AGU PUBLICATIONS

GeoHealth

RESEARCH ARTICLE

10.1002/2016GH000033

Key Points:

- Incidence of cocci is inversely related to soil moisture levels in previous years
- A combination of modeled and observed soil moisture is now available through the U.S. Climate Reference Network
- The diagnostic soil moisture equation is used to extend historical records in Arizona and California

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Citation:
Coopersmith, E. J., J. E. Bell, K. Benedict, J. Shriber, O. McCotter, and M. H. Cosh (2017), Relating coccidioidomycosis (valley fever) incidence to soil moisture conditions, *GeoHealth*, *1*, 51–63, doi:10.1002/2016GH000033.

Received 21 NOV 2016
Accepted 20 FEB 2017
Accepted article online 6 MAR 2017
Published online 25 MAR 2017

Relating coccidioidomycosis (valley fever) incidence to soil moisture conditions

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Abstract Coccidioidomycosis (also called Valley fever) is caused by a soilborne fungus, *Coccidioides* spp., in arid regions of the southwestern United States. Though some who develop infections from this fungus remain asymptomatic, others develop respiratory disease as a consequence. Less commonly, severe illness and death can occur when the infection spreads to other regions of the body. Previous analyses have attempted to connect the incidence of coccidioidomycosis to broadly available climatic measurements, such as precipitation or temperature. However, with the limited availability of long-term, in situ soil moisture data sets, it has not been feasible to perform a direct analysis of the relationships between soil moisture levels and coccidioidomycosis incidence on a larger temporal and spatial scale. Utilizing in situ soil moisture gauges throughout the southwest from the U.S. Climate Reference Network and a model with which to extend those estimates, this work connects periods of higher and lower soil moisture in Arizona and California between 2002 and 2014 to the reported incidence of coccidioidomycosis. The results indicate that in both states, coccidioidomycosis incidence is related to soil moisture levels from previous summers and falls. Stated differently, a higher number of coccidioidomycosis cases are likely to be reported if previous bands of months have been atypically wet or dry, depending on the location.

1. Introduction

Coccidioidomycosis is caused by the fungus *Coccidioides* spp., which is found in the soils of the southwestern United States, south central Washington State, and regions of South America, Central America, and Mexico. This disease can cause flu-like symptoms, which can persist for weeks or even months. In a minority of cases, the infection can lead to pulmonary complications or spread from the lungs to other organ systems, leading to conditions of greater severity, such as meningitis [*Rosenstein et al*., 2001; *Galgiani et al*., 2005] or death [*Kolivras et al*., 2001; *Huang et al*., 2012]. Though inhalation of these spores does not always cause illness, those who do become ill are hospitalized in over 40% of cases, with 75% of patients unable to perform their normal daily activities for a median of 47 days [*Tsang et al*., 2010].

Previous research has noted relationships between climatic features for which data are widely available and the incidence of coccidioidomycosis, noting proposed hydroclimatic and biological mechanisms by which these infections occur. *Kolivras and Comrie* [2003], focusing their study upon Pima county in Arizona, hypothesized that a dry foresummer or fall kills other microorganisms that might compete with *Coccidioides*. Subsequently, winter rainfall leads to the spore formation that results in high incidence during the following year. A subsequent analysis by *Comrie* [2005] also addressed the seasonal patterns of precipitation and temperature as they relate to the reported cases of coccidioidomycosis. They, too, noted that precipitation during the preceding year's summer or even the summer from 2 years previous is inversely related to reported cases of coccidioidomycosis. This "grow and blow" hypothesis, in which wetter conditions cause spore formation and drier conditions facilitate their distribution, is corroborated in *Tamerius and Comrie* [2011], where fall precipitation is correlated with exposures during the subsequent year. Other works attempted to locate the ecological niche for *Coccidioides* within the arid Southwest [*Baptista-Rosas et al*., 2007] using soil characteristics and other features, including moisture. Finally, *Stacy et al.* [2012] employed normalized difference vegetation index as a proxy for soil moisture, showing antecedent winter precipitation's impact on incidence during the following year.

Unfortunately, in none of these cases were soil moisture data available in sufficient temporal and spatial scope to allow a more direct analysis—the effects of soil moisture on coccidioidomycosis incidence. Three

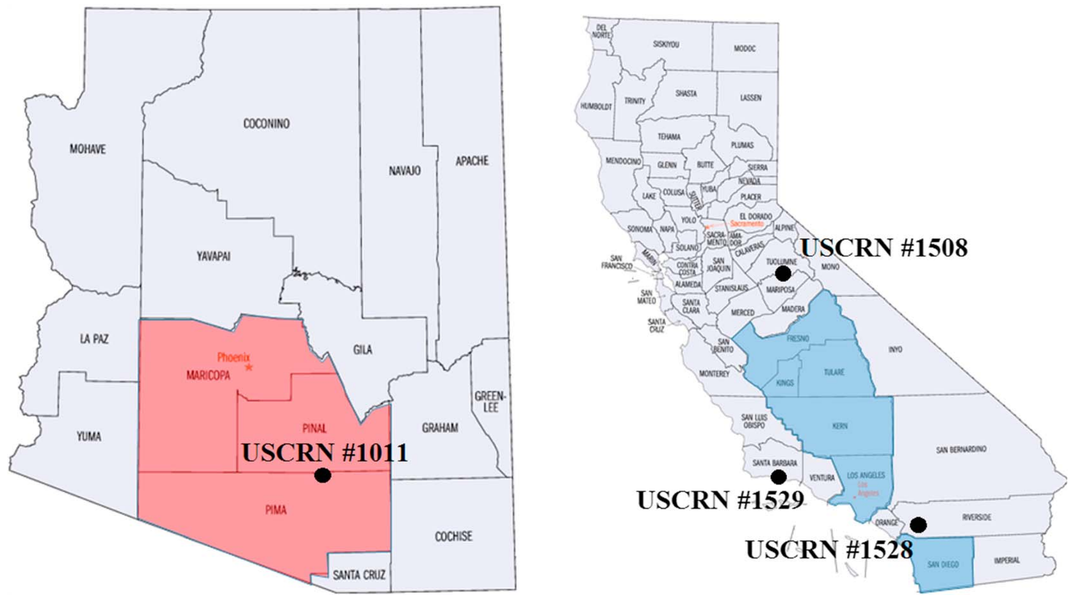

Figure 1. (U.S. Climate Reference Network) USCRN soil moisture gauges within county maps of (left) Arizona and (right) California. Counties with sufficient reported coccidioidomycosis cases in Arizona and California are shaded red and blue.

figures from some of the works cited within the literature review are worth mentioning. Figure 5 from *Kolivras et al*. [2001] presents bimodal annual precipitation patterns in Arizona along with the annual pattern of valley fever incidence. This figure illustrates that the monthly precipitation pattern in Pima county, AZ, does not describe (at least in large part) the pattern of coccidioidomycosis incidence. Figures 1 and 2 from *Comrie* [2005] illustrate, in the same county, annual and monthly precipitation patterns that do not align with coccidioidomycosis incidence rates. As a result, soil moisture data provide an additional layer of insight to the analysis. However, in addition to precipitation gauges at U.S. Climate Reference Network (USCRN) [*Bell et al*., 2013; *Diamond et al*., 2013] locations in California and Arizona (Figure 1), an in situ record has become available after 2010. Moreover, USCRN sites contain colocated precipitation instruments. Many of these instruments predate the installation of soil moisture gauges by several years, facilitating the calibration of a precipitation driven soil moisture model (the diagnostic soil moisture equation) [*Pan et al*., 2003; *Pan*, 2012] that can be used to achieve two objectives. The first is to extend the soil moisture record backward temporally to the original installation of precipitation sensors—this was done in *Coopersmith et al*. [2015a]. Second, by generating such a model, gaps in the soil moisture record (e.g., a day when a sensor was damaged by ambient meteorological conditions and a period during which readings were not recorded) can be filled with the model's estimate. As a result, a longer, more robust soil moisture record in Arizona and California is now available, enabling the types of direct comparisons not previously plausible with earlier in situ sensory resources.

2. Methodology

2.1. Defining the Coccidioidomycosis Data Set

Coccidioidomycosis is currently a reportable disease in 22 states and is nationally notifiable to the U.S. Centers for Disease Control and Prevention through the National Notifiable Diseases Surveillance System (NNDSS). We used the number of monthly coccidioidomycosis cases reported to NNDSS, by county, in Arizona and California during 2000–2014 to facilitate appropriate comparisons to determine robust relationships between soil moisture conditions and coccidioidomycosis. We normalized the numbers of reported cases by the populations of the counties in which those cases are reported. In California, 2000 and 2010 county census estimates are publically available from http://censusviewer.com/counties/CA. The 2014 population figures by county can be obtained from http://quickfacts.census.gov/qfd/maps/california_map.html. For years between 2000 and 2010 or between 2010 and 2014, a linear interpolation was performed.

Table 1. Incidence of Coccidioidomycosis per 1,000,000 Residents, Selected Counties in Arizona and California (2000–2014)

Year	# of Reported Cases per 1,000,000 Residents (Arizona)	# of Reported Cases per 1,000,000 Residents (California)
2000	460.5306325	89.48572189
2001	503.6564143	189.9703495
2002	635.5023968	239.6480424
2003	487.4520426	309.3800018
2004	723.4897709	367.8734306
2005	679.2749888	556.5844856
2006	997.392081	1045.732803
2007	914.9692501	619.8972283
2008	844.526981	700.8052481
2009	1656.425735	829.5482692
2010	1825.660079	1267.326671
2011	2420.537466	1045.615295
2012	1999.852074	775.0142713
2013	1012.168952	328.2901243
2014	982.4871174	248.2403409

The linear interpretation was performed for every year and county in California for which reported cases of coccidioidomycosis were available, and in analogous fashion for Arizona (data are available from and http://censusviewer.com/counties/AZ and http://quickfacts.census.gov/qfd/maps/arizona_map.html, respectively). From here, we converted every monthly county estimate as shown in equation (1):

$$\text{normalized\_}VF_{c,m,\,y} = \frac{VF_{c,\,m,\,y}}{P_y} * 1,000,000. \quad (1)$$

In equation (1), $VF_{c,m,\,y}$ signifies the reported cases of coccidioidomycosis in a given county during a given month of a given year, P_y denotes the estimated population during that year, and normalized_$VF_{c,m,y}$ represents the number of cases reported per one million residents.

Counties with small populations and few reported cases can skew results. For this reason, counties in which the averages of reported coccidioidomycosis cases did not exceed 10 per month were excluded from subsequent analysis. The resulting subset of data included three counties in Arizona (Pima, Pinal, and Maricopa) and six counties in California (Fresno, Kern, Kings, Los Angeles, San Diego, and Tulare).

A long-term annual trend, more specifically an overall increase in coccidioidomycosis incidence (until 2012—incidence falls thereafter), has been noted in Arizona and California during the time period in question [*Centers for Disease Control and Prevention*, 2003, 2009]. It is worth noting that changes in laboratory testing and reporting practices occurred during this time [*Centers for Disease Control and Prevention*, 2013]. In Table 1, we observe a positive annual trend in coccidioidomycosis incidence in the selected counties in both California (blue) and Arizona (red). Before performing subsequent analysis, these data are once again detrended to ensure that the changes observed in reported cases of coccidioidomycosis are related to soil moisture patterns rather than the consequence of long-term trends.

First, we present a simple, linear model for an annual trend in reported cases of coccidioidomycosis.

$$\text{normalized\_}VF_y = \beta_0 + \beta_1 y. \quad (2)$$

In equation (2), normalized_VF_y denotes the population-normalized number of reported cases of coccidioidomycosis in year y, while β_0 and β_1 represent the coefficients describing intercept and slope, respectively. Two relationships were developed of this form, one for Arizona and another for California. Continuing, for each county, for each month, within a year y, the number of annual reported cases was normalized as shown:

$$\text{detrended\_}VF_{c,m,y} = \frac{\text{normalized\_}VF_{c,m,y}}{\beta_0 + \beta_1 y} * \frac{\sum_{i=2000}^{2013} \text{normalized\_}VF_i}{14}. \quad (3)$$

In equation (3), the detrended value for coccidioidomycosis cases reported (already normalized for population, see equation (1)) is denoted by detrended_$VF_{c,m,y}$, obtained by dividing the population-normalized value for reported cases of coccidioidomycosis, normalized_$VF_{c,m,y}$ by the expected total for the year in question, subsequently multiplied by the average annual, population normalized total between 2000 and 2013, $\frac{\sum_{i=2000}^{2013} \text{normalized\_}VF_i}{14}$.

2.2. Defining the Corresponding Soil Moisture Data Set

With soil moisture playing an increasingly important role in precision agricultural decision support [*Coopersmith et al*., 2014a], complex hydrologic models [e.g., *Grayson et al*., 1997; *Bell et al*., 2010], drought monitoring [e.g., *Sheffield et al*., 2004; *Bell et al*., 2015], and General Circulation Models [e.g., *Koster and Milly*, 1997; *Belair et al*., 2005; *Campoy et al*., 2013; *De Rosnay et al*., 2013; *Joetzjer et al*., 2013], the availability of in situ soil moisture resources has increased dramatically in the past decade. As discussed in the previous section, an in situ network, the U.S. Climate Reference Network (USCRN), formed the basis of this inquiry [*Diamond et al*., 2013; *Bell et al*., 2013]. USCRN provides quality controlled soil moisture and precipitation measurements at multiple for locations across the United States. USCRN soil moisture measurements are produced in triplicate at each recorded depth (5 cm, 10 cm, 20 cm, 50 cm, and 100 cm). For the purpose of this study, only the 5 cm soil moisture measurement was used, as this depth corresponds best with the capacity of dust particles to become airborne. Please review the descriptions in *Bell et al*. [2013] for more specific information about the operation, quality assurance/quality control procedures, and logistics of the USCRN soil instrumentation.

As the soil moisture gauges contain colocated precipitation instruments, it is possible to calibrate models that transform a time series of antecedent precipitation into a soil moisture time series. One such model, developed by *Pan et al*. [2003] and subsequently updated by *Pan* [2012], is the diagnostic soil moisture equation. As a simple, lumped-bucket model, this equation convolutes the antecedent precipitation series and, via six parameters that can be calibrated via a genetic algorithm [*Coopersmith et al*., 2014b], returns a soil moisture estimate as shown in equations (4) and (5).

$$\theta_{\text{est}} = \theta_{\text{re}} + (\phi_e - \theta_{\text{re}})\left(1 - e^{-c_4\beta}\right) \tag{4}$$

$$\beta = \sum_{i=2}^{i=n-1} \left[\frac{P_i}{\eta_i}\left(1 - e^{-\frac{\eta_i}{z}}\right)e^{-\sum_{j=1}^{j=i-1}\left(\frac{\eta_j}{z}\right)}\right] + \frac{P_1}{\eta_1}\left(1 - e^{-\frac{\eta_1}{z}}\right). \tag{5}$$

In equation (4), θ_{est} represents the model's soil moisture estimate via three parameters (θ_{re}, ϕ_e, and c_4). Those three parameters signify the residual soil moisture (the level below which moisture levels will not fall, even after prolonged absences of precipitation), the porosity (the maximum quantity of moisture the soil can hold when saturated), and a drainage rate (note that a soil with $c_4 = 0$ drains infinitely rapidly, returning instantly to θ_{re}, a soil where c_4 is large drains extremely slowly, remaining at ϕ_e in perpetuity). The "beta series," β, in equation (5), convolutes an exponentially decaying series of precipitation totals, P_i, over a series of receding time stamps, *i,* from 1 to *n* (the maximum temporal distance at which rainfall can be considered relevant—that is, we ignore rainfall occurring farther back in time than *n* hours). The prediction depth is signified by *z*, and the "eta series," η_i, a sinusoidal estimate with a period of 1 year defining moisture losses due to evapotranspiration and deep drainage. The eta series contains the remaining three parameters, defining the sinusoid's amplitude, horizontal, and vertical shift (its period is known to be 1 year). For further information regarding the calibration of these models and their implementation, please review the original literature [*Pan et al*., 2003; *Pan,* 2012] or the literature describing their more recent, machine learning-based updates in *Coopersmith et al*. [2014b].

Parameters calibrated in this manner are shown to be viable for modeling soil moisture in other locations, provided that those locations are hydroclimatically and texturally similar to the calibration site *Coopersmith et al*. [2014b]. Although the USCRN soil moisture gauges sites included in this analysis are not perfect edaphic matches for included counties, given the arid climate of the American southwest, perfunctory similarity will suffice. In turn, these models have been used to extend the soil moisture records at these sites back to the initial installation of precipitation instruments [*Coopersmith et al*., 2015a] or to validate the performance of remotely sensed satellite estimates [*Coopersmith et al*., 2015b]. For the purposes of this analysis, these modeled estimates will allow us to consider the performance of two related soil moisture time series in estimating future reported cases of coccidioidomycosis. The first series denotes the modeled estimates, using the

Table 2. Comparison of USCRN In Situ and AMSR-E Satellite Estimates[a]

County	USCRN	RMSE, AMSR-E, Ascending	RMSE, AMSR-E, Descending
Fresno	1508	**0.050**	**0.051**
Kern	1529	*0.073*	*0.074*
Kings	1508	**0.051**	**0.052**
Los Angeles	1528	*0.073*	*0.072*
Maricopa	1011	**0.036**	**0.036**
Pima	1011	**0.035**	**0.035**
Pinal	1011	**0.035**	**0.035**
San Diego	1528	*0.073*	*0.077*
Tulare	1508	**0.046**	**0.051**

[a]Bolded values are from USCRN sensors used in the subsequent analysis.

parameters calibrated at the location relevant location. The second series is a "merged" series, utilizing the in situ estimate when one is available and the modeled estimate when one is not.

For selected counties in Arizona and California (Figure 1) with reported coccidioidomycosis cases, a soil moisture record is selected using the most geographically proximate in situ record from USCRN (Figure 1). In Arizona, the nearest in situ record is located at the USCRN gauge near Tucson (USCRN #1011, nearest to Maricopa, Pima, and Pinal counties). In California, the nearest in situ records are located near Yosemite Village (USCRN #1508, nearest to Fresno, Kings, and Tulare counties), Fallbrook (USCRN #1528, nearest to Los Angeles and San Diego counties), and Santa Barbara (USCRN #1529, nearest to Kern county). The next section discusses the possible relationships to be explored with those soil moisture data.

Given the spatial disparity between these counties and the chosen USCRN sensors for which model estimates extend historical records, it is prudent at this stage to assess the capacity of these distant sensors to approximate the local soil moisture of interest. First, the Advanced Microwave Scanning Radiometer–EOS (AMSR-E) satellite estimates of soil moisture (available between June 2002 and October 2011) are extracted for the center of each of the counties considered. As the in situ records at these USCRN locations typically begin in 2010 or 2011, the remotely sensed soil moisture values from AMSR are compared with the model estimates produced to extend the historical records at the USCRN locations utilized for the purposes of this analysis. In *Coopersmith et al.* [2015b], these model estimates were compared to AMSR-E data at the USCRN locations themselves. The average accuracy reported in that analysis, after inclusion of an optimal gain and offset, was 0.047 m^3/m^3. The corresponding statistics, using AMSR-E within the county rather than at the USCRN location itself, are reported in Table 2.

Of the nine counties listed, the RMSE values between the local AMSR-E estimates and the model estimates at the nearest USCRN sensor are roughly in line with the reported RMSE values between USCRN model estimates and the local AMSR-E retrievals. Thus, these six counties are retained for further analysis. Kern, Los Angeles, and San Diego, are subsequently removed via this criterion.

2.3. Defining Relationships to Consider

With soil moisture records in place, the next step is to consider the various types of relationships for potential correlations. Analogous to the 8 day averages of soil moisture utilized in *Wang et al.* [2007], this analysis focuses upon the monthly average soil moisture value. As the period of record for coccidioidomycosis incidence falls between 2000 and 2014, ideally, the soil moisture record with which to compare these figures should cover the maximum proportion of these years. For this reason, the extended records at the USCRN gauges (which begin when precipitation data are first available) are preferable to the in situ records for soil moisture. In turn, just as *Wang et al.* [2007] utilized period averages with variable daily lags, the following monthly aggregations and lags are considered: (a) the number of months to aggregate of the independent variable (1 to 6). That is, the average soil moisture from January to March (an aggregation of 3 months), only February (an aggregation of 1 month), or the entire first half of the calendar year (an aggregation of 6 months); (b) the number of months to aggregate of the dependent variable (1 to 6, a normalized estimate of reported coccidioidomycosis cases per 1,000,000 residents, with the annual trend removed), that is, we can estimate the total in August and September (an aggregation of 2 months) or a longer/shorter window; (c) the number of months of "lag" time between the independent range and the dependent range (0 to 36 months), for example, using the total number of hours above 10% between April and June of year *X* to forecast

Table 3. Soil Moisture Levels and Coccidioidomycosis Impacts in Arizona and California

Year	Month	Modeled SM (m^3/m^3), AZ	Detrended Cocci Incidence, AZ	Modeled SM (m^3/m^3), CA	Detrended Cocci Incidence, CA
2002	9	0.018688498	238.6835648	0	0
2002	10	0.030761552	291.4209886	0	0
2002	11	0.042590859	402.4278317	0	0
2002	12	0.079504266	314.7253879	0	0
2003	1	0.040706236	217.6314323	0	0
2003	2	0.047960111	118.9956718	0	0
2003	3	0.058734527	139.3982875	0	0
2003	4	0.023598582	93.20229356	0	0
2003	5	0.021576505	111.0593612	0	0
2003	6	0.032606535	140.6273795	0	0
2003	7	0.034824275	205.3632434	0	0
2003	8	0.063790721	316.7377084	0	0
2003	9	0.070075447	211.4483979	0	0
2003	10	0.073544563	213.733152	0	0
2003	11	0.07633426	195.8249965	0	0
2003	12	0.077928581	285.6830261	0	0
2004	1	0.080290731	211.9314125	0	0
2004	2	0.086659528	224.0742793	0	0
2004	3	0.091885505	178.9580231	0	0
2004	4	0.076389722	147.1321316	0	0
2004	5	0.048595993	249.0750831	0	0
2004	6	0.050074095	311.3864712	0	0
2004	7	0.053449079	297.3654862	0	0
2004	8	0.075714144	239.3006426	0	0
2004	9	0.08334769	272.7333319	0	0
2004	10	0.088344984	284.3028402	0	0
2004	11	0.114069337	244.1796974	0	0
2004	12	0.134465145	282.5061027	0	0
2005	1	0.14126691	160.2114796	0	0
2005	2	0.138735481	112.0010048	0	0
2005	3	0.069427576	119.1015506	0	0
2005	4	0.026501304	140.9278206	0	0
2005	5	0.029467254	126.9506981	0	0
2005	6	0.034264098	159.824663	0	0
2005	7	0.047369151	205.4515105	0	0
2005	8	0.121873645	271.667615	0	0
2005	9	0.084187959	173.3887346	0	0
2005	10	0.085661459	246.0509143	0	0
2005	11	0.075487162	394.0148302	0	0
2005	12	0.049257706	360.4681667	0	0
2006	1	0.047195764	223.8126685	0	0
2006	2	0.046754592	406.0198996	0	0
2006	3	0.06377237	321.6875436	0	0
2006	4	0.02168984	303.6157508	0	0
2006	5	0.020238768	250.91043	0	0
2006	6	0.033135632	262.8592065	0	0
2006	7	0.063432066	300.9350003	0	0
2006	8	0.07439608	237.5421378	0	0
2006	9	0.066061927	174.8022503	0	0
2006	10	0.049548081	181.9017814	0	0
2006	11	0.019553513	229.6054128	0	0
2006	12	0.028981184	385.3860391	0	0
2007	1	0.082276498	268.2745264	0	0
2007	2	0.045478735	218.1070116	0	0
2007	3	0.031602907	188.4985045	0	0
2007	4	0.030831453	222.0207718	0	0
2007	5	0.019434795	215.5676418	0	0
2007	6	0.020675259	208.739997	0	0
2007	7	0.059385878	194.8435303	0	0
2007	8	0.102940045	202.1052942	0	0

Table 3. (continued)

Year	Month	Modeled SM (m^3/m^3), AZ	Detrended Cocci Incidence, AZ	Modeled SM (m^3/m^3), CA	Detrended Cocci Incidence, CA
2007	9	0.056300585	154.3844403	0.014422721	73.24354314
2007	10	0.019089717	258.6904939	0.024020918	122.4520226
2007	11	0.020181495	328.867631	0.033769359	88.38095769
2007	12	0.1268061	284.8079076	0.093992526	141.1553566
2008	1	0.058864981	186.2714123	0.127940179	98.77108245
2008	2	0.087335354	183.1635086	0.136142251	84.16943733
2008	3	0.0312175	156.0432876	0.092026298	124.1939281
2008	4	0.018939927	184.5926911	0.031635149	138.2376122
2008	5	0.018688498	181.4596586	0.050772315	88.72175773
2008	6	0.035782162	169.1139229	0.055040674	148.2855919
2008	7	0.0974885	187.4741605	0.015210755	154.9923056
2008	8	0.060875011	168.7508884	0.014531239	209.7241664
2008	9	0.07512169	162.096754	0.014422721	187.3930841
2008	10	0.020771004	158.8994241	0.04266662	283.9230749
2008	11	0.026019206	234.5093129	0.090540463	229.5195126
2008	12	0.073159039	357.3659874	0.087234657	226.0364025
2009	1	0.090310458	208.6114782	0.099837552	205.0517373
2009	2	0.080561563	142.2644019	0.153602611	169.053763
2009	3	0.027221068	172.1079466	0.141206739	162.2426741
2009	4	0.030790148	200.0208542	0.106122067	167.963602
2009	5	0.024223187	255.0951336	0.099469892	186.0101461
2009	6	0.019587086	504.074028	0.070716571	240.6823074
2009	7	0.057748034	463.3385302	0.015893807	169.1293229
2009	8	0.042787633	400.7169535	0.019870677	256.5202823
2009	9	0.058145327	439.1085566	0.019882989	171.3287105
2009	10	0.022637066	435.7276248	0.079732534	177.9751628
2009	11	0.02392507	558.6542474	0.033060175	132.8129363
2009	12	0.063440636	449.4906599	0.1092558	163.2937272
2010	1	0.07671407	326.2683504	0.109604861	100.7023111
2010	2	0.119726452	313.5462057	0.128848332	96.26017989
2010	3	0.070742721	264.8940373	0.135993041	75.9748846
2010	4	0.024556352	270.9795176	0.151917328	132.6715156
2010	5	0.020438031	287.2457407	0.134641752	82.5704694
2010	6	0.018688498	327.7077512	0.058616255	164.3313195
2010	7	0.027323524	344.1021857	0.014422721	210.2631608
2010	8	0.064003282	345.901653	0.014422721	454.4814074
2010	9	0.028944447	355.8207601	0.014422721	593.7086878
2010	10	0.065683901	431.1084195	0.101268402	582.5730995
2010	11	0.023181293	484.2991517	0.118288892	333.3063386
2010	12	0.048068155	586.3832791	0.140973261	354.1640009
2011	1	0.055805589	502.2475781	0.090887304	158.7225719
2011	2	0.024228836	401.9814256	0.10315471	133.4254945
2011	3	0.036633795	481.0993594	0.160069858	106.374115
2011	4	0.034765333	473.9231599	0.132507947	112.7479356
2011	5	0.018688498	452.6495429	0.10387384	83.61927096
2011	6	0.018688498	455.186837	0.09917383	168.5966146
2011	7	0.051480698	480.1178372	0.06641851	171.2034696
2011	8	0.04691028	482.0019436	0.015082458	365.7117288
2011	9	0.062969664	335.0672556	0.044938206	397.2492863
2011	10	0.029757534	408.5573527	0.0677866	303.5982769
2011	11	0.081169463	465.1782025	0.054869883	258.751319
2011	12	0.113030655	441.0465071	0.01651865	229.0002529
2012	1	0.053559181	379.7756753	0.067839679	343.8025035
2012	2	0.024232378	375.8936545	0.105581676	264.8739533
2012	3	0.038539565	455.2590395	0.13065999	159.1349569
2012	4	0.03481477	469.8929287	0.149004521	128.2456794
2012	5	0.019257559	436.8999502	0.062313905	149.4690067
2012	6	0.029961968	388.2121592	0.05113879	152.0041124
2012	7	0.056216902	393.0521333	0.016870897	84.79048292
2012	8	0.079493489	252.761961	0.018147495	91.49446931

Table 3. (continued)

Year	Month	Modeled SM (m^3/m^3), AZ	Detrended Cocci Incidence, AZ	Modeled SM (m^3/m^3), CA	Detrended Cocci Incidence, CA
2012	9	0.059601122	204.2646714	0.014742877	111.4972694
2012	10	0.018797563	296.1976982	0.035507406	87.61401271
2012	11	0.031084186	320.5746086	0.094424432	88.10425661
2012	12	0.074000038	200.897139	0.157289468	93.24951635
2013	1	0.061580616	215.8309765	0.079910734	60.37819332
2013	2	0.097161785	189.9210826	0.06503031	74.84739532
2013	3	0.043805947	103.0214633	0.099472384	69.00899078
2013	4	0.023682717	102.1139398	0.102119484	65.23757778
2013	5	0.018688498	134.5468404	0.029101883	71.32973163
2013	6	0.018688498	180.7191826	0.032773113	88.66521014
2013	7	0.057232007	131.1258734	0.02314116	46.88582094
2013	8	0.04777314	197.0633332	0.014627682	47.77677455
2013	9	0.044216847	137.3913779	0.032197353	28.87948204
2013	10	0.018688498	129.1651728	0.036543682	35.1306167
2013	11	0.055693437	248.1182123	0.055573595	45.90899133
2013	12	0.089243157	222.1762911	0.056617057	74.27440333
2014	1	0.026467379	190.936132	0.020651353	42.60643006
2014	2	0.022966894	170.9610033	0.137219354	79.96855895
2014	3	0.034498843	223.2393164	0.119463294	34.32090332
2014	4	0.019020564	157.5879583	0.11920279	32.97535816
2014	5	0.018920869	232.5313611	0.090978637	55.46088978
2014	6	0.018688498	161.9626934	0.025230896	43.39143342
2014	7	0.093122684	93.59387799	0.03509858	58.15198009
2014	8	0.06704296	146.0930835	0.018512132	45.60214862
2014	9	0.078068763	109.0883894	0.030480576	49.30911926
2014	10	0.070803184	91.14695079	0.037730295	30.08484286
2014	11	0.020658284	132.0806601	0.077829588	25.89108171
2014	12	0.095039508	118.7038301	0.12214687	13.89858433

coccidioidomycosis in August and September and year $X + 1$ would represent a lag of 13 months; and (d) the 12 possible months (or aggregations thereof), to wit, utilizing a 3 month window for independent or dependent variables, one can consider January–March versus February–April versus March–May, etc.

The next section will outline how this analysis will refine that profusion of potential relationships into a coherent set of insights relating soil moisture estimates to reported cases of coccidioidomycosis.

2.4. Focusing the Lens

Our methods are quite similar to those of *Wang et al.* [2007], beginning with the removal of a long-term trend, the application of correlation analysis to lagged data, and even the usage of composites of temporal ranges by aggregating between time stamps for independent variable generation. In Table 3, we visualize the average modeled soil moisture by month and the annually detrended number of reported coccidioidomycosis cases.

In California (upper panel), we observe that soil moisture arrives in clusters of roughly 6 months, which aligns with hydroclimatic research addressing Pacific climates, where precipitation arrives primarily during the fall/winter seasons [e.g., *Coopersmith et al*., 2012]. In Arizona (lower panel), we observe soil moisture clusters of shorter periods of 3 months, aligning with the monsoon rainfall pattern of the arid Southwest. Thus, for California and Arizona, we will aggregate soil moisture monthly averages into clusters of six and three, respectively. In terms of the dependent variables, in California (upper panel), we notice clusters of roughly 3 months of coccidioidomycosis incidence that rise and fall in relation to the soil moisture levels observed, with lags of several months. In Arizona, cocci responses seem inversely related (drier periods are succeeded by higher coccidioidomycosis incidence), with somewhat longer lag periods.

To distill a large number of comparisons, we focus on those that show the more significant, consistent, robust relationships. If fewer than 18 comparisons are available, the comparison cannot be considered for use in the study. A threshold of 18 has now been adopted to ensure at least one pair of independent and dependent

Table 4. Annually Detrended Cases of Coccidioidomycosis (July–September) Versus 6 Month Average Soil Moisture (December–May), California

Modeled SM	Reported Cases
0.115	115.5262
0.128	298.9765
0.122	227.4943
0.089	56.39648
0.089	12.70564
0.091	25.9088
0.089	41.74433
0.115	46.81051
0.128	36.58167
0.122	27.86085
0.089	21.22929
0.089	13.19565
0.091	13.49517
0.089	32.53876
0.115	36.65603
0.128	83.92622
0.122	56.03302
0.089	18.30164
0.089	15.2794
0.091	11.61712

ranges per county per year, from 2007 (the year at which precipitation data become available in California) and 2014 (when the incidence data set concludes). For example, if we are considering comparisons of coccidioidomycosis incidence from February to March with the average in situ soil moisture estimate from June to August of the preceding summer, over all counties in California, a single data point is valid if, and only if, coccidioidomycosis estimates are available in that county in February and March, and in situ soil moisture estimates are available within that same county in June, July, and August of the previous year. As stated, 18 such points are required before comparisons can be further considered.

Finally, the statistically significant relationships that remain are examined in greater detail. Relationships that "recur" or show higher rates of significance/correlation between the independent variable (a soil moisture measurement metric) and the dependent variable (reported cases of coccidioidomycosis) become the relationships concluded to be most robust. Note a relationship "recurs" if the same independent variable demonstrates strong, statistically significant relationships between numerous temporal windows of the subsequent year.

3. Results

In this section, the results of the correlation analysis are deployed to evaluate the performance of those comparisons for the two states in question.

3.1. California

In Tables 4 and 5, we observe the positive correlation between average modeled soil moisture levels over a specific 6 month period (December-to-May) and the number of reported cases of coccidioidomycosis in the subsequent 3 month bands covering the summer and fall. Table 5 demonstrates the relationship between summer/fall incidence of coccidioidomycossis and the average soil moisture the preceding winter and spring. The results of these relationships are summarized in Table 1, all of which are statistically significant at the $\alpha = 0.05$ level.

It is worth noting that all of these relationships illustrate summer/fall periods of coccidioidomycosis incidence responding to the same 6 month band beginning during the fall of the preceding year. Interestingly, while the "wetter" 6 month bands do not necessarily cause a higher number of reported cases, the "drier" bands are fairly consistent with respect to their lower number of cases reported. It is also important to note that, in Southern California, a disproportionate quantity of rainfall is observed during the fall/winter/early-spring

Table 5. Statistically Significant Relationship Displaying Recurrent Patterns, California

Ind_var Range	Ind_var Type	Dep_var Range	ρ	p Value	n
Dec–May (y^{-1})	Average Soil Moisture (m^3/m^3)	Jun–Aug	0.503	0.020	21
Dec–May (y^{-1})	Average Soil Moisture (m^3/m^3)	Jul–Sep	0.539	0.012	21
Dec–May (y^{-1})	Average Soil Moisture (m^3/m^3)	Aug–Oct	0.535	0.013	21
Dec–May (y^{-1})	Average Soil Moisture (m^3/m^3)	Sep–Nov	0.529	0.014	21
Dec–May (y^{-1})	Average Soil Moisture (m^3/m^3)	Oct–Dec	0.501	0.021	21

Table 6. Annually Detrended Cases of Coccidioidomycosis (February) Versus 6 Month Average Soil Moisture (May–July), Arizona

Modeled SM	Reported Cases
0.030	90.0965
0.051	35.88342
0.037	144.1528
0.039	74.286
0.033	66.92434
0.051	55.48029
0.034	144.2103
0.022	194.4925
0.030	157.8867
0.035	64.43757
0.032	65.09426
0.030	70.94503
0.051	41.20407
0.037	125.5012
0.039	64.94447
0.033	58.86291
0.051	41.38267
0.034	80.80375
0.022	79.60832
0.030	98.13995
0.035	55.82523
0.032	54.94693
0.030	63.03275
0.051	34.91351
0.037	136.3659
0.039	78.87655
0.033	57.37626
0.051	45.40144
0.034	88.53221
0.022	127.8806
0.030	119.867
0.035	69.65828
0.032	50.91981
0.030	90.0965
0.051	35.88342
0.037	144.1528
0.039	74.286
0.033	66.92434
0.051	45.40144
0.034	88.53221
0.022	127.8806
0.030	119.867
0.035	69.65828
0.032	50.91981
0.051	45.40144
0.034	88.53221
0.022	127.8806
0.030	119.867

months, which would, in turn, suggest the greatest variability of soil moisture between December and May, which, in turn, displays consistent relationships with respect to coccidioidomycosis incidence during the summer and fall thereafter.

3.2. Arizona

In Tables 6 and 7, we observe analogous examples in Arizona, albeit with an inverted statistical relationship. Once again, we note that one particular band of average soil moisture values during the summer season when much of the Arizona rain falls presents statistically significant relationships with respect to coccidioidomycosis incidence in each month between January and May. All of these relationships are statistically significant at the $\alpha = 0.01$ level. Though the correlation is inverted, this would seem to corroborate the grow and blow hypothesis proposed by *Tamerius and Comrie* [2011], in which drier periods allow spores to travel freely.

Additionally, much like the Californian results, in which wetter periods may or may not yield subsequent periods of higher incidence, but drier periods were consistently succeeded by lower number of reported cases of coccidioidomycosis, a similar pattern emerges in Arizona. To wit, in Table 6, an extremely dry summer may or may not cause the highest levels of coccidioidomycosis incidence in the subsequent winter and spring, but an atypically wet summer produces consistently low incidence rates. In California and Arizona, wet and dry conditions, respectively, are necessary, but not sufficient conditions for heightened incidence rates.

Table 7. Statistically Significant Relationship Displaying Recurrent Patterns, Arizona

Ind_var Range	Ind_var Type	Dep_var Range	ρ	*p* Value	*n*
May–Jul (y^{-1})	Average Soil Moisture (m^3/m^3)	Jan	−0.521	0.002	33
May–Jul (y^{-1})	Average Soil Moisture (m^3/m^3)	Feb	−0.552	0.001	33
May–Jul (y^{-1})	Average Soil Moisture (m^3/m^3)	Mar	−0.532	0.001	33
May–Jul (y^{-1})	Average Soil Moisture (m^3/m^3)	Apr	−0.449	0.009	33
May–Jul (y^{-1})	Average Soil Moisture (m^3/m^3)	May	−0.501	0.003	33

Table 8. Precipitation During the California and Arizona Calendar Years

Year	Annual Precipitation (mm), AZ	Annual Precipitation (mm), CA
2003	173.228	242.57
2004	202.692	414.528
2005	178.816	477.774
2006	138.43	233.172
2007	128.27	124.206
2008	243.332	279.908
2009	82.804	189.738
2010	232.156	509.27
2011	118.364	250.698
2012	108.712	225.806
2013	213.868	92.71
2014	212.598	242.57

4. Discussion

4.1. The 21st Century Precipitation

Utilizing publically available California monthly precipitation data NOAA's monthly data from appropriately located gauges in Arizona (http://w2.weather.gov/climate/xmacis.php? wfo=psr) and California (http://w2.weather.gov/climate/xmacis.php?wfo=lox), one can observe qualitatively, some of the climatic patterns in play during the time periods in question. With the USCRN precipitation record in California beginning in 2007 at most installation sites, Table 8 presents the precipitation observed during each year from Southern California (near Los Angeles) and Arizona (near Phoenix). In Table 3, we noted a gradual increase in the incidence of coccidioidomycosis, observing a spike in cases reported in 2011 (followed by a sharp decrease in 2012 and 2013). In California, as our previous analysis would suggest, an atypically wet year in 2011 may have (at least temporarily) slowed a long-standing positive trend. Table 8 presents the rainfall during each year. However, the increase in 2011 (Table 9) may be exacerbated by an exceptionally wet 2010 followed by a drier summer in central Arizona (though not in the south), perhaps facilitating wider spreading of spores by wind, as hypothesized in *Kolivras and Comrie* [2003]. The steep dropoff thereafter may be, perhaps, partially explained by the extremely wet 2012. Changes in surveillance methodologies, including changes in testing and reporting practices, may also have partially contributed to the 2011 peak [*Centers for Disease Control and Prevention*, 2013]. For example, California transitioned to a laboratory-based reporting system during 2010, though some jurisdictions such as Kern county had already been implementing such a reporting system [*Centers for Disease Control and Prevention*, 2013].

The Pacific Decadal Oscillation (PDO) is known to influence the variability of precipitation in the Southwest, specifically during Arizona winters [*Sheppard et al*., 2002]. An image of the PDO from 1870 through the time period under inspection in this study can be located at https://www.ncdc.noaa.gov/teleconnections/pdo/. The time period during which the spike in reported cases of coccidioidomycosis is observed in Arizona and California corresponds with the nadir of the Pacific Decadal Oscillation (PDO). Shortly thereafter, as the sign of the PDO switches, a sharp decrease in coccidioidomycosis incidence is observed (Table 1). The PDO's connection to historical outbreaks of coccidioidomycosis could be researched by, in addition to removing a long-term annual trend as shown in equations (2) and (3), fitting a relationship between the PDO and coccidioidomycosis incidence. "Sequential normalization" specifies that multiple superimposed trends can be removed in order of the longest repeating period; see *Coopersmith et al*. [2011], leveraging a method from *Maidment and Parzen* [1984]. This would allow coccidioidomycosis incidence to explore in terms of moisture and anthropogenic features, in the absence of climatic trends.

Table 9. Monthly Incidence of Coccidioidomycosis per 1,000,000 Residents, Selected Counties in Arizona and California (2000–2014)

Month	# of Reported Cases per 1,000,000 Residents (Arizona)	# of Reported Cases per 1,000,000 Residents (California)
1	92.95431443	45.85162106
2	81.63523957	38.46853154
3	78.20629274	37.23905642
4	79.10389713	33.56534757
5	81.45724761	32.31102624
6	87.14588194	41.04605894
7	93.04145815	36.92932236
8	89.63543347	53.02804748
9	75.26866006	58.9060512
10	88.80439084	64.11905656
11	110.4812564	59.41757467
12	110.9498537	56.3356386

4.2. Limitations

Limitations of coccidioidomycosis surveillance data include the passive nature of the surveillance system, which almost certainly underestimates the true number of cases. In addition to the incubation period, some patients report experiencing substantial delays between seeking care as well as coccidioidomycosis diagnosis [*Tsang et al*., 2010], and further delays may occur between diagnosis and case reporting to public health. Therefore, the month to which cases are assigned may not necessarily reflect the month that he or she was infected with *Coccidioides*. Earlier analyses utilized time lags in their attempts to account for the time between exposure and symptom onset [e.g., *Park et al*., 2005], though a subsequent analysis of model sensitivity quality control determined that employing case data "as is" did not cause significant deterioration of results [*Comrie and Glueck*, 2005]. Future analyses may allow for more comprehensive linkage between environmental conditions for *Coccidioides* growth and observed incidence by incorporating factors that account for dispersal and human exposure, ideally with methods to detect *Coccidioides* in air. Currently, laboratory detection of airborne *Coccidioides* DNA has only been successful with artificially created dust clouds [*Chow et al*., 2016]. However, future research is needed to enable this technology to be used for routine monitoring of *Coccidioides* in ambient air and to quantify spore count.

5. Conclusions

Ultimately, despite the differing hydroclimates presented by the data in Arizona and California, in both states, robust, significant, recurring relationships do emerge. In both states, drought tends to correlate with higher incidence of reported coccidioidomycosis in the following year, whether that be a drier foresummer monsoon season in Arizona or a drier winter/spring in California. In Arizona, these impacts tend to be noticed earlier in the subsequent year, whereas in California, these impacts are noted later in the year. While other research challenges the impact of climatic factors in Kern county, CA [*Talamantes et al*., 2007], this analysis reveals relationships in California and Arizona using climatic data to produce a time series of soil moisture.

With the descriptive capacity of soil moisture verified by statistical significance tests and demonstrated over periods between several months and over 2 years, it is possible that future predictive models could enable public health officials to prospectively identify periods of expected increased coccidioidomycosis incidence and notify healthcare providers and the public to remain vigilant for identification of this infection, potentially minimizing delays in diagnosis. We are hopeful that this analysis, in cooperation with subsequent research and stakeholders, will form the basis to do just that.

Acknowledgments
This work was supported by the NASA Terrestrial Hydrology Program (NNH10ZDA001N-THP) and USDA Agricultural Research Service (ARS 58-8042-5-077). USDA is an equal opportunity provider and employer. This work was also supported by NOAA through the Cooperative Institute for Climate and Satellites-North Carolina under Cooperative Agreement NA14NES432003. The reported cases of coccidioidomycosis were obtained from National Notifiable Diseases Surveillance System (NNDSS) available (https://wwwn.cdc.gov/nndss/data-and-statistics.html). The findings and conclusions in this report are those of the authors and do not necessarily represent the official position of the Centers for Disease Control and Prevention.

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