lab. *PLOS Computational Biology*, *16*(10), e1008210. https://doi.org/10.1371/journal.pcbi.1008210
22. Chavez, V. (Director). (2012, August 9). *Cultural Humility (complete)*. https://www.youtube.com/watch?v=SaSHLbS1V4w
23. Chu, W., Hart, M. J., Kirchner, K. N., Paton, M. J., & Black, C. J. (2022). Addressing race and diversity in graduate education: Practices from student activism. *Journal of Diversity in Higher Education*, *15*(1), 7–11. https://doi.org/10.1037/dhe0000380
24. Clancy, K. (n.d.). *Asmeret Berhe—I would choose a healthy workplace climate over anything* (May 8, 2020). https://courageous-scientist.libsyn.com/asmeret-berhe-i-would-choose-a-healthy-workplace-climate-over-anything
25. CLEAR. (2021). *CLEAR Lab Book: A living manual of our values, guidelines, and protocols* (Vol. 3). Civic Laboratory for Environmental Action Research, Memorial University of Newfoundland and Labrador. https://civiclaboratory.nl/clear-lab-book/
26. Cochran-Smith, M., & Lytle, S. L. (2009). *Inquiry as stance: Practitioner research for the next generation*. Teachers College Press.
27. Cox, M. D. (2001). 5 Faculty Learning Communities: Change Agents for Transforming Institutions into Learning Organizations. *To Improve the Academy: A Journal of Educational Development*, *19*. http://dx.doi.org/10.3998/tia.17063888.0019.008
28. Cronin, M. R., Alonzo, S. H., Adamczak, S. K., Baker, D. N., Beltran, R. S., Borker, A. L., Favilla, A. B., Gatins, R., Goetz, L. C., Hack, N., Harenčár, J. G., Howard, E. A., Kustra, M. C., Maguiña, R., Martinez-Estevez, L., Mehta, R. S., Parker, I. M., Reid, K., Roberts, M. B., … Zavaleta, E. S. (2021). Anti-racist interventions to transform ecology, evolution and conservation biology departments. *Nature Ecology & Evolution*, *5*(9), Article 9. https://doi.org/10.1038/s41559-021-01522-z
29. Dancy, T. E., Edwards, K. T., & Earl Davis, J. (2018). Historically White Universities and Plantation Politics: Anti-Blackness and Higher Education in the Black Lives Matter Era. *Urban Education*, *53*(2), 176–195. https://doi.org/10.1177/0042085918754328
30. Davis, N. R., & Schaeffer, J. (2019). Troubling Troubled Waters in Elementary Science Education: Politics, Ethics & Black Children's Conceptions of Water [Justice] in the Era

of Flint. *Cognition and Instruction*, *37*(3), 367–389. https://doi.org/10.1080/07370008.2019.1624548
31. Devine, P. G., & Ash, T. L. (2022). Diversity Training Goals, Limitations, and Promise: A Review of the Multidisciplinary Literature. *Annual Review of Psychology*, *73*, 403–429. https://doi.org/10.1146/annurev-psych-060221-122215
32. Dobbin, F., & Kalev, A. (2016, July 1). Why Diversity Programs Fail. *Harvard Business Review*. https://hbr.org/2016/07/why-diversity-programs-fail
33. Engeström, Y. (2001). Expansive Learning at Work: Toward an activity theoretical reconceptualization. *Journal of Education and Work*, *14*(1), 133–156. https://doi.org/10.1080/13639080020028747
34. Environmental Science, Policy, and Management Graduate Diversity Council. (2020, June 8). *Environmental Science, Policy, and Management Graduate Diversity Council Letter to Faculty*. https://ourenvironment.berkeley.edu/sites/ourenvironment.berkeley.edu/files/ESPM_Letter_to_Faculty%20%284%29.pdf
35. Esmonde, I., & Booker, A. N. (Eds.). (2017). Power and privilege in the learning sciences: Critical and sociocultural theories of learning. Routledge.
36. Estrada, M., Burnett, M., Campbell, A. G., Campbell, P. B., Denetclaw, W. F., Gutiérrez, C. G., Hurtado, S., John, G. H., Matsui, J., McGee, R., Okpodu, C. M., Robinson, T. J., Summers, M. F., Werner-Washburne, M., & Zavala, M. (2016). Improving Underrepresented Minority Student Persistence in STEM. *CBE Life Sciences Education*, *15*(3), es5. https://doi.org/10.1187/cbe.16-01-0038
37. Estrada, M., Eroy-Reveles, A., & Matsui, J. (2018). The Influence of Affirming Kindness and Community on Broadening Participation in STEM Career Pathways: Kindness, Community, & STEM. *Social Issues and Policy Review*, *12*(1), 258–297. https://doi.org/10.1111/sipr.12046
38. Estrada, M., Hernandez, P. R., & Schultz, P. W. (2018). A Longitudinal Study of How Quality Mentorship and Research Experience Integrate Underrepresented Minorities into STEM Careers. *CBE Life Sciences Education*, *17*(1), ar9. https://doi.org/10.1187/cbe.17-04-0066
39. Evans-Winters, V. E. (2014). Are Black Girls Not Gifted? Race, Gender, and Resilience. *Interdisciplinary Journal of Teaching and Learning*, *4*(1), 22–30.
40. Fasching-Varner, K. J., Albert, K., Mitchell, R., & Allen, C. (Eds.). (2015). *Racial battle fatigue in higher education: Exposing the myth of post-racial America*. Rowman & Littlefield.
41. Fligstein, N., & McAdam, D. (2012). *A theory of fields* (1 edition). Oxford University Press.
42. Free Radicals. (2020). *Research Justice Worksheet*. Free Radicals. https://freerads.org/wp-content/uploads/2020/06/research-justice-worksheet.pdf
43. Freire, P. (1994). Pedagogy of hope: Reliving Pedagogy of the oppressed. Continuum.
44. Freire, P. (2018). *Pedagogy of the oppressed* (50th anniversary edition). Bloomsbury Academic.
45. Garcia, A. (2020). Picking a Thousand Scabs: Coping in A-Sharp. *Journal Committed to Social Change on Race and Ethnicity*, *6*(1), 217–221. https://doi.org/10.15763/issn.2642-2387.2020.6.1.217-221

46. Giroux, H. A. (2010). Rethinking Education as the Practice of Freedom: Paulo Freire and the Promise of Critical Pedagogy. *Policy Futures in Education*, *8*(6), 715–721. https://doi.org/10.2304/pfie.2010.8.6.715
47. Giroux, H. A., & McLaren, P. (1994). Between borders: Pedagogy and the politics of cultural studies. Routledge.
48. Graves, J. L. (2019). African Americans in evolutionary science: Where we have been, and what's next. *Evolution: Education and Outreach*, *12*(1), 18. https://doi.org/10.1186/s12052-019-0110-5
49. Gray, R., & Sheikh, S. (2021, January 27). The coloniality of planting: Legacies of racism and slavery in the practice of botany. *Architectural Review*. https://www.architectural-review.com/essays/the-coloniality-of-planting
50. Griffin, K. A., Baker, V. L., & O'Meara, K. (2020). Doing, Caring, and Being: "Good" Mentoring and Its Role in the Socialization of Graduate Students of Color in STEM. In J. C. Weidman & L. DeAngelo (Eds.), *Socialization in Higher Education and the Early Career* (Vol. 7, pp. 223–239). Springer International Publishing. https://doi.org/10.1007/978-3-030-33350-8_13
51. Gutiérrez, K. D. (2008). Developing Sociocritical Literacy in the Third Space. *Reading Research Quarterly*, *43*(2), 148–164. https://doi.org/10.1598/RRQ.43.2.3
52. Hale, C. R. (Ed.). (2008). Engaging contradictions: Theory, politics, and methods of activist scholarship. University of California Press.
53. Hansson, L. (2018). Science Education, Indoctrination, and the Hidden Curriculum. In M. R. Matthews (Ed.), *History, Philosophy and Science Teaching: New Perspectives* (pp. 283–306). Springer International Publishing. https://doi.org/10.1007/978-3-319-62616-1_11
54. Harley, D. A. (2008). Maids of Academe: African American Women Faculty at Predominately White Institutions. *Journal of African American Studies*, *12*(1), 19–36. https://doi.org/10.1007/s12111-007-9030-5
55. Harris, B. N., McCarthy, P. C., Wright, A. M., Schutz, H., Boersma, K. S., Shepherd, S. L., Manning, L. A., Malisch, J. L., & Ellington, R. M. (2020). From panic to pedagogy: Using online active learning to promote inclusive instruction in ecology and evolutionary biology courses and beyond. *Ecology and Evolution*, *10*(22), 12581–12612. https://doi.org/10.1002/ece3.6915
56. Harris, M. (2017). Stories from the Front of the Room: How Higher Education Faculty of Color Overcome Challenges and Thrive in the Academy. Rowman & Littlefield Education.
57. Hartley, J., Benington, J., & Binns, P. (1997). Researching the Roles of Internal-Change Agents in the Management of Organization Change. *British Journal of Management*, *8*(1), 61. https://doi.org/10.1111/1467-8551.00040
58. Hayes, T. (2020). My Dreams Come True: An Open Letter to My Colleagues. *Rothfels Lab*. https://rothfelslab.berkeley.edu/2020/06/04/the-rothfels-lab-stands-against-racism-everywhere/
59. Henderson, G. M. (2002). Transformative Learning as a Condition for Transformational Change in Organizations. *Human Resource Development Review*, *1*(2), 186–214. https://doi.org/10.1177/15384302001002004
60. hooks, bell. (1994). Teaching to Transgress: Education as the Practice of Freedom. Routledge.

61. hooks, bell. (2003). Teaching community: A pedagogy of hope. Routledge.
62. Ikeda, R., Nham, K., Armstrong, L., Diec, F., Kim, N., Parada, D., Sanchez, D., Zhen, K., & Robinson, V. (2021). Designing for Liberation: A Case Study in Antiracism Instructional Design. *The Journal of Applied Instructional Design*, *10*(4). https://edtechbooks.org/jaid_10_4/designing_for_libera
63. Jennings, V., & Osborne Jelks, N. (2020, March 26). Reinvigorating the Dialogue on Conservation and Social Equity | Social Equity | Parks & Recreation magazine | NRPA. *Parks & Recreation*. https://www.nrpa.org/parks-recreation-magazine/2020/april/reinvigorating-the-dialogue-on-conservation-and-social-equity/
64. Jokikokko, K. (2016). Reframing teachers' intercultural learning as an emotional process. *Intercultural Education*, *27*(3), 217–230. https://doi.org/10.1080/14675986.2016.1150648
65. Jones, S. (2016). More than an intervention: Strategies for increasing diversity and inclusion in STEM. *Journal for Multicultural Education*, *10*(2), 234–246. https://doi.org/10.1108/JME-12-2015-0046
66. Kaddoura, M. (2013). Think Pair Share: A Teaching Learning Strategy to Enhance Students' Critical Thinking. *Educational Research Quarterly*, *36*(4), 3–24.
67. Kandaswamy, P. (2007). Beyond Colorblindness and Multiculturalism: Rethinking Anti-Racist Pedagogy in the University Classroom. *Radical Teacher*, *80*, 6-11,48.
68. Karpicz, J. R. (2020). "Just My Being Here is Self-Advocacy": Exploring the Self-Advocacy Experiences of Disabled Graduate Students of Color. *Journal Committed to Social Change on Race and Ethnicity*, *6*(1), 137–163. https://doi.org/10.15763/issn.2642-2387.2020.6.1.137-163
69. Kelly, A. V. (2009). The Curriculum: Theory and Practice. SAGE.
70. Kendi, I. X. (2019). *How to be an antiracist* (First Edition). One World.
71. Kezar, A. (2010). Faculty and Staff Partnering With Student Activists: Unexplored Terrains of Interaction and Development. *Journal of College Student Development*, *51*(5), 451–480. https://doi.org/10.1353/csd.2010.0001
72. Kezar, A. J. (2001). Understanding and facilitating organizational change in the 21st century: Recent research and conceptualizations. Jossey-Bass.
73. King, A. (1993). From Sage on the Stage to Guide on the Side. *College Teaching*, *41*(1), 30–35. https://doi.org/10.1080/87567555.1993.9926781
74. Kishimoto, K. (2018). Anti-racist pedagogy: From faculty's self-reflection to organizing within and beyond the classroom. *Race Ethnicity and Education*, *21*(4), 540–554. https://doi.org/10.1080/13613324.2016.1248824
75. Kohn, A., & Blum, S. D. (2020). *Ungrading: Why Rating Students Undermines Learning (and What to Do Instead)*. West Virginia University Press. https://muse.jhu.edu/book/78367
76. Ladson-Billings, G. (1998). Just what is critical race theory and what's it doing in a nice field like education? *International Journal of Qualitative Studies in Education*, *11*(1), 7–24. https://doi.org/10.1080/095183998236863
77. Lantz, M. M., Fix, R. L., Davis, B. L., Harrison, L. N., Oliver, A., Crowell, C., Mitchell, A. M., & García, J. J. (2016). Grad Students Talk: Development and Process of a Student-Led Social Justice Initiative. *Journal of Diversity in Higher Education*, *9*(3), 290–306. https://doi.org/10.1037/dhe0000033

78. Leonardo, Z., & Grubb, W. N. (2019). *Education and racism: A primer on issues and dilemmas* (Second edition). Routledge.
79. Leonardo, Z., & Porter, R. K. (2010). Pedagogy of fear: Toward a Fanonian theory of 'safety' in race dialogue. *Race Ethnicity and Education*, *13*(2), 139–157. https://doi.org/10.1080/13613324.2010.482898
80. Liboiron, M., Ammendolia, J., Winsor, K., Zahara, A., Bradshaw, H., Melvin, J., Mather, C., Dawe, N., Wells, E., Liboiron, F., Fürst, B., Coyle, C., Saturno, J., Novacefski, M., Westscott, S., & Liboiron, G. (2017). Equity in Author Order: A Feminist Laboratory's Approach. *Catalyst: Feminism, Theory, Technoscience*, *3*(2), 1–17. https://doi.org/10.28968/cftt.v3i2.28850
81. Marín-Spiotta, E., Barnes, R. T., Berhe, A. A., Hastings, M. G., Mattheis, A., Schneider, B., & Williams, B. M. (2020). Hostile climates are barriers to diversifying the geosciences. *Advances in Geosciences*, *53*, 117–127. https://doi.org/10.5194/adgeo-53-117-2020
82. Martinez-Cola, M. (2020). Collectors, Nightlights, and Allies, Oh My. *Understanding and Dismantling Privilege*, *10*(1), 61–82.
83. Masta, S. (2021). Classroom counterspaces: Centering Brown and Black students in doctoral education. *Teaching in Higher Education*, *26*(3), 354–369. https://doi.org/10.1080/13562517.2021.1894119
84. Matusov, E. (2001). Intersubjectivity as a way of informing teaching design for a community of learners classroom. *Teaching and Teacher Education*, *17*(4), 383–402. https://doi.org/10.1016/S0742-051X(01)00002-6
85. McCoy, D. L., Luedke, C. L., & Winkle-Wagner, R. (2017). Encouraged or Weeded Out: Perspectives of Students of Color in the STEM Disciplines on Faculty Interactions. *Journal of College Student Development*, *58*(5), 657–673. https://doi.org/10.1353/csd.2017.0052
86. McCoy, D. L., Winkle-Wagner, R., & Luedke, C. L. (2015). Colorblind mentoring? Exploring white faculty mentoring of students of color. *Journal of Diversity in Higher Education*, *8*(4), 225–242. https://doi.org/10.1037/a0038676
87. Miriti, M. N., Bailey, K., Halsey, S. J., & Harris, N. C. (2020). Hidden figures in ecology and evolution. *Nature Ecology & Evolution*, *4*(10), 1282–1282. https://doi.org/10.1038/s41559-020-1270-y
88. Montgomery, B. L. (2017). Mapping a Mentoring Roadmap and Developing a Supportive Network for Strategic Career Advancement. *SAGE Open*, *7*(2), 215824401771028. https://doi.org/10.1177/2158244017710288
89. Morales-Doyle, D. (2017). Justice-centered science pedagogy: A catalyst for academic achievement and social transformation. *Science Education*, *101*(6), 1034–1060. https://doi.org/10.1002/sce.21305
90. Moreau, C. S., Darby, A. M., Demery, A.-J. C., Arcila Hernández, L. M., & Meaders, C. L. (2022). A framework for educating and empowering students by teaching about history and consequences of bias in STEM. *Pathogens and Disease*, *80*(1), ftac006. https://doi.org/10.1093/femspd/ftac006
91. Museus, S. D., & Sifuentez, B. J. (2021). Toward a Critical Social Movements Studies: Implications for Research on Student Activism in Higher Education. In L. W. Perna (Ed.), *Higher Education: Handbook of Theory and Research* (Vol. 36, pp. 275–321). Springer International Publishing. https://doi.org/10.1007/978-3-030-44007-7_4

92. Mustaffa, J. B. (2017). Mapping violence, naming life: A history of anti-Black oppression in the higher education system. *International Journal of Qualitative Studies in Education*, *30*(8), 711–727. https://doi.org/10.1080/09518398.2017.1350299
93. Nejadmehr, R. (2020). *Kantian Genesis of the Problem of Scientific Education: Emergence, Development and Future Prospects*. Routledge. https://www.routledge.com/Kantian-Genesis-of-the-Problem-of-Scientific-Education-Emergence-Development/Nejadmehr/p/book/9781138393370
94. Noy, S., & Ray, R. (2012). Graduate Students' Perceptions of Their Advisors: Is There Systematic Disadvantage in Mentorship? *The Journal of Higher Education*, 83(6), 876–914. https://doi.org/10.1080/00221546.2012.11777273
95. Patrick, S. K., & Fletcher, J. j. (1998). Faculty Developers as Change Agents: Transforming Colleges and Universities into Learning Organizations. *To Improve the Academy: A Journal of Educational Development*, *17*. http://dx.doi.org/10.3998/tia.17063888.0017.014
96. Pendry, L. F., Driscoll, D. M., & Field, S. C. T. (2007). Diversity training: Putting theory into practice. *Journal of Occupational & Organizational Psychology*, *80*(1), 27–50. https://doi.org/10.1348/096317906X118397
97. Perez, R. J., Motshubi, R., & Rodriguez, S. L. (2022). "We are a huge source of labor": Exploring STEM Graduate Students' Roles in Changing Departmental Climate. *The Review of Higher Education*, *46*(1), 33–66. https://doi.org/10.1353/rhe.2022.0012
98. Pfund, C., Byars-Winston, A., Branchaw, J., Hurtado, S., & Eagan, K. (2016). Defining Attributes and Metrics of Effective Research Mentoring Relationships. *AIDS and Behavior,* 20(2), 238–248. https://doi.org/10.1007/s10461-016-1384-z
99. Phillips, N., & Lawrence, T. B. (2019). *Constructing Organizational Life: How Social-Symbolic Work Shapes Selves, Organizations, and Institutions*. Oxford University Press. https://doi.org/10.1093/oso/9780198840022.001.0001
100. Pickrell, J. (2020, March 11). Scientists push against barriers to diversity in the field sciences. *Science*. https://www.science.org/content/article/scientists-push-against-barriers-diversity-field-sciences
101. Porter, K. B., Posselt, J. R., Reyes, K., Slay, K. E., & Kamimura, A. (2018). Burdens and benefits of diversity work: Emotion management in STEM doctoral students. *Studies in Graduate and Postdoctoral Education*, *9*(2), 127–143. https://doi.org/10.1108/SGPE-D-17-00041
102. Posselt, J. R. (2020). Equity in Science: Representation, Culture, and the Dynamics of Change in Graduate Education. Stanford University Press.
103. Price, A., Bhattacharya, J., & Warren. (2020, June 18). Centering Blackness: The Path to Economic Liberation for All. *Insight Center for Community Economic Development*. https://insightcced.org/centering-blackness-framework/
104. Purdy, J. (2015, August 13). Environmentalism's Racist History. *The New Yorker*. https://www.newyorker.com/news/news-desk/environmentalisms-racist-history
105. Raby, M. (2017, June 15). The Colonial Origins of Tropical Field Stations. *American Scientist*, *105*(4). https://www.americanscientist.org/article/the-colonial-origins-of-tropical-field-stations
106. Raes, A., Detienne, L., Windey, I., & Depaepe, F. (2020). A systematic literature review on synchronous hybrid learning: Gaps identified. *Learning Environments Research*, *23*(3), 269–290. https://doi.org/10.1007/s10984-019-09303-z

107. Rhoads, R. A. (2016). Student activism, diversity, and the struggle for a just society. *Journal of Diversity in Higher Education*, *9*(3), 189–202. https://doi.org/10.1037/dhe0000039
108. Roberts-Gregory, F. (2020). Surviving Departmental Toxicity: An Autoethnographic Reflection of Navigating Gendered and Racialized Violence in Environmental Science, Policy, and Management. *Women, Gender, and Families of Color*, *8*(2), 126–133.
109. Rodríguez, D. (2012). Beyond "Police Brutality": Racist State Violence and the University of California. *American Quarterly*, *64*(2), 301–313.
110. Rogoff, B., Matusov, E., & White, C. (1998). Models of Teaching and Learning. In *The Handbook of Education and Human Development* (pp. 373–398). John Wiley & Sons, Ltd. https://doi.org/10.1111/b.9780631211860.1998.00019.x
111. Roy, R. D. (2018). *Decolonise science – time to end another imperial era*. The Conversation. http://theconversation.com/decolonise-science-time-to-end-another-imperial-era-89189
112. Rozas, L. W., & Miller, J. (2009). Discourses for Social Justice Education: The Web of Racism and the Web of Resistance. *Journal of Ethnic & Cultural Diversity in Social Work*, *18*(1–2), 24–39. https://doi.org/10.1080/15313200902874953
113. Sangha, J., & Bramesfeld, K. (2021). Using a mindfulness-based deep listening exercise to engage students in difficult dialogues about diversity, equity, and inclusion. In S. Ferguson & E. Price (Eds.), *Diversity in quantitative research: Acknowledging and contextualizing intersectionality in psychological research* (pp. 160–167). https://www.researchgate.net/profile/Sarah-Ferguson-2/publication/348339763_Diversity_in_quantitative_research_Acknowledging_and_contextualizing_intersectionality_in_psychological_research/links/5ff8d8aba6fdccdcb83ed95d/Diversity-in-quantitative-research-Acknowledging-and-contextualizing-intersectionality-in-psychological-research.pdf#page=20
114. Santas, A. (2000). Teaching Anti-Racism. *Studies in Philosophy and Education*, *19*(4), 349–361. https://doi.org/10.1023/A:1005298916161
115. Schell, C. J., Guy, C., Shelton, D. S., Campbell-Staton, S. C., Sealey, B. A., Lee, D. N., & Harris, N. C. (2020). Recreating Wakanda by promoting Black excellence in ecology and evolution. *Nature Ecology & Evolution*, *4*(10), Article 10. https://doi.org/10.1038/s41559-020-1266-7
116. Segura, D. A., Brooks, S., Shin, J. H., & Romo, L. (2011). Report of the American Sociological Association (ASA) Committee on the Status of Racial and Ethnic Minorities (SREM) in Sociology: Results of the Graduate Student Survey. Council of the American Sociological Association. https://www.asanet.org/wp-content/uploads/savvy/Final_ASA_SREM_Committee_Report_2011.pdf
117. Shelton, S. Z. (2020). Disability Justice, White Supremacy, and Harm Reduction Pedagogy: Enacting Anti-Racist Crip Teaching. *Journal Committed to Social Change on Race and Ethnicity*, *6*(1), 190–208. https://doi.org/10.15763/issn.2642-2387.2020.6.1.190-208
118. Smith, L. T. (2012). Decolonizing methodologies: Research and indigenous peoples (Second edition). Zed Books.
119. Smith, W. A., Yosso, T. J., & Solórzano, D. G. (2006). Challenging racial battle fatigue on historically White campuses: A critical race examination of race-related stress. In C.

A. Stanley (Ed.), *Faculty of color: Teaching in predominantly White colleges and universities*. Anker Publishing Company.
120. Spalter-Roth, R., Shin, J. H., Mayorova, O. V., & White, P. E. (2013). The Impact of Cross-Race Mentoring for "Ideal" PhD Careers in Sociology. *Sociological Spectrum*, 33(6), 484–509. https://doi.org/10.1080/02732173.2013.836141
121. Stanley, C. A. (Ed.). (2006). Faculty of color: Teaching in predominantly White colleges and universities. Anker Publishing Company.
122. Taylor, D. E. (2014). The State of Diversity in Environmental Organizations. 192.
123. Trisos, C. H., Auerbach, J., & Katti, M. (2021). Decoloniality and anti-oppressive practices for a more ethical ecology. *Nature Ecology & Evolution*, *5*(9), Article 9. https://doi.org/10.1038/s41559-021-01460-w
124. Tuitt, F. (2020). More Than a Hashtag: Nurturing Black Excellence in Traditionally White Institutions. *Journal of Minority Achievement, Creativity, and Leadership*, 1(2), 274–300. https://doi.org/10.5325/minoachicrealead.1.2.0274
125. Tuitt, F. H., Haynes, C., & Stewart, S. (2018). Transforming the Classroom at Traditionally White Institutions to Make Black Lives Matter. *To Improve the Academy: A Journal of Educational Development*, *37*(1), 63–76. http://dx.doi.org/10.3998/tia.17063888.0037.108
126. University of California, Berkeley Office of the Chancellor. (2019). *My Experience Survey 2019: Campus Findings and Recommendations*. University of California, Berkeley.
127. Wagner, A. E. (2005). Unsettling the academy: Working through the challenges of anti-racist pedagogy. *Race Ethnicity and Education*, *8*(3), 261–275. https://doi.org/10.1080/13613320500174333
128. Wallerstein, N., Duran, B., Oetzel, J. G., & Minkler, M. (Eds.). (2018). *Community-based participatory research for health: Advancing social and health equity* (Third edition). John Wiley & Sons, Inc., published by Jossey-Bass, a Wiley Brand.
129. Watanabe, T. (2020, July 20). UC Berkeley has a poor reputation among Black students. It's trying to change that. *Los Angeles Times*. https://www.latimes.com/california/story/2020-07-20/heres-how-uc-berkeley-is-repairing-its-reputation-as-the-worst-uc-campus-for-black-students
130. Welton, A. D., Owens, D. R., & Zamani-Gallaher, E. M. (2018). Anti-Racist Change: A Conceptual Framework for Educational Institutions to Take Systemic Action. *Teachers College Record*, *120*(14), 1–22. https://doi.org/10.1177/016146811812001402
131. Zembylas, M. (2008). Engaging With Issues of Cultural Diversity and Discrimination Through Critical Emotional Reflexivity in Online Learning. *Adult Education Quarterly*, *59*(1), 61–82. https://doi.org/10.1177/0741713608325171

Conclusion

The overall vision of my dissertation was to explore complex drivers of infectious diseases from an environmental and epidemiologic lens and provide an exemplary framework for anti-racist pedagogy in environmental science. In my dissertation, I uncovered (1) abiotic and biotic factors influencing the soil niche of the two, recognized fungal species in the *Coccidioides* genus (the soil-dwelling fungus that causes coccidioidomycosis), (2) disease dynamics of COVID-19 and its unequal impacts on communities of color, and (3) a pedagogical framework for anti-racist training and action. Specifically, the pedagogical framework aimed to create a community of change agents ready to address systemic racism in research, institutions, and individual researchers.

In my first chapter, reviewed the soil niche of *Coccidioides* species. This chapter concluded that *Coccidioides* has generally been associated with arid and semi-arid environments with characteristic climate patterns of alternating wet and dry seasons. In the soil, *Coccidioides* has been associated with porous, sandy-loam soil, with high alkalinity and pH and high levels of organic matter, including from animal-derived keratin. Beyond this, there is limited understanding of the specific soil conditions that encourage or inhibit fungal growth, spore development, and spore dispersal. This limits our ability to establish strong inference on the spatio-temporal distribution of the fungus across landscapes and regions and hinders pathogen surveillance and control strategies for coccidioidomycosis. Several critical gaps in our understanding of the *Coccidioides* soil niche remain, including the role of small mammals as potential reservoir hosts of the fungus; a broader understanding of the microbial community within which *Coccidioides* is found; and how climate and land-use change may drive shifts in the *Coccidioides* endemic range.

For my second chapter, I used a novel set of SuperLearner algorithms to assess variable importance for several cross-sectional COVID-19 outcomes. The results revealed that racial composition of counties and intensity of public transportation use therein seem to be the most important risk factors for both the initial rapid growth and subsequent high incidence of COVID-19 and help explain variations in mortality rates across counties.

There are many was to implement anti-racist practices in higher education. For my third and final chapter, I detailed the pedagogical framework for an anti-racism course. The outcome of the course was a transition of a community of learners to a community of change agents capable of working effectively both inside and outside of academia, at different scales, for the long term. This chapter provided a framework for inspiring others to design similar courses and to highlight the components that were essential to its success. Through the experience of developing anti-racist praxis, course participants will be better equipped for making substantive changes at different scales and levels. Anti-racism is essential to creating substantial transformations in the current, oppressive systems that impact environmental sciences, academia, and beyond.

While race is an outdated social construct, racism remains a pervasive reality in modern society that leads to the exclusion, marginalization, and violence against non-white people. My work shows that racism influences much of our societal infrastructure from disease dynamics e.g., transmission and health outcomes (Chapter 2) to access and training in higher education (Chapter

3). Additionally, racism influences how, where, and who is studied, and this has unequal consequences for racially minoritized communities. To move forward, it's important that we remain proactive and incorporate anti-racist mindsets, praxis, training programs, and research practices in all academic settings where necessary. Lastly, implementing anti-racist ideologies will require that we develop sustainable actions plans (Chapter 3). There is a long overdue need to integrate JEDI practices in workplaces across the country, including academia.

Chapter 2 Appendix

Materials from: Supplemental Document for the *Ensemble Machine Learning of Factors Influencing COVID-19 Across US Counties* Publication

Because of the diverse number of variables and sources of information we provide this supplementary document that explains the variable aggregation methods and gives a breakdown of the variable types and distributions. Additionally, we give metrics on the fit of each of our SuperLearners calculated through cross-validation as well as details on the heatmap presented in the main body of the manuscript.

Data Dictionary

This table gives a detail for each variable used in modeling, its source, and a descriptions:

Table S1. Variables used in modeling with sources, sub-categories and details.

Variable Name / Measure	New or generated data?	Category	Sub-category	Definition	Source
FIPS	no	identifier		FIPS code to identify geographic area (county); integer	
CountyRelativeDay25Cases	yes	outcome		Number of cumulative cases on day 25 of the outbreak by county per capita	USAFacts
TotalCasesUpToDate	yes	outcome		Number of total cumulative cases to date per capita	USAFacts
USRelativeDay100Deaths	yes	outcome		Number of cumulative deaths on day 100 of the outbreak per county per capita	USAFacts
TotalDeathsUpToDate	yes	outcome		Number of total cumulative deaths up to date per capita	USAFacts
FirstCaseDay	yes	outcome		Day of the first case starting after Jan. 21 2020	USAFacts
Population	no	demography	demography	Adjusted population size, 2020	USAFacts
GDP	no	demography	demography	Real gross domestic product (GDP) by County, 2018, from December 12, 2019 release	Bureau of Economic Analysis (BEA)
pct_female_2018	yes	demography	demography	Percentage of the population that identifies as female, 2014-2018	5-Year American Community Survey (ACS), Sex by, Age, 2014 - 2018

pct_black_only_2018	yes	demography	Ethnicity	Percentage of the population that identifies as Black or African American alone, 2014-2018	5-Year American Community Survey (ACS), Race, 2014 - 2018
pct_american_indian.alaskan_native_only_2018	yes	demography	Ethnicity	Percentage of the population that identifies as American Indian and Alaska Native alone, 2014-2018	5-Year American Community Survey (ACS), Race, 2014 - 2018
pct_asian_only_2018	yes	demography	Ethnicity	Percentage of the population that identifies as Asian alone, 2014-2018	5-Year American Community Survey (ACS), Race, 2014 - 2018
pct_hawaiian_or_pacific_islander_only_2018	yes	demography	Ethnicity	Percentage of the population that identifies as Native Hawaiian and Other Pacific Islander alone, 2014-2018	5-Year American Community Survey (ACS), Race, 2014 - 2018
pct_some_other_race_alone_2018	yes	demography	Ethnicity	Percentage of the population that identifies as Some other race alone, 2014-2018	5-Year American Community Survey (ACS), Race, 2014 - 2018
pct_2_or_more_races_2018	yes	demography	Ethnicity	Percentage of the population that identifies as two or more races alone, 2014-2018	5-Year American Community Survey (ACS), Race, 2014 - 2018
pct_hispanic_or_latino_2018	yes	demography	Ethnicity	Percentage of the population that identifies as hispanic or Latino, 2014-2018	5-Year American Community Survey (ACS), Hispanic or Latino Origin by Race, 2014 - 2018
CentroidLat	yes	geography	location	Latitude for mean position of all the points in the geometric object determined by legal boundaries for a county based on the 2019 Census Bureau's MAF/TIGER database for use with Esri's ArcGIS	TIGER/Line Geodatabases
CentroidLon	yes	geography	location	Longitude for mean position of all the points in the geometric object determined by legal boundaries for a county based on the 2019 from the Census Bureau's MAF/TIGER database for use with Esri's ArcGIS	TIGER/Line Geodatabases
NearestAirportDistance	yes	geography	airport	Distance from county centroid to the nearest airport (km)	TIGER/Line Geodatabases; Federal Aviation Administration (FAA)

NearestAirportEnplanements	yes	geography	airport	Number of enplanements for the nearest airport to the county centroid, 2018	TIGER/Line Geodatabases; Federal Aviation Administration (FAA)
NearestAirportOver5000000Distance	yes	geography	airport	Distance from county centroid to the nearest airport that has 50,000,000 or more enplanements (km)	TIGER/Line Geodatabases; Federal Aviation Administration (FAA)
NearestAirportOver5000000Enplanements	yes	geography	airport	Number of enplanements for the nearest airport to the county centroid that has 50,000,000 or more enplanements, 2018	TIGER/Line Geodatabases; Federal Aviation Administration (FAA)
AreaLand	yes	geography	geography	Area of the county geometry from 2019 tiger census shapefile (square km)	TIGER/Line Geodatabases
urban_rural_status	no	healthcare	healthcare	Number of Hospitals by county, 2017	Interactive Atlas of Heart Disease and Stroke (2014-2016)
all_stroke_deathrate	no	health	disease prev	Stroke Death Rate per 100,000, 35+, All Races/Ethnicities, Both Genders, 2016-2018	Interactive Atlas of Heart Disease and Stroke (2014-2016)
Premature.death.raw.value	no	health	disease prev	Years of potential life lost before age 75 per 100,000 population (age-adjusted)	County Health Rankings & Roadmaps
Adult.smoking.raw.value	no	health	disease prev	Percentage of adults who are current smokers.	County Health Rankings & Roadmaps
Adult.obesity.raw.value	no	health	disease prev	Percentage of the adult population (age 20 and older) that reports a body mass index (BMI) greater than or equal to 30 kg/m^2	County Health Rankings & Roadmaps
Food.environment.index.raw.value	no	health	health envir.	Index of factors that contribute to a healthy food environment, from 0 (worst) to 10 (best).	County Health Rankings & Roadmaps
Access.to.exercise.opportunities.raw.value	no	health	health envir.	Percentage of population with adequate access to locations for physical activity.	County Health Rankings & Roadmaps
Excessive.drinking.raw.value	no	health	health envir.	Percentage of adults reporting binge or heavy drinking.	County Health Rankings & Roadmaps
HIV.prevalence.raw.value		health	disease prev		
Sexually.transmitted.infections.raw.value	no	health	disease prev	Number of newly diagnosed chlamydia cases per 100,000 population	County Health Rankings & Roadmaps

Life.expectancy.raw.value	no	health	health envir.	Average number of years a person can expect to live.	County Health Rankings & Roadmaps
Food.insecurity.raw.value	no	health	health envir.	Percentage of population who lack adequate access to food.	County Health Rankings & Roadmaps
prev_2017_over_65_Alzheimer.s.Disease.Dementia	no	health	disease prev	Prevalence of Alzheimer's Disease and Related Dementia, All Fee-for-Service Beneficiaries, 2017 (%)	Centers for Medicare & Medicaid Services (CMS)
prev_2017_all_ages_Arthritis	no	health	disease prev	Prevalence of Arthritis (Osteoarthritis and Rheumatoid), All Fee-for-Service Beneficiaries, 2017 (%)	Centers for Medicare & Medicaid Services (CMS)
prev_2017_all_ages_Asthma	no	health	disease prev	Prevalence of Asthma, All Fee-for-Service Beneficiaries, 2017 (%)	Centers for Medicare & Medicaid Services (CMS)
prev_2017_all_ages_Cancer	no	health	disease prev	Prevalence of Cancer (Breast, Colorectal, Lung, and Prostate), All Fee-for-Service Beneficiaries, 2017 (%)	Centers for Medicare & Medicaid Services (CMS)
prev_2017_all_ages_Chronic.Kidney.Disease	no	health	disease prev	Prevalence of Chronic Kidney Disease, All Fee-for-Service Beneficiaries, 2017 (%)	Centers for Medicare & Medicaid Services (CMS)
prev_2017_all_ages_COPD	no	health	disease prev	Prevalence of Chronic Obstructive Pulmonary Disease, All Fee-for-Service Beneficiaries, 2017 (%)	Centers for Medicare & Medicaid Services (CMS)
prev_2017_all_ages_Depression	no	health	disease prev	Prevalence of Depression, All Fee-for-Service Beneficiaries, 2017 (%)	Centers for Medicare & Medicaid Services (CMS)
prev_2017_all_ages_Diabetes	no	health	disease prev	Prevalence of Diabetes, All Fee-for-Service Beneficiaries, 2017 (%)	Centers for Medicare & Medicaid Services (CMS)
prev_2017_all_ages_Drug.Abuse.Substance.Abuse	no	health	disease prev	Prevalence of Drug Abuse/ Substance Abuse, All Fee-for-Service Beneficiaries, 2017 (%)	Centers for Medicare & Medicaid Services (CMS)
prev_2017_all_ages_Hyperlipidemia	no	health	disease prev	Prevalence of Hyperlipidemia (High cholesterol), All Fee-for-Service Beneficiaries, 2017 (%)	Centers for Medicare & Medicaid Services (CMS)
prev_2017_all_ages_Hypertension	no	health	disease prev	Prevalence of Hypertension (High blood pressure), All Fee-for-Service Beneficiaries, 2017 (%)	Centers for Medicare & Medicaid Services (CMS)
prev_2017_all_ages_Ischemic.Heart.Disease	no	health	disease prev	Prevalence of Ischemic Heart Disease, All Fee-for-Service Beneficiaries, 2017 (%)	Centers for Medicare & Medicaid Services (CMS)

prev_2017_all_ages_Osteoporosis	no	health	disease prev	Prevalence of Osteoporosis, All Fee-for-Service Beneficiaries, 2017 (%)	Centers for Medicare & Medicaid Services (CMS)
prev_2017_all_ages_Schizophrenia.Other.Psychotic.Disorders	no	health	disease prev	Prevalence of Schizophrenia and Other Psychotic Disorders, All Fee-for-Service Beneficiaries, 2017 (%)	Centers for Medicare & Medicaid Services (CMS)
num_hospitals	no	healthcare	healthcare	Number of Hospitals by county, 2017	Interactive Atlas of Heart Disease and Stroke (2014-2016)
Uninsured.raw.value	no	healthcare	healthcare	Percentage of the population under age 65 that has no health insurance coverage	County Health Rankings & Roadmaps
Primary.care.physicians.raw.value	no	healthcare	healthcare	Number of primary care physicians per 100,000 population	County Health Rankings & Roadmaps
Preventable.hospital.stays.raw.value	no	healthcare	healthcare	Hospital discharge rate for ambulatory care-sensitive conditions per 100,000 fee-forservice Medicare enrollees	County Health Rankings & Roadmaps
Flu.vaccinations.raw.value	no	healthcare	healthcare	Percentage of fee-for-service Medicare enrollees that had an annual flu vaccination	County Health Rankings & Roadmaps
Percentage.of.households.with.overcrowding	no	housing	density	Percentage of households with overcrowding – more than 1 person per room	County Health Rankings & Roadmaps
pct_in_labor_force_employed_2018	yes	occupation	occupation	Percentage of population employed in labor force, 2014-2018	5-Year American Community Survey (ACS), Health Insurance Coverage Status and Type by Employment Status, 2014 - 2018
percent_park_access	no	physical environment	physical environment	Percentage of Population Living Within Half a Mile of a Park, 2015	Interactive Atlas of Heart Disease and Stroke (2014-2016)
Air.pollution...particulate.matter.raw.value	no	physical environment	physical environment	Average daily density of fine particulate matter in micrograms per cubic meter (PM2.5) in a county	County Health Rankings & Roadmaps
Drinking.water.violations.raw.value	no	physical environment	physical environment	Indicator of the presence of health-related drinking water violations. 0=No, 1=Yes	County Health Rankings & Roadmaps

pcp_m1	no	physical environment	physical environment	Precipitation in January 2020 (in)	National Centers for Environmental Information / National Oceanic and Atmospheric Administration (NOAA)
High.school.graduation.raw.value	no	social	education	Percentage of ninth-grade cohort that graduates in four years.	County Health Rankings & Roadmaps
Some.college.raw.value	no	social	education	Percentage of adults ages 25-44 with some post-secondary education.	County Health Rankings & Roadmaps
Unemployment.raw.value	no	social	occupation	Percentage of the civilian labor force, age 16 and older, that is unemployed but seeking work	County Health Rankings & Roadmaps
Income.inequality.raw.value	no	social	economic	Ratio of household income at the 80th percentile to income at the 20th percentile.	County Health Rankings & Roadmaps
Median.household.income.raw.value	no	social	economic	The income where half of households in a county earn more and half of households earn less.	County Health Rankings & Roadmaps
EPL_PCI	no	social	economic	Percentile per capita income estimate	CDC's Social Vulnerability Index (SVI)
EPL_AGE65	no	demography	age	Percentile percentage of persons aged 65 and older estimat	CDC's Social Vulnerability Index (SVI)
EPL_AGE17	no	demography	age	Percentile percentage of persons aged 17 and younger estimate	CDC's Social Vulnerability Index (SVI)
EPL_DISABL	no	health	disease prev	Percentile percentage of civilian noninstitutionalized population with a disability estimate	CDC's Social Vulnerability Index (SVI)
EPL_SNGPNT	no	social	economic	Percentile percentage of single parent households with children under 18 estimate	CDC's Social Vulnerability Index (SVI)
EPL_MINRTY	no	social	Ethnicity	Percentile percentage minority (all persons except white, non - Hispanic) estimate	CDC's Social Vulnerability Index (SVI)
EPL_LIMENG	no	social	Ethnicity	Percentile percentage of persons (age 5+) who speak English "less than well" estimate	CDC's Social Vulnerability Index (SVI)
EPL_MUNIT	no	social	economic	Percentile percentage housing in structures with 10 or more units estimate	CDC's Social Vulnerability Index (SVI)
EPL_MOBILE	no	social	economic	Percentile percentage mobile homes estimate	CDC's Social Vulnerability Index (SVI)
EPL_NOVEH	no	social	economic	Percentile percentage households with no vehicle available estimate	CDC's Social Vulnerability Index (SVI)

EPL_GROUPQ	no	social	density	Percentile percentage of persons in institutionalized group quarters estimate	CDC's Social Vulnerability Index (SVI)
pct_no_workers_in_household_2018	yes	social	economic	Percentage of the households with no workers, 2014 2018	5-Year American Community Survey (ACS), Household size by number of workers in household, 2014 - 2018
pct_poverty_income_ratio_under_100	yes	social	economic	Percentage of population with a ratio of income to poverty level in the past 12 months under 1.00, 2014 2018	5-Year American Community Survey (ACS), Ratio of income to poverty levels in the Past 12 Months, 2014 - 2018
pct_poverty_income_ratio_100to200	yes	social	economic	Percentage of population with a ratio of income to poverty level in the past 12 months from 1.00 to 2.00, 2014-2018	5-Year American Community Survey (ACS), Ratio of income to poverty levels in the Past 12 Months, 2014 - 2018
Driving.alone.to.work.raw.value					
pct_taking_Public_transportation_2018	yes	transit	transit	Percentage of the population with public transportation (excluding taxicab) as means of transportation to work, 2014-2018	5-Year American Community Survey (ACS), Means of Transportation to Work, 2014 - 2018
agg_commuting_by_residence_place	no	transit	transit	Residence County to Workplace County Commuting Flows by Residence	5-Year American Community Survey (ACS), Commuting Flows, 2011-2015
occ_all_federal		occupation	occupation	10 Total, all industries federal	Quarterly Census of Employment and Wages
occ_all_state		occupation	occupation	10 Total, all industries state	Quarterly Census of Employment and Wages
occ_all_local		occupation	occupation	10 Total, all industries local	Quarterly Census of Employment and Wages
occ_goods_prod		occupation	occupation	10 Total, all industries private	Quarterly Census of Employment and Wages
occ_natural_mining		occupation	occupation	101 Goods-producing	Quarterly Census of Employment and Wages
occ_construction		occupation	occupation	1011 Natural resources and mining	Quarterly Census of Employment and Wages
occ_Manufacturing		occupation	occupation	1012 Construction	Quarterly Census of Employment and Wages

occ_servic_prov		occupation	occupation	1013 Manufacturing	Quarterly Census of Employment and Wages
occ_trade_trans_util		occupation	occupation	102 Service-providing	Quarterly Census of Employment and Wages
occ_Info		occupation	occupation	1021 Trade, transportation, and utilities	Quarterly Census of Employment and Wages
occ_financial		occupation	occupation	1022 Information	Quarterly Census of Employment and Wages
occ_prof_business		occupation	occupation	1023 Financial activities	Quarterly Census of Employment and Wages
occ_educ_health		occupation	occupation	1024 Professional and business services	Quarterly Census of Employment and Wages
occ_leisure		occupation	occupation	1025 Education and health services	Quarterly Census of Employment and Wages
rep_ratio		social	demography	ratio of republican votes to total votes in 2016 election	MIT election lab
soc_assc_rate		social	density	social associates per 10k	
pct_mental_distress		social	disease prev	mental distress	
pct_insufficient_sleep		social	disease prev	no sleep	
grocery_pharmacy		transit	transit	google mobility data from x to y	Google
parks		transit	transit	google mobility data from x to y	Google
residential		transit	transit	google mobility data from x to y	Google
retailAndRecreation		transit	transit	google mobility data from x to y	Google
transitStations		transit	transit	google mobility data from x to y	Google
workplaces		transit	transit	google mobility data from x to y	Google
occ_total_all_industries		occupation	occupation	10 Total, all industries total	Quarterly Census of Employment and Wages

Statistical Breakdown of Variables Used

Table S2. Range, mean, median, standard deviation and variable type for variables used

Variable Name / Measure	Variable Type	Minimum	Maximum	Mean	Standard Deviation	Median
FIPS	Identifier	10001	56045	33139.3309	13169.53632	31170
CountyRelativeDay25Cases	Outcome	1	13869	92.7729008	518.748661	13
TotalCasesUpToDate	Outcome	1	95557	966.081679	4184.672423	109
USRelativeDay100Deaths	Outcome	0	5228	20.2358779	185.0200739	0
TotalDeathsUpToDate	Outcome	0	7171	42.7446565	288.2969229	2
FirstCaseDay	Outcome	1	148	67.9083969	17.38025651	64
Population	Predictor	625	5150233	95405.6099	258464.9638	27036.5
GDP	Predictor	26968	711974400	5743017.64	23894006.96	1084813.5
pct_female_2018	Predictor	0.21003945	0.579226911	0.49942708	0.022607205	0.50380189
pct_black_only_2018	Predictor	0	0.874122807	0.08770954	0.139326185	0.02371927
pct_american_indian.alaskan_native_only_2018	Predictor	0	0.855333658	0.01679006	0.066543522	0.00327476
pct_asian_only_2018	Predictor	0	0.252645515	0.01177309	0.019401881	0.00589667
pct_hawaiian_or_pacific_islander_only_2018	Predictor	0	0.021386093	0.00064471	0.00148338	0.00015202
pct_some_other_race_alone_2018	Predictor	0	0.570095949	0.01898913	0.035467631	0.00831348
pct_2_or_more_races_2018	Predictor	0	0.189837877	0.02268693	0.016756945	0.01920718
pct_hispanic_or_latino_2018	Predictor	0	0.990687702	0.08689204	0.133408979	0.03829681
CentroidLat	Predictor	25.04678033	48.82961587	38.4291696	4.895100602	38.6032232
CentroidLon	Predictor	-124.2152207	-67.60905949	-90.484675	10.74667917	-89.16483
NearestAirportDistance	Predictor	0.823168814	259.7738866	63.7217757	34.40582912	59.6056734
NearestAirportEnplanements	Predictor	2636	51865797	2459136.18	7337672.281	178057
NearestAirportOver5000000Distance	Predictor	2.365905464	940.4769079	237.439957	140.2947943	216.912479
NearestAirportOver5000000Enplanements	Predictor	5790847	51865797	17699825.3	12418360.15	15292670
AreaLand	Predictor	58690498	47090939040	2243334237	2886455082	1493745478
urban_rural_status	Predictor	1	4	3.47022901	0.772938108	4
all_stroke_deathrate	Predictor	27.9	180.2	76.9034525	15.46103681	75.8
Premature.death.raw.value	Predictor	0.001361519	14.85136496	0.58586235	0.902767497	0.31160837
Adult.smoking.raw.value	Predictor	0.059087195	0.41491309	0.17579878	0.034875938	0.17028337
Adult.obesity.raw.value	Predictor	0.124	0.577	0.3313771	0.051878141	0.333
Food.environment.index.raw.value	Predictor	0	10	7.53204008	1.057107542	7.7
Access.to.exercise.opportunities.raw.value	Predictor	0	1	0.62644697	0.223111815	0.65741808
Excessive.drinking.raw.value	Predictor	0.078096324	0.286237394	0.17591714	0.031203184	0.17599619
HIV.prevalence.raw.value	Predictor	0	0.248412138	0.00736452	0.014083134	0.00483243
Sexually.transmitted.infections.raw.value	Predictor	0.000125644	3.243402226	0.02185311	0.074035055	0.01104916
Life.expectancy.raw.value	Predictor	61.62562897	89.48944483	77.418201	2.770746091	77.4617427

Food.insecurity.raw.value	Predictor	0.029	0.363	0.13127405	0.038301995	0.127
prev_2017_over_65_Alzheimer.s.Disease.Dementia	Predictor	4.1825	30.4888	11.8556835	1.934830368	11.8481335
prev_2017_all_ages_Arthritis	Predictor	18.7	62.7	33.2101908	4.953532759	33.3
prev_2017_all_ages_Asthma	Predictor	1.4	11.6	4.43556586	1.125369051	4.4
prev_2017_all_ages_Cancer	Predictor	3.5	12.1	7.50248374	1.222017884	7.5
prev_2017_all_ages_Chronic.Kidney.Disease	Predictor	9.2	51.5	23.1284733	4.302205402	23.1
prev_2017_all_ages_COPD	Predictor	3.6	32.1	13.0471292	3.678299314	12.6
prev_2017_all_ages_Depression	Predictor	7.2	35.9	17.843388	3.333253322	17.8
prev_2017_all_ages_Diabetes	Predictor	8.5	49.6	27.2415267	4.714199177	27.3
prev_2017_all_ages_Drug.Abuse.Substance.Abuse	Predictor	0	16.7	3.32540462	1.671097625	3.1
prev_2017_all_ages_Hyperlipidemia	Predictor	10.3	67.6	38.6522901	8.526103848	39.9
prev_2017_all_ages_Hypertension	Predictor	28.8	74.9	57.0606489	8.143505106	58.7
prev_2017_all_ages_Ischemic.Heart.Disease	Predictor	13.9	46.9	27.1161832	5.165785826	26.8
prev_2017_all_ages_Osteoporosis	Predictor	1.1	16.6	5.43661487	1.566943886	5.3
prev_2017_all_ages_Schizophrenia.Other.Psychotic.Disorders	Predictor	0	17.5	2.73111041	1.09223365	2.6
num_hospitals	Predictor	0	48	1.39122137	2.030504115	1
Uninsured.raw.value	Predictor	0.022627241	0.337495997	0.11477122	0.052698789	0.104963
Primary.care.physicians.raw.value	Predictor	0	0.005144483	0.00053876	0.000318108	0.00049405
Preventable.hospital.stays.raw.value	Predictor	0.001008498	5.8528	0.33787854	0.499945044	0.16874969
Flu.vaccinations.raw.value	Predictor	0.07	0.66	0.42367503	0.094675985	0.44
Percentage.of.households.with.overcrowding	Predictor	0	0.169398907	0.02247575	0.017162914	0.01837327
pct_in_labor_force_employed_2018	Predictor	0.375917178	0.920989144	0.71177429	0.079392843	0.71810713
percent_park_access	Predictor	0	100	19.0835878	18.16042269	14
Air.pollution...particulate.matter.raw.value	Predictor	3	15	9.11667939	1.830299595	9.4
Drinking.water.violations.raw.value	Predictor	0	1	0.36564885	0.481703575	0
pcp_m1	Predictor	0.01	29.49	3.52638889	2.947930471	3.155
High.school.graduation.raw.value	Predictor	0.404	1	0.89007109	0.066892687	0.89946144
Some.college.raw.value	Predictor	0.151758794	0.903365627	0.5769537	0.116502609	0.5779264
Unemployment.raw.value	Predictor	0.013020833	0.132632633	0.04090638	0.013371092	0.03862468
Income.inequality.raw.value	Predictor	2.543128746	11.97063933	4.48940161	0.731134841	4.37970134
Median.household.income.raw.value	Predictor	25973	140382	52705.2481	13257.01787	50823.5
EPL_PCI	Predictor	-999	0.9997	0.11969782	19.52893859	0.49535
EPL_AGE65	Predictor	0	1	0.49607832	0.281636685	0.4893
EPL_AGE17	Predictor	0.0003	0.9997	0.49978683	0.286041997	0.504
EPL_DISABL	Predictor	0.0006	1	0.49540557	0.282012813	0.4906
EPL_SNGPNT	Predictor	0.0035	0.9997	0.49902534	0.279350547	0.49
EPL_MINRTY	Predictor	0.001	1	0.47889603	0.286503968	0.4691
EPL_LIMENG	Predictor	0	1	0.47251286	0.295415662	0.4642

EPL_MUNIT	Predictor	0	1	0.49441481	0.285252688	0.4947
EPL_MOBILE	Predictor	0	1	0.5005024	0.286942573	0.4963
EPL_NOVEH	Predictor	0	0.9997	0.4947934	0.283593037	0.5002
EPL_GROUPQ	Predictor	0	1	0.493535	0.292441641	0.4995
pct_no_workers_in_household_2018	Predictor	0.108412006	0.710758474	0.31763254	0.076205339	0.31053048
pct_poverty_income_ratio_under_100	Predictor	0.023031051	0.550965018	0.15559534	0.063928187	0.14623987
pct_poverty_income_ratio_100to200	Predictor	0.05874302	0.527681661	0.2493857	0.061402222	0.24786896
Driving.alone.to.work.raw.value	Predictor	0.060475223	0.951658768	0.80523337	0.059576755	0.81362847
pct_taking_Public_transportation_2018	Predictor	0	0.613605424	0.00845089	0.030240253	0.00319651
agg_commuting_by_residence_place	Predictor	0.162467905	0.621885522	0.42507364	0.062269901	0.42728234
occ_all_federal	Predictor	2.86589E-05	0.0112	0.00060409	0.000633156	0.00040924
occ_all_state	Predictor	1.43568E-06	0.0048	0.00058637	0.000533827	0.00045857
occ_all_local	Predictor	2.76046E-05	0.017564403	0.00145498	0.001351828	0.00106089
occ_goods_prod	Predictor	0.000219491	0.065294535	0.00535705	0.003327967	0.00443767
occ_natural_mining	Predictor	3.52558E-06	0.061036196	0.00162764	0.002512533	0.00083342
occ_construction	Predictor	0.000202491	0.02947627	0.00264463	0.001567839	0.00232076
occ_Manufacturing	Predictor	5.11274E-05	0.007529572	0.00111367	0.000573892	0.00103843
occ_servic_prov	Predictor	0.002658623	0.085833617	0.01942579	0.00727905	0.01824523
occ_trade_trans_util	Predictor	0.000715783	0.018966335	0.00582727	0.002227406	0.00535803
occ_Info	Predictor	2.19342E-05	0.003171843	0.00037287	0.000256216	0.00031025
occ_financial	Predictor	0.000147113	0.013595295	0.00214443	0.001035159	0.00195662
occ_prof_business	Predictor	0.000117536	0.027233208	0.00318709	0.001945994	0.00267935
occ_educ_health	Predictor	0.000204666	0.032647896	0.00318074	0.002368195	0.00269972
occ_leisure	Predictor	9.82608E-05	0.016111708	0.00250664	0.001455836	0.00226896
rep_ratio	Predictor	0.094605554	0.945848375	0.63884179	0.146748554	0.66530701
soc_assc_rate	Predictor	0	52.3138833	11.9612474	5.598064461	11.4234988
pct_mental_distress	Predictor	8.003230952	21.0132251	12.9909953	1.934384709	12.9401388
pct_insufficient_sleep	Predictor	23.22678619	46.70778346	33.1342874	4.018470442	33.0518716
grocery_pharmacy	Predictor	-0.68000604	0.001057082	-0.2002382	0.142066326	-0.2106614
parks	Predictor	-1.590154032	0.878284506	-0.0650332	0.555193587	0.07656297
residential	Predictor	0.316520689	0.640138931	0.438045	0.072091058	0.42706131
retailAndRecreation	Predictor	-1.707188161	-0.986106916	-1.2988005	0.183307021	-1.2733313
transitStations	Predictor	-1.989429175	-0.400483238	-1.1413261	0.386738545	-1.1984295
workplaces	Predictor	-1.405919662	-0.738900634	-1.0598425	0.144216957	-1.0742978
occ_total_all_industries	Predictor	0.004090189	0.106247869	0.02741209	0.010299583	0.02528717

Cross Validated Risk of the Estimators

Table S3. Cross-Validated Coefficients and Risk for Day of First Case Outcome

Learner	Coefficient	Mean Risk	SE Risk	Fold SD	Fold Min Risk	Fold Max Risk
Conditional Mean	0.00	326.50	16.83	21.96	303.41	354.08
Poisson Xgboost depth = 5, rounds = 100	0.08	195.00	10.83	26.21	175.12	239.99
Poisson Xgboost depth = 10, rounds = 200	0.12	201.06	11.25	22.38	181.37	234.70
Poisson Ridge Regression	0.07	203.47	11.86	18.99	181.00	230.33
Poisson Lasso Regression	0.00	227.91	29.42	59.21	185.14	331.88
Poisson Gradient Boosting Machine	0.72	177.07	9.83	15.58	165.87	203.52
Elastic Net, alpha = 0.25	0.01	210.91	18.95	38.65	179.15	274.90
Elastic Net, alpha = 0.50	0.00	220.47	24.80	51.71	179.24	306.17
Elastic Net, alpha = 0.75	0.00	224.28	28.53	60.82	178.31	327.66
SuperLearner	NA	178.00	9.98	16.26	162.74	204.02

Table S4. Cross-Validated Coefficients and Risk for Number of Cases at Day 25

Learner	Coefficient	Mean Risk	SE Risk	Fold SD	Fold Min Risk	Fold Max Risk
GLM	0.00	124.28	123.25	275.33	0.37	616.80
Conditional Mean	0.25	1.10	0.37	1.23	0.35	3.26
Ridge Regression	0.00	48.01	46.99	104.79	0.32	235.46
Elastic Net	0.00	36.60	35.58	79.28	0.32	178.42
Lasso Regression	0.00	30.88	29.86	66.49	0.31	149.79
Xgboost, nrounds = 50, depth =2, eta =0.001	0.00	54800.39	9.26	31.51	54748.31	54831.68
Xgboost, nrounds = 50, depth =4, eta =0.001	0.00	54800.39	9.26	31.51	54748.31	54831.68
Xgboost, nrounds = 50, depth =6, eta =0.001	0.00	54800.39	9.26	31.51	54748.31	54831.68
Xgboost, nrounds = 50, depth =8, eta =0.001	0.00	54800.39	9.26	31.51	54748.31	54831.68
Xgboost, nrounds = 50, depth =8, eta =0.01	0.00	22179.65	5.79	21.39	22144.36	22201.03
Random Forest, ntrees = 10	0.25	1.07	0.34	1.10	0.44	3.03
Xgboost, nrounds = 50, depth =4, eta =0.2	0.25	1.20	0.35	1.01	0.47	2.99
Xgboost, nrounds = 50, depth =4, eta =0.3	0.25	1.34	0.36	0.98	0.62	3.05
SuperLearner	NA	13.23	12.20	26.95	0.49	61.40

Table S5. Cross-Validated Coefficients and Risk for Total Cases to-date

Learner	Coefficient	Mean Risk	SE Risk	Fold SD	Fold Min Risk	Fold Max Risk
GLM	0.00	416.94	293.75	698.71	66.12	1664.87
Conditional Mean	0.00	182.98	23.67	56.45	108.74	247.13
Ridge Regression	0.13	120.26	21.51	54.20	62.28	194.47
Elastic Net	0.01	142.90	31.48	100.09	61.35	310.72
Lasso Regression	0.01	141.39	31.47	100.07	60.23	310.72
Xgboost, nrounds = 50, depth =2, eta =0.001	0.00	586264.00	387.48	1041.23	585286.52	587872.96
Xgboost, nrounds = 50, depth =4, eta =0.001	0.00	586264.00	387.48	1041.23	585286.52	587872.96
Xgboost, nrounds = 50, depth =6, eta =0.001	0.00	586264.00	387.48	1041.23	585286.52	587872.96
Xgboost, nrounds = 50, depth =8, eta =0.001	0.00	586264.00	387.48	1041.23	585286.52	587872.96
Xgboost, nrounds = 50, depth =8, eta =0.01	0.00	237383.68	240.87	704.53	236711.62	238471.76
Random Forest, ntrees = 10	0.23	110.35	20.25	43.24	71.89	180.76
Xgboost, nrounds = 50, depth =4, eta =0.2	0.32	101.36	18.00	36.39	69.40	157.70
Xgboost, nrounds = 50, depth =4, eta =0.3	0.30	113.92	18.48	35.33	78.80	168.75
SuperLearner	NA	103.72	18.92	46.89	61.26	175.62

Table S6. Cross-Validated Coefficients and Risk for Deaths at day 100

Learner	Coefficient	Mean Risk	SE Risk	Fold SD	Fold Min Risk	Fold Max Risk
GLM	0.13	0.06	0.06	0.13	0.00	0.30
Conditional Mean	0.13	0.00	0.00	0.13	0.00	0.30
Ridge Regression	0.13	0.00	0.00	0.00	0.00	0.00
Elastic Net	0.13	0.00	0.00	0.00	0.00	0.00
Lasso Regression	0.13	0.00	0.00	0.00	0.00	0.00
Xgboost, nrounds = 50, depth =2, eta =0.001	0.00	11989.94	0.18	0.00	0.00	0.00
Xgboost, nrounds = 50, depth =4, eta =0.001	0.00	11989.94	0.18	0.58	11989.25	11990.56
Xgboost, nrounds = 50, depth =6, eta =0.001	0.00	11989.94	0.18	0.58	11989.25	11990.56
Xgboost, nrounds = 50, depth =8, eta =0.001	0.00	11989.94	0.18	0.58	11989.25	11990.56
Xgboost, nrounds = 50, depth =8, eta =0.01	0.00	4852.61	0.12	0.58	11989.25	11990.56
Random Forest, ntrees = 10	0.12	0.00	0.00	0.40	4852.14	4853.04
Xgboost, nrounds = 50, depth =4, eta =0.2	0.12	0.00	0.00	0.00	0.00	0.00
Xgboost, nrounds = 50, depth =4, eta =0.3	0.13	0.00	0.00	0.00	0.00	0.00
SuperLearner	NA	0.00	0.00	0.00	0.00	0.00

Table S7. Cross-Validated Coefficients and Risk for Total Deaths to-date

Learner	Coefficient	Mean Risk	SE Risk	Fold SD	Fold Min Risk	Fold Max Risk
GLM	0.13	0.06	0.06	0.13	0.00	0.30
Conditional Mean	0.13	0.00	0.00	0.00	0.00	0.00
Ridge Regression	0.13	0.00	0.00	0.00	0.00	0.00
Elastic Net	0.13	0.00	0.00	0.00	0.00	0.00
Lasso Regression	0.13	0.00	0.00	0.00	0.00	0.00
Xgboost, nrounds = 50, depth =2, eta =0.001	0.00	11989.94	0.18	0.58	11989.25	11990.56
Xgboost, nrounds = 50, depth =4, eta =0.001	0.00	11989.94	0.18	0.58	11989.25	11990.56
Xgboost, nrounds = 50, depth =6, eta =0.001	0.00	11989.94	0.18	0.58	11989.25	11990.56
Xgboost, nrounds = 50, depth =8, eta =0.001	0.00	11989.94	0.18	0.58	11989.25	11990.56
Xgboost, nrounds = 50, depth =8, eta =0.01	0.00	4852.61	0.12	0.40	4852.14	4853.04
Random Forest, ntrees = 10	0.12	0.00	0.00	0.00	0.00	0.00
Xgboost, nrounds = 50, depth =4, eta =0.2	0.12	0.00	0.00	0.00	0.00	0.00
Xgboost, nrounds = 50, depth =4, eta =0.3	0.13	0.00	0.00	0.00	0.00	0.00
SuperLearner	NA	0.00	0.00	0.00	0.00	0.01

Table S8. Breakdown of outcome quantiles across the county dendrogram clusters

	COVID-19 Cases at Day 25				COVID-19 Cases Total to-date				Deaths at Day 100			Deaths Total to-date			
Cluster	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q1	Q2	Q3	Q4
1	9	16	67	292	5	21	64	294	40	66	278	17	24	64	279
2	213	323	320	220	202	278	364	232	532	336	208	288	265	288	235
3	193	166	129	85	192	186	141	54	356	141	76	234	158	108	73
4	254	171	104	58	265	163	84	75	454	91	42	346	124	73	44

Chapter 3 Appendix

Appendix 1: Pedagogical Approach

Here we provide more in-depth explanations of our pedagogical approach as well as a link to download the course syllabi. We include this supplementary material particularly for anyone interested in creating similar anti-racism courses.

Curriculum

The course curriculum consisted of six modules, each with learning objectives that built upon knowledge developed in prior modules. In this section, we expand on the information provided in the Main Text to outline the curriculum for the inaugural 2020 course and discuss iterative changes for the 2021 version honed through our own learning (see Main Text Table 2 for module breakdown.)

Course Modules

We began first with a module on "Framing the Conversation." Beginning with trust- and community-building was vital, because it allowed for more open, honest, and fruitful conversations around difficult topics. This initial approach fostered a shared understanding of anti-racism and a strengthened set of collective values (Rozas & Miller 2009). Drawing on our anti-racism definition, which includes an emphasis on lifelong learning, action, and critical self-reflection, we emphasized the need for individual commitment to maintaining an "inquiry as stance." Cochran-Smith and Lytle (2009) define an "inquiry stance" as "a continual process of making current arrangements problematic" (p. 121).

The second module, "Centering Black, Indigenous, and other People of Color (BIPOC) Voices," began with a "two-way interview" between two Black and Latinx graduate student members of the teaching team about their racialized experiences (see further details on this methodology under "Teaching Practices," below and in the Main Text). Next, we invited two Black scholars who had graduated from ESPM to present their work. These acts of centering sought to upend the status quo whereby the academy upholds whiteness, white experiences, and white scholarship as more legitimate and more worthy of curricular attention (Masta, 2021; Tuitt et al., 2018). Simultaneously, by welcoming and prioritizing Black personal narratives in the tradition of critical race theory (Ladson-Billings, 1998), the course gave credence and visibility to the merit of Black lived experiences as important sources of knowledge about course topics (Tuitt et al., 2018). Centering and uplifting Black voices and expertise was particularly vital for our course given that anti-racism trainings themselves all too often center at white experiences, perspectives, and subjectivities at the expense of BIPOC experiences, thereby reinforcing white supremacy (Ikeda et al., 2021).

Module 3 focused on mentorship in academia due to the critical importance of mentor-mentee relationships in helping students achieve end goals, such as degree attainment (Pfund et al., 2016). Several studies demonstrate that BIPOC students do not receive sufficient and/or adequate mentorship in comparison to their white counterparts (Noy & Ray, 2012; Segura et al., 2011; Spalter-Roth et al., 2013). Therefore, we allocated two class sessions to this module. We primarily focused on faculty as mentors and graduate students as mentees while also discussing career-long mentorship from undergraduate to faculty levels. Guest lectures, readings, and activities focused on the unique needs and experiences of students of color, particularly with white mentors (Estrada et al., 2018b; Griffin et al., 2020; Martinez-Cola, 2020; McCoy et al., 2015; McCoy et al., 2017). Course participants also engaged with potential tools (e.g., joint expectation contracts) to use in navigating mentor-mentee relationships. Additionally, an important topic discussed included the importance of micro-affirmations in mentorships (Estrada et al., 2018).

In Module 4 we homed in on key organizational structures and practices within academia. Within STEM disciplines, the individual lab is often the space that is most central to a graduate student and postdoc's development as an academic (Austin, 2002; Barnes & Austin, 2009), yet lab culture is not typically interrogated through a critical lens. We held small group discussions to work through Chaudhary & Berhe's[10] (2020) "Ten Simple Rules for Building an Anti-Racist Lab," and role-played an activity on authorship order inspired by Liboiron et al.'s (2017) "Equity in Author Order."[11] Recruitment and retention of racially minoritized faculty at Predominately White Institutions has been a topic of extensive scholarship for two decades (e.g., Fasching-Varner et al., 2015; Harley, 2008; Harris, 2017; Stanley, 2006), yet graduate students, postdocs, and even faculty-to-faculty peers rarely get an honest glimpse inside the black box of the process. Our readings (e.g., Clancy, 2020; Hayes, 2020) and classroom activities for this session highlighted the personal experience of minoritized faculty within ESPM and adjacent environmental science departments at Berkeley, demonstrating the critical race theory tradition of "counternarrative" (Ladson-Billing, 1998).

The last component of our module on academic settings focused on the classroom. Again, anti-racism in postsecondary classrooms has been the topic of decades of academic scholarship (e.g., Blakeney, 2005; hooks, 1994; Kandaswamy, 2007; Kishimoto, 2018; Santas, 2000; Wagner, 2005). Post-2020 academic work indicates renewed interest in the topic of anti-racist classrooms (e.g., Alderman et al., 2021; Blonder et al., 2022; Bratman & DeLince, 2022; Ikeda et al., 2021; Moreau et al., 2022). The classroom—with its attendant pedagogical threads of curriculum, classroom structure, and teaching practices—could easily have been the topic of a full semester-long course unto itself. Given the almost limitless directions this session could take, we used it as an opportunity to focus on the intersection of anti-racism and disability justice in the classroom (Garcia, 2020; Karpicz, 2020; Shelton, 2020). The readings and guest speaker drew from critical pedagogy, critical race theory, and critical disability studies. In the 2021 course we expanded

[10] Berhe is an ESPM alumnae.
[11] Most students and faculty in ESPM's social science division, Society and Environment, do not work in lab environments and typically produce texts with single authors or a maximum of 2–3 authors. This session on lab culture and authorship was thus most relevant to the 75% of ESPM that is in the biophysical sciences.

"the classroom" into its own 2-week module. (See Main Text Box 1 for a course action project focused on the classroom.)

Module 5 focused on colonialism in the research process (Bang et al., 2012; Gray & Sheikh, 2021; Nejadmehr, 2020; Raby, 2017; Roy, 2018; Smith, 2012). Guest lectures introduced the critical need for decolonial research to move away from racializing "settler ecologies" that degrade non-European epistemologies and dispossess Indigenous peoples of their lands (Avalos, 2020; Smith, 2012; Trisos et al., 2021). Guest panelists from ESPM also discussed the practice of community-based participatory research (Balazs & Morello-Frosch, 2013; Wallerstein et al., 2018). Activities invited participants to consider what decolonizing their own research processes might look like. We used the Free Radicals (2020) Research Justice Worksheet for participants to reflect on the political and social influences, power dynamics, and consequences of their research, and to examine their own positionality in relation to their field sites (Baker et al., 2019). Finally, we focused on anti-racist, anti-ableist, and LGBTQ+-inclusive guidelines for fieldwork (CLEAR, 2021; Pickrell, 2020).

Module 6 "Scaling Out" expanded anti-racist work beyond academia. This short but critical final module reiterated both the pervasiveness of racism in the environmental sphere and the importance of pursuing anti-racist action beyond the ivory tower. We began the module by discussing assigned readings and ended the module with group presentations for actions plans.

Classroom Structures

Reframing Authority

A strength of our course was that everyone was able to bring their unique and valuable perspectives to the conversation based on lived experiences and identity., which is key to learning about how racism, colonialism, and other systemic oppressions have informed scientific disciplines and higher education. As such, we worked to overturn the traditional academic hierarchy of "teacher(s)" and "learner(s)," which does not accurately represent the wealth of knowledge present in the classroom. Relatedly, the racist heteropatriarchy results in an academic funnel such that faculty are whiter and more male than graduate students (Estrada et al., 2016; Graves, 2019; Marín-Spiotta et al, 2020), with less expertise in engaging in anti-racist praxis and fewer racialized lived experiences to inform this work (Perez et al. 2022). In this traditional hierarchy, graduate students are usually restricted to the "learner" position. Professional staff are typically excluded from the classroom space altogether, despite having unique knowledge of strategies for navigating institutional bureaucracy. Faculty, for their part, have long-term experience in the nuances of power structures that they rarely get to share with students. By engaging in a multi-positional dialogical community of co-teacher-learners, we increased the potential for actualized change (Jones, 2016; Perez et al., 2022; Posselt, 2020).

Within the graduate student teaching team, each member contributed equally to developing the course materials, and we all showed up in the classroom itself as instructors. Each course module was rotationally led by different members of the teaching team. One team member served as lead instructor and held greater responsibility for content delivery and evaluation of assignments (and was paid as a formal graduate student instructor, inclusive of tuition and fee remission);[12] however, each session was collaboratively co-led by rotating members of the full teaching team. A faculty member served as instructor of record for the course, yet entered the classroom as a student and modeled "professor as learner" behavior for other faculty participants. Behind the scenes, the instructor of record also championed the course in administrative spaces as necessary.

The fact that ESPM is by design a highly interdisciplinary department (e.g., geography, sociology, ecology, organismal biology, data science, forestry, agroecology, etc.) helped foster what hooks (1994) calls a dialogue across boundaries "erected by race, gender, class, professional standing, and a host of other differences" (p. 130). While interdisciplinarity does not guarantee non-hierarchical classroom spaces, we could build on our collective experience in "intellectual border-crossing" (Giroux & McLaren, 1994) to subvert power dynamics in the classroom. We also knew that while we had instigated the course, we were not specialists in either anti-racist environmental science or anti-racist pedagogy and did not want to present ourselves as such. This informed our second structural approach to classroom power dynamics. From the beginning, we framed the teaching team as "non-experts" intent on learning alongside course participants. We aimed to create an overarching ethos of a "community of learners" (Brown & Campione, 1994; Matusov, 2001; Rogoff et al., 1998), which Matusov (2001) defines as a space where "the students and the teacher have collaboratively shared responsibility and ownership for guidance and learning" and "the teacher [is] a learner in a community of students who are also learners" (p. 383–84). Through iterations of the course, the intersectional identities of the teaching team shifted, and we were mindful of when the lived experiences discussed in class were not shared by the teaching team. In the 2021 course, for instance, we struggled to center Black voices without asking minoritized colleagues to take on unpaid labor. One strategy we employed was presenting existing materials from Black creators, including quotes from the readings, in-class videos, poetry, podcasts, and other media.

Designing Tasks for Active Learning

We initially designed this course entirely online because of the COVID-19 pandemic. While the remote learning environment might intuitively seem less conducive to the intimacy necessary for meaningful anti-racist dialogue, we leveraged unique elements of the online classroom to encourage vulnerable, fully-present participation. For example, extensive use of the Zoom chat function lowered barriers to engagement, fostered lively, multi-topic, simultaneous conversations in informal language (including heavy use of emojis and internet slang), and enabled continued discussion as a class and in semi-private conversations between classmates. The chat function, combined with professional captioning, also increased accessibility for non-hearing participants.[13] The remote environment further allowed for participation of those who were not physically located in Berkeley—as a result, participants who were engaged in fieldwork (who

[12] Other graduate student teaching team members received modest compensation for their work.
[13] While the chat feature enhanced accessibility overall, it should be noted that some participants might find the simultaneous use of the chat feature to be distracting or that the chat might make it difficult to focus on the speaker.

would not typically be taking classes) or otherwise living remotely during the pandemic were able to "return" to classroom learning. The privacy and structure of breakout rooms also facilitated one-on-one and small group conversations and exposed as many participants to each other as possible through intentional mixing across positions and identities. This kind of privacy is difficult to foster in a physical classroom. The online space also enabled us to invite a wide array of paid guest speakers to engage with the class from afar. In 2021, while most Berkeley courses had returned to full in-person instruction, we decided to continue with online learning to capture many of the same benefits we observed in 2020. However, we found that in 2021, as participants returned to in person activities, they were less active in the Zoom chat during class sessions and shared fewer in-depth posts in discussion forums (See Teaching Practices, below). Therefore, midway through the semester we pivoted to holding four hybrid class sessions. In the 2021 course evaluations, participants reported how meaningful it was to have the opportunity for engagement, energy, and community-building among classmates when face-to-face.[14]

Participant Evaluation and Accountability

In addition to the measures outlined in the Main Text to engage all participants in the course, we added faculty, postdocs, and staff members to the course portal in Berkeley's learning management system, Canvas, so that they accessed course materials and turned in assignments via the same structure as enrolled graduate students. In the 2020 iteration of the course, almost 100% of the 13 faculty showed up for the course with full engagement, as did postdoc and staff participants. Concerns about less motivation and participation from non-graduate student participants were a non-issue. However, in 2021, as university functions began to return in full force after the end of California's COVID-19 Shelter in Place, we had only five faculty participate in total and most were less able to fully commit as course participants.

We also attempted to mitigate tension between faculty and graduate student commitment to anti-racist work through accountability structures in the Collaborative Action Projects. Graduate student activism in STEM departments often comes at the price of students' well-being, academic success, and access to professional opportunities, and can also unintentionally promote faculty inaction (Perez et al., 2022). To counter these risks in our mixed-position course, we encouraged graduate students and postdocs to act as catalysts of change and simultaneously held faculty and staff accountable to leveraging their power and implementing those changes. However, the Course and resulting action projects continue to be predominantly graduate student-led, and we continue to strategize ways to avoid minoritized graduate students taking the most responsibility—and paying the highest costs—for anti-racist efforts.

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[14] However, it should be noted that managing a hybrid classroom brought the additional challenge of a disconnect between those attending virtually and in-person, diminishing the advantages of a virtual setting (Raes et al., 2020). Moving forward, we plan to hold the course primarily in-person, utilizing virtual settings as needed for guest speakers, as we feel that it will better align with the community-building intentions of the course.

Teaching Practices

Two-Way Participant Interviews

We conducted two separate two-way interviews in the 2020 course. The first was between two members of our teaching team in the first module, "Uplifting Our BIPOC Community," during which they described their experiences in the department from their positions as racialized graduate students. The second interview took place in the "Improving Academic Settings" module between two faculty members, with one faculty member identifying as Mexican American and a first-generation college student and the other faculty member identifying as white, LGBTQ+, and a first-generation college student. This discussion covered the interviewees' trajectories as faculty, from campus visits during their job applications to negotiating job offers to advancing through the tenure process. In 2021, instead of a two-way conversation, we hosted a conversation between five faculty members from both ESPM and Plant and Microbial Biology, with a similar "witnessing" structure from other course participants.[15]

Inclusive Selection of Guest Speakers and Topics

For sessions with guest experts, speakers presented hour-long lectures followed by ample time for questions and discussion. Inclusion of participatory, dialogical elements (Freire, 2018) in speaker presentations yielded more engaged and productive classroom discussions that were more impactful for participants. In recruiting speakers for the course, particularly for the centering module, we asked invitees to choose the topic—rather than asking for a "diversity" talk, we invited speakers to discuss their research and/or personal academic journey. We also solicited reading suggestions from guest speakers, whether from their own work or others.

Balancing Lecture and Dialogue

Class sessions started with members of the teaching team providing a brief introduction and presentation of materials relevant for a given week. This included a summary of core concepts and key terms from the readings, presentation of relevant historical information, and examples to connect specific concepts to environmental scholarship. Participants generally appreciated the quick lectures to refresh on the readings and set the stage for the remainder of the class discussion. We kept the lecture portion of class to 10–20 minutes so that the remaining time could be devoted to the pair, small group, and full group dialogue described in the Main Text (in 2020 class sessions were 80 minutes and in 2021 they were 110 minutes—even these longer sessions flew by quickly).

[15] While this was a useful way for course participants to listen to a variety of perspectives, it did not recreate the same level of intimacy. In course evaluations, 2021 participants did not highlight the panel in particular, whereas the majority of 2020 participants emphasized the power of the two-way interviews.

Peer-to-Peer Learning

In addition to the small group discussions mentioned in the Main Text, we occasionally held two-person breakout room activities to cultivate an opportunity for participants to get to know one another at a deeper level. We would also combine pair sharing with individual reflection: the whole class would first spend time individually writing a response to a prompt, and then join two-person breakout rooms where they took turns speaking and practicing deep listening (Sangha & Bramesfeld, 2021), followed by dialogue. We would then hold a full group discussion, while simultaneously respecting that personal stories would only be shared with permission of both members of a pair. This teaching strategy, known as "think-pair-share," provides participants an opportunity for self-reflection, confidence building, and cooperative knowledge generation (Kaddoura, 2013). We received feedback that for some participants this more intimate pair-sharing was one of the most impactful learning activities, while for others it could create discomfort, particularly in graduate student-faculty pairings where fears about the potential consequences of expressing vulnerability across academic hierarchy crept into the space. In future iterations of the course, we will hold affinity-based discussion opportunities by shared identity categories and academic position.

Course Assignments

We selected readings for each module to highlight a broad diversity of knowledge outside of strict academic definitions—these included peer-reviewed academic publications alongside podcasts, blog posts, poetry, and news and popular media publications. When guest lecturers were in attendance, readings were selected by the visiting lecturer and often included their own publications. The weekly reflection assignments, as described in the Main Text, were submitted without names on a Google form and only seen by the Graduate Student Instructor member of the teaching team to encourage Course participants to engage without the fear of "having everything right." In addition, at the end of each module, participants shared reflections on an online full-class discussion forum and engaged with at least 1–2 other participants' posts to encourage learning from one another. Prompts for these discussion forums changed for each module.

For all three of these assignments—readings, private reflections, online discussion forums—participant engagement and investment in the activity related directly to how worthwhile the assignments felt. Mid- and end-of-semester evaluations showed that participants greatly appreciated the readings; even when they could not complete all readings for a given week, many liked having a longer list of readings that they could revisit in the future. Participants noted that discussions of readings could have been more integrated into the class period, something we struggled to regularly incorporate into once-per-week class sessions. Individual written reflections did not work equally well for all participants, as some participants found the weekly process to be redundant. In 2020, all class participants were actively engaged in the online discussion forums, both writing long, deeply personal reflections and engaging thoughtfully with each other's posts. However, as noted above, in 2021 when most Berkeley courses were fully in-person, we found that participants were less interested in the discussion forums as a learning modality.

Collaborative Action Projects

The Action Projects enabled participants to practice change-making at the level of individual labs, the department, and the college. The six curricular module topics served as a frame for participants to envision which aspects of institutional culture and structures they wanted to address through their action projects. In the tradition of socio-cultural literacy (Gutiérrez, 2008) and justice-centered scientific pedagogy (Davis & Schaeffer, 2019; Morales-Doyle, 2017), we encouraged participants to draw on their own lived experiences in the department to identify and inform the specific topics for the action project. Midway through the semester, we provided classroom time for participants to brainstorm potential projects and solidify teams. Teams then submitted written project commitments two-thirds of the way through the semester. For the final deliverable, teams presented their in-process projects to the whole class and submitted a written plan with the project's next steps, a timeline, and a team reflection on the project's progression. Built into the assignment was the understanding that the course deliverable was only the beginning—to effectively advance departmental change, participants would need to continue to work beyond the semester. While not all projects maintained momentum beyond the structure of the course, many projects did continue and several have gone on to acquire independent funding to broaden the impact of their work. Here, faculty participation in the course created an opportunity for ongoing impact: faculty can make use of their greater institutional power to move the levers necessary for change and infuse anti-racism into existing departmental priorities. Committed faculty participation has been critical for projects that have successfully maintained momentum. Additionally, many aspects of the Action Projects were incorporated into wider efforts from faculty (e.g. ESPM faculty working groups, UC Berkeley Diversity Leadership Academy, Life Sciences DEIB initiatives).

Iterative Course Changes

Syllabus

In the 2021 iteration of the course, much of the core module structure remained the same, with some reshuffling to organize and differentiate anti-racism priorities in department, classroom, and research settings more clearly. Specifically, conversations about retention and department culture were moved to the mentoring module, the section on classroom environments became its own expanded module, and we incorporated discussions of lab environments into the research process module. Because the second iteration of the course included participants from two UC Berkeley departments—ESPM and Plant and Microbial Biology—we tailored relevant readings and guest speakers to better cater to both groups. For example, the "centering" module in 2021 included a Plant and Microbial Biology alum guest speaker, and readings on colonialism and the research process shifted to include botanical literature. We also updated readings and classroom resources across the syllabus to reflect new scholarship and up-to-date contexts, both within and outside academia.

Mid-Semester Course Evaluations

Throughout the semester, we created opportunities for participants to provide feedback so that we might adjust how the course was structured to best meet participant needs. For example, after the mid-semester evaluation, we gave participants the option to discuss readings during office hours in lieu of submitting individual weekly reflections. We also incorporated changes based on feedback from the first year for the second iteration: this included expanding and contracting certain modules, shortening required reading lists, and beginning work on final action plans earlier in the semester.

Funding

In 2020, the course Graduate Student Instructor (GSI) was funded through the College of Natural Resources Office of the Dean and guest speakers were funded through the Office for Graduate Diversity. ESPM provided modest awards to the full teaching team to recognize their work in developing and co-teaching the course. In 2021, ESPM provided funding but it was not adequate for course team course development and a full GSI. We experimented with dividing development and teaching between two teams, rather than five teaching team members working simultaneously. One team of three graduate students worked on pre-semester course development and then handed off course delivery responsibility to a team of two graduate students and a faculty member. All teaching team members had either co-taught in 2020 or taken the 2020 version of the course, including the faculty team member (see Main Text Table 1 for details). In this configuration, the faculty member was more active in co-leading the course. Because this structure more resembled traditional classroom authority, we held frequent discussions throughout the teaching process to resist the reintroduction of academic hierarchies.

Cross-Positional Participant Engagement

In both years, we were cognizant of the ways in which member positionalities and identities influenced inter-team relationships as well as teaching team-class participant relationships. Moving forward, we continue to reflect and adapt with the orienting goal of flattening academic hierarchies. Importantly, we are pursuing ways to provide institutional incentives for non-graduate student course participants. For example, we plan to frame participation as long-form professional development—with the hope that course participation fits within the tenure and promotion structures or requirements—to increase course buy-in and engagement from those not receiving units as enrolled students. We are also navigating how to best facilitate in-person community building in future course iterations. Importantly, we will continue to incorporate participant feedback and lessons learned in our preparation for future iterations of this course.

Download the full syllabi for the 2020 and 2021 iterations of the Course at:
https://docs.google.com/forms/d/e/1FAIpQLSf16pl2SDKLRZ0rMkweWjE6LUugu0ayk6qLqsfcIiCuStcVCw/viewform?usp=sf_link

Appendix 2: Sample Participant Feedback from Course Evaluations

The quotes below are representative of repeated themes articulated in the midpoint and end of semester anonymous course evaluation surveys.

Overall Course Impact

Participants reflected on the potential for lasting impact from the course:
- "One of the most inspiring things I have done in my 25-year career."
- "This was an incredible experience- and I **wish that all members of the community can take this class** (and repeat it every several cycles of learning). This is a class which I hope we can teach every semester (sometime soon), as there are so many items to discuss, and so many students, faculty, staff, and postdocs interested in doing this work."
- "The entire teaching team...made profound contributions and the course was one of the very best organized that I have taken or participated in during my life. They all brought their different experiences and perspectives into the class [and] did a phenomenal job of facilitating the classes. It was a learning journey for you all—**you managed to create a course that will have a lasting impact on ESPM."**

Curriculum

Participants gained competencies in course materials and the confidence to put them to immediate use:
- "**Micro-affirmations**—something that **I can use right away** with my lab, mentees and students. The importance of mentoring and understanding each mentee's positionality and intersectionality—mentoring seems to be a foundational block on which much anti-racism work is built."
- "I learned a great deal about what "centering" actually means and a great deal about the ways in which racism shows up specifically in academia. I feel that **I have a better understanding of the ways in which race and racism intersect with the challenges of mentoring, fieldwork, and the entire research process**. I also feel better equipped to confront these challenges and racial injustices, having been given the tools to articulate the problems...and hope for changing them…. I also know from this class that anti-racism is an ongoing journey that is at once incredibly personal and incredibly structural in nature…. I have a long way to go in this journey, but I feel like this class has provided a solid, comprehensive foundation from which to build on."
- "I gained a more **nuanced perspective on what anti-racism is and how settler colonialism persists in our institutions and culture to date**. Broadly allowing me to better frame critiques of various systems (academia, carceral, etc.) and develop/understand efforts that can be decolonizing. Specifically, I have a much more informed perspective on how racist/colonial/white supremacist/exclusionary ideals and systems have persisted in academia and the field of environmental studies. This perspective also **lends itself to developing tangible (both in short and long-term) ways** that I and elements of the institution around me can work to be anti-racist and decolonial

in our actions. **This notably includes methods that make for a more engaging and effective educational and research environment."**

Classroom Structures

Participants expressed **a strengthened sense of community** as a result of the course:

- "I also really appreciated and found valuable the interactive aspect of the class and the discussions in sub-groups to deepen my understanding and share my own reflections and ideas. This course allowed ESPM members to get to know each other more, **and it created a sense of community within the department, which was missing in my personal experience."**
- "[The teaching team was] phenomenal. The care, labor, and expertise you brought to the work of planning and facilitating were fully evident. **You created a wonderful structure for learning that both built community and relationships while meeting the learning needs and styles of a diverse student group."**

Teaching Practices

Participants found the two-way interviews to be a particularly effective teaching practice:

- "[The two graduate students in conversation] were role models in terms of centering themselves and being allies to each other. I can learn from that."
- "I like the dynamic that has been created when we are listening to two or more people engage in conversation…It was especially powerful to hear two faculty members grapple with discriminatory practices in their own careers; hearing about their struggles and frustrations seemed to help folks be more open and vulnerable in breakout rooms."