RESEARCH ARTICLE
10.1029/2019WR026877

Key Points:
- Sixteen percent of droughts (defined by precipitation minus evaporation) that affect continents start over the ocean and travel onto land
- Landfalling droughts are larger, more intense, and grow faster after making landfall, and compared to ocean-only and land-only droughts
- Landfalling droughts appear to arise from reduced moisture transport over the ocean linked to anticyclonic atmospheric pressure patterns

Supporting Information:
- Supporting Information S1

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Citation:
Herrera-Estrada, J. E., Diffenbaugh, N. S. (2020). Landfalling droughts: Global tracking of moisture deficits from the oceans onto land. Water Resources Research, 56, e2019WR026877. https://doi.org/10.1029/2019WR026877

Received 1 DEC 2019
Accepted 29 AUG 2020
Accepted article online 9 SEP 2020

Abstract
Droughts threaten food, energy, and water security, causing death and displacement of millions of people and billions of dollars in damages. However, there are still important gaps in the understanding of drought mechanisms and behaviors, inhibiting the accuracy of early-warning systems designed to protect communities worldwide. We use an object-tracking algorithm to track clusters of precipitation-minus-evaporation moisture deficits across land and ocean areas of the globe from 1981–2018. This analysis reveals a new type of “landfalling drought” that originates over the ocean and “migrates” onto land. We find that 16% of droughts that affected the continents worldwide from 1981–2018 were landfalling droughts. These droughts were significantly larger (220–425%) and more intense (4–30%)—and grew (253–285%) and intensified (9–28%) faster—than droughts that developed solely over the land or ocean. To identify potential underlying mechanisms, we analyze moisture transport associated with landfalling droughts over western North America. We find that landfalling droughts in this region are associated with anomalously anticyclonic atmospheric pressure patterns that reduce moisture fluxes over the Pacific Ocean toward the continent. By advancing understanding of the spatiotemporal evolution of droughts, our findings offer the potential to improve seasonal-scale prediction and long-term projection of global drought risks.

Plain Language Summary
Droughts can have devastating impacts on a region’s domestic water supply, electricity generation, agriculture, and ecosystem health. However, the processes by which droughts arise, develop, and end are not yet fully understood, creating barriers for accurate prediction. In this study, we define droughts as instances when the quantity of precipitation minus evaporation is below normal, allowing us to identify droughts over both the land and ocean. Tracking droughts from where they start to where they end reveals that 16% of droughts that affect continents start over the ocean and travel onto land. We find that these “landfalling droughts” are larger, more intense, and grow faster after making landfall, compared to droughts that start and end completely over land. While the role of sea surface temperatures has been studied in relation to drought development over the continents, fewer studies have analyzed moisture deficits over the oceans. Our results suggest that monitoring and tracking moisture deficits offshore has the potential to yield improvements in drought prediction, warning, and preparation.

1. Introduction
Droughts can have devastating impacts on crops (Burke & Lobell, 2010; Leng & Hall, 2019), energy generation (Herrera-Estrada et al., 2018; van Vliet et al., 2016; Voisin et al., 2016), and water resources (Trindade et al., 2017), with severe humanitarian and financial consequences (Abel et al., 2019; Burke & Lobell, 2010; Smith, 2020). These risks are likely to intensify as climate change increases the frequency and severity of droughts around the world (Berg & Sheffield, 2018; Cook et al., 2018; Diffenbaugh et al., 2015; Herrera-Estrada & Sheffield, 2017; Touma et al., 2015).

Recent advances in satellite observations, climate modeling, and computing have improved global drought monitoring and forecasting capabilities (Wood et al., 2015). Much of the predictive capacity arises from the ocean’s role in drought development (Baek et al., 2019; Findell & Delworth, 2010; Giannini et al., 2003; Hoerling & Kumar, 2009; Kam et al., 2014; Schubert et al., 2009, 2016; Veldkamp et al., 2015), including the “teleconnections” through which sea surface temperatures (SSTs) induce large-scale atmospheric patterns that promote the development of dry conditions over continents (Baek et al., 2019; Findell & Delworth, 2010; Giannini et al., 2003; Hoerling &
Kumar, 2009; Kam et al., 2014; Schubert et al., 2009, 2016; Veldkamp et al., 2015). These teleconnections account for 10–60% of precipitation variability over different regions and seasons (Baek et al., 2019; Schubert et al., 2016), with the remaining variance attributed to internal atmospheric variability (Baek et al., 2019) and land-atmosphere feedbacks (Klingaman et al., 2008; Seneviratne et al., 2010).

However, because the specific spatiotemporal processes that control drought onset, development, and termination are not fully understood, not all severe droughts are accurately forecasted (Roy et al., 2019). A promising area for improvement has been tracking the spatiotemporal development of droughts over land (Andreadis et al., 2005; Diaz et al., 2020; Herrera-Estrada et al., 2017, 2019; Lloyd-Hughes, 2012; Sheffield et al., 2009; Xu et al., 2015). This approach has revealed that droughts can travel thousands of kilometers across continents (Herrera-Estrada et al., 2017). Extending this spatiotemporal analysis over the ocean could yield important insights into drought controls, including processes that climate models must capture to accurately characterize drought risk on seasonal to decadal time scales.

Beyond the ocean’s role via atmospheric teleconnections, drought studies are generally restricted to the continents (e.g., Sheffield & Wood, 2011), largely because most drought impacts take place on land. Further, the study of the maritime hydrologic cycle has been particularly challenging due to the relative lack of comprehensive monitoring networks (Lagerloef et al., 2010). Sea surface salinity (SSS) has been proposed as a potential “rain gauge” over the ocean, with forecasting capability for drought over land (Liu et al., 2018). However, accurately attributing changes in SSS to variability in precipitation and evaporation, or to advection due to ocean dynamics, has posed a key challenge (Lagerloef et al., 2010; Yu, 2011). Recent deployment of floats and satellite sensors has improved observational coverage of the global oceans (Boutin et al., 2019; Durack & Wijffels, 2010; Good et al., 2013), informing model simulations of SSS variability (Gordon, 2016; Ponte & Vinogradova, 2016). Yet, the relationship between oceanic and terrestrial moisture deficits remains relatively unexplored.

Research on identifying and tracking droughts is in early development. However, there are potential parallels with other Earth System phenomena, such as extratropical cyclones (Neu et al., 2013) and atmospheric rivers (Shields et al., 2018). For example, some algorithms used to identify and track atmospheric rivers impose relative conditions for object identification and use a Lagrangian approach to track objects through time and space (Shields et al., 2018). These implementations are similar to those that have been used to track drought clusters (Andreadis et al., 2005; Herrera-Estrada et al., 2017; Sheffield et al., 2009; Zhan et al., 2016). Additionally, some atmospheric river identification algorithms impose geometric requirements (Shields et al., 2018), as is common when identifying drought clusters (Andreadis et al., 2005; Herrera-Estrada et al., 2017; Sheffield et al., 2009; Zhan et al., 2016).

To understand the role of moisture deficits over the ocean in drought development over land, we first identify and track moisture deficits across global land and ocean areas from 1981–2018. Using this unique drought cluster data set, we identify all droughts that originate over the ocean and migrate onto land. We then compare multiple characteristics of these landfalling droughts with moisture deficits that originate and persist only over ocean or only over land.

2. Materials and Methods

2.1. Data

We use monthly total precipitation and evaporation data from three reanalyses: (i) ERA-Interim (Dee et al., 2011) at 0.75° resolution from 1979–2018; (ii) MERRA2 (Gelaro et al., 2017) at 0.5° × 0.625° resolution from 1980–2018; and (iii) CFSR (Saha et al., 2010) at 0.5° resolution from 1979–2010, complemented by CFSv2 from 2011–2018 (Saha et al., 2014). We perform quantile matching of CFSR using CFSv2 to remove discontinuities in precipitation and latent heat flux estimates (later converted to evaporation) that arise from model changes between CFSR and CFSv2 (Saha et al., 2014).

We adapt the moisture deficit identification of Herrera-Estrada et al. (2017), replacing soil moisture with monthly precipitation minus evaporation (P – E) to uniformly track moisture deficits over land and ocean. We first subtract evaporation from precipitation for each month in each reanalysis. Then, we calculate the monthly anomalies of P – E over each grid cell by subtracting the respective calendar month mean from each month’s value (e.g., subtract the average across all January values from each individual January
value). Calculating the anomaly relative to the monthly climatology is necessary to assess dry and wet conditions relative to the seasonality of each region (e.g., Andreadis et al., 2005; Herrera-Estrada et al., 2017, 2019).

Because we are interested in moderate-to-long time scale moisture deficits that would result in severe agricultural and hydrological droughts (Sheffield & Wood, 2011), we sum the monthly $P - E$ anomalies using a 12 month moving window, yielding a monthly time series of 12 month cumulative anomalies of $P - E$ at each grid cell. (We test the sensitivity of our results using moving windows of 3, 6, and 9 months.) We replace each individual cumulative anomaly value with its respective percentile calculated from the Weibull plotting positions (Andreadis et al., 2005) at each grid cell. An illustrative example of these calculations is shown in supporting information Figure S1 for a single grid cell over the southwestern United States.

Percentiles normalize the 12 month cumulative $P - E$ anomalies across grid cells, enabling identification of moisture deficit clusters that span regions with different hydroclimates (Andreadis et al., 2005; Herrera-Estrada et al., 2017). This normalization is common across drought indices, such as the Standardized Precipitation Index (SPI), the Palmer Drought Severity Index (PDSI), and the Standardized Precipitation Evapotranspiration Index (SPEI), since it allows for a relative comparison of “below normal” conditions across different regions. However, it also means that a change of 1% will translate to large/small changes in absolute values in regions with high/low variability in $P - E$.

We compare $P - E$ anomalies with monthly anomalies in volumetric soil water integrated down to 1 m from ERA-Interim (1981–2018). We also compare $P - E$ anomalies to two independent observational data sets of SSS: (i) Layer 4 SSS from the European Space Agency Climate Change Initiative (ESA CCI) centered on the fifteenth day of each month at 25 km resolution from January 2010 to November 2018 (Boutin et al., 2019) and (ii) the EN4.2.1 objective analyses of SSS with the Gouretski and Reseghetti (2010) corrections at 1° resolution and integrated down to 10 m from the UK Met Office Hadley Center (Good et al., 2013) (i.e., the data used in Liu et al., 2018). ESA CCI’s data set is based on collections from three satellites (ESA’s SMOS and NASA’s SMAP and Aquarius), while the Hadley Center’s analyses are derived from in-situ profile measurements gap-filled with the 1979–2000 climatology. Hadley Center’s data include observation weights that describe the weighting of the in situ observations versus the climatology for each value in the data set. To reduce the influence of the climatology gap fill, we filter values with observation weights below 0.95 and only calculate correlations for grid cells with at least 60 months of observations.

### 2.2. Drought Definition, Clustering Algorithm, and Classification of Drought Clusters

We focus on moisture deficits that arise from large-scale atmospheric patterns (Sheffield & Wood, 2011) and employ the clustering algorithm outlined by Andreadis et al. (2005) and implemented by Herrera-Estrada et al. (2017). We improve the robustness of the identification of moisture deficit clusters by first applying a 2-D median filter to the global map of $P - E$ percentiles at each time step (Figure S2). This spatial smoothing reduces small-scale heterogeneity and is a common preprocessing step in drought clustering analyses (Andreadis et al., 2005; Herrera-Estrada et al., 2017; Sheffield et al., 2009; Vernieuwe et al., 2019).

We define drought as the instances that fall below the 20th percentile in each grid cell and define drought clusters in 2-D as contiguous areas with $P - E$ below the 20th percentile threshold at each time step. (We test the sensitivity of our results using the 10th, 15th, and 25th percentile thresholds.) We identify all 2-D drought clusters for each time step that are at least 10,000 km$^2$ (roughly the size of the island of Jamaica).

To track clusters through time, we link clusters that have overlapping grid cells between time $t$ and time $t + 1$ and assign an ID number to each tracked cluster through time. If a cluster splits into two or more clusters, the cluster with the largest area maintains the original ID number. Similarly, if two or more clusters merge, the merged cluster maintains the ID number of the largest constituent cluster.

After initially identifying and tracking all clusters of at least 10,000 km$^2$, we extract the large-scale drought clusters that have the potential for considerable impacts. Thus, we ultimately only classify and analyze clusters that reach a maximum area of at least 100,000 km$^2$ (roughly the size of Guatemala). The lower threshold used for identifying droughts (i.e., 10,000 km$^2$) allows for improved temporal connectivity, so we continue tracking these large-scale clusters even if they start or end below the 100,000 km$^2$ threshold.
To maintain contiguous land areas, we shift the initial grid for the reanalysis data to span between 170°W and 190°E. However, the clustering algorithm follows the drought clusters if they cross the map edges at 170°W (left) and 190°E (right), roughly matching the International Date Line. To match the coverage period across the three data sets, we identify and track drought clusters between 1981 and 2018.

Drought clusters are classified into four categories: (i) Ocean-only, (ii) Land-only, (iii) Landfalling, and (iv) Other. Ocean-only clusters appear, develop, and terminate completely over the ocean. Likewise, Land-only clusters appear, develop, and terminate completely over the continents. Landfalling droughts are clusters that originate 100% over the ocean and, at some instance, cover at least 100,000 km² over land. Droughts that start over land and end over the ocean, or that start partly over ocean and partly over land, are classified as “Other.” Clusters must last at least 3 months to capture the three stages of Landfalling droughts (i.e., before landfall, landfall, and after landfall). Thus, we remove all clusters that last less than 3 months. Note that the duration of a drought cluster in this study is the number of months during which the moisture anomalies accumulated over the previous 12 months fall below the 20th percentile.

We carry out these classifications and most subsequent analyses for each data set separately. While each data set's land mask may introduce uncertainties, this approach allows for internal consistency within each reanalysis, particularly in coastal areas. In addition, we test the sensitivity of our Landfalling drought definition to the land coverage thresholds by (i) allowing Landfalling drought clusters to have up to 10% of their area over land during genesis (rather than 0%), and (ii) defining landfall when at least 33% of the cluster is over land (rather than at least 100,000 km²).

We calculate the centroid of each cluster at each time step from the latitudes and longitudes of the grid cells belonging to the cluster, using the grid cells' normalized intensity-related metric as weights, as shown in Equation 1:

\[ c_{\text{lon}, t} = \frac{\sum_{i=0}^{n} x_i Q_{i,t}}{\sum_{i=0}^{n} (1 - \hat{e}_{i,t})}, \quad c_{\text{lat}, t} = \frac{\sum_{i=0}^{n} y_i Q_{i,t}}{\sum_{i=0}^{n} (1 - \hat{e}_{i,t})} \]

where \( c_{\text{lon}, t} \) and \( c_{\text{lat}, t} \) are the longitude and latitude coordinates of the drought cluster's centroid, respectively, at time \( t \); \( n \) is the number of grid cells belonging to the drought cluster at time \( t \); \( x_i \) and \( y_i \) are the longitude and latitude coordinates of grid cell \( i \) at time \( t \), respectively; \( \hat{e}_{i,t} \) is the percentile at grid cell \( i \) and time \( t \); and \( Q_{i,t} \) is a normalized metric related to the intensity of the drought in grid cell \( i \) at time \( t \). Thus, the centroid of the drought cluster is defined based on both the location and intensity. We likewise use the grid cells of the drought clusters that occur over land to calculate the centroids of the land areas during landfall.

### 2.3. Characteristics of Landfalling Droughts

We calculate several metrics to quantify the behavior of Landfalling droughts (see Table 1 for equations and summary descriptions). We quantify the annual frequency as the number of Landfalling clusters that affect a given grid cell during the 1981–2018 period, divided by the number of years (\( n = 38 \)). We calculate mean annual exposure as the total number of months that Landfalling droughts cover each grid cell during the 1981–2018 period, divided by the number of years. Note that frequency refers to the number of Landfalling drought clusters, while exposure includes information about the droughts’ duration (i.e., the number of months where the moisture deficit during the antecedent year is below the 20th percentile of historical 12 month cumulative \( P - E \) anomalies). We calculate the mean extent and intensity over each grid cell by recording the areas and intensities (see definition below) of Landfalling drought clusters that affect each grid cell and then dividing by the number of months that each grid cell is exposed to Landfalling droughts.

To calculate the intensity of a drought cluster at each time step, we use the following set of equations:

\[ I_t = -\frac{1}{n} \sum_{i=1}^{n} \phi_{i,t} \]

where \( \phi_{i,t} \) is the 12 month cumulative anomaly of precipitation minus evaporation in grid cell \( i \) at time \( t \), and \( \max(\bar{M}_i) \) and \( \min(\bar{M}_i) \) are the maximum and minimum values, respectively, of these anomalies in
Table 1
Metrics of Landfalling Drought Clusters

| Metric name                              | Equation                                                                 | Description                                                                                                                                                                                                 |
|------------------------------------------|--------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Frequency of Landfalling droughts        | \( F_i = \frac{n_i}{N_{\text{years}}} \)                             | This frequency \( F \) in grid cell \( i \) is the ratio between the number of Landfalling drought clusters \( n_i \) that affected the grid cell, divided by the number of years in the study \( N_{\text{years}} \). |
| Frequency of genesis of Landfalling droughts | \( F_i = \frac{n_{i,o}}{N_{\text{years}}} \)                        | This frequency \( F \) in ocean grid cell \( i \) is the ratio between the number of Landfalling drought clusters that started in the grid cell \( n_{i,o} \), divided by the number of years in the study \( N_{\text{years}} \). |
| Frequency of Landfalling droughts in transit | \( F_i = \frac{1}{N_{\text{years}}} \sum_{j=1}^{n_i} \sum_{t_j=0}^{T_j-1} \frac{1}{T_j} \) | This frequency \( F \) in grid cell \( i \) is the number of monthly cluster instances that affected the grid cell between the month after the clusters genesis and the month before landfall, divided by the number of years in the study. |
| Average exposure                         | \( E_j = \frac{1}{N_{\text{years}}} \sum_{i=1}^{n_i} \sum_{t_i=0}^{T_i-1} \frac{1}{T_i} \) | For each grid cell \( i \), average exposure is the number of months that a Landfalling drought cluster \( j \) occupied the grid cell throughout the cluster’s duration \( T_j \), divided by the number of years in the study \( N_{\text{years}} \). |
| Average extent                           | \( A_i = \frac{1}{E_j} \sum_{j=1}^{n_i} \sum_{t_i=0}^{T_i} a_{i,t_i} \) | For each grid cell \( i \), the average extent is the sum of the areas of Landfalling drought clusters \( j \) that occupied the grid cell throughout the clusters’ duration \( T_j \), divided by the exposure of that grid cell as defined in the row above. |
| Average intensity                        | \( A_i = \frac{1}{E_j} \sum_{j=1}^{n_i} \sum_{t_i=0}^{T_i} I_{i,t_i} \) | For each grid cell \( i \), the average intensity is the sum of the intensities of all the Landfalling drought clusters \( j \) (calculated from Equations 2 and 3) that affected the grid cell throughout the duration of the clusters \( T_j \), divided by the exposure of that grid cell as defined above. |

Note. Equations and descriptions of the metrics calculated for Landfalling droughts displayed in Figure 2.

grid cell \( i \) throughout the study period. Thus, \( \phi_{i,t} \) represents the normalized cumulative anomalies of precipitation minus evaporation. \( I_{i,t} \) is the intensity of a given cluster at time \( t \) and is given by \(-1\) multiplied by the average of all the normalized cumulative anomalies of precipitation minus evaporation over the \( n \) grid cells that belong to that cluster at time \( t \). The negative sign is necessary because the normalized cumulative anomalies are by definition negative for droughts. This intensity metric is positive and ranging from 0 to 1, with higher values representing higher intensities. For Landfalling droughts, we calculate the intensity of the whole cluster, as well as of the land portion of the cluster (by only including the cluster grid cells over land in Equation 3).

For each Landfalling cluster, we calculate (i) the number of months between genesis and landfall, (ii) the distance between the location of genesis and the location of landfall, and (iii) the maximum extent reached over land. Likewise, we quantify the frequency of Landfalling drought genesis in each ocean grid cell (based on the location of each cluster’s first appearance), along with the frequency with which clusters pass through each ocean grid cell between genesis and landfall (i.e., “in transit”).

We calculate these metrics for each reanalysis separately. We then interpolate each metric to the coarsest resolution grid (ERA-Interim) and average the values to obtain a single estimate for each grid cell. We overlay hatching where there is less than two thirds consensus across the reanalyses.

2.4. Comparison of Cluster Dynamics Across Drought Types

For the different drought cluster types, we measure the empirical distributions of monthly areas and intensities and their positive monthly rates of change (i.e., increases in area and intensity). Drought onset and development are characterized by growth and intensification, so comparing how these behaviors vary across drought cluster types may provide insights into their underlying mechanisms (Baek et al., 2019; Findell & Delworth, 2010; Giannini et al., 2003; Hoerling & Kumar, 2009; Kam et al., 2013; Schubert et al., 2009, 2016; Sheffield & Wood, 2011; Wood et al., 2015). Conversely, negative changes in area and intensity—which are associated with drought recovery—are likely to be governed by mechanisms that are independent from
those responsible for drought onset and development (Kam et al., 2013; Parry et al., 2016), so we do not include them in this study.

We calculate the distributions of area, intensity, growth rate, and intensification rate for the Ocean-only, Land-only, and Landfalling drought clusters. We separate the measurements related to Landfalling clusters into three subcategories: the prelandfall period (“Pre-Landfall”), the postlandfall period measured over the full cluster (“Post-Landfall\text{full}”), and the postlandfall period measured only over the land area covered by the cluster (“Post-Landfall\text{land}”). Because a Landfalling drought may “retreat” toward the ocean after landfall and subsequently return onto land, we define the end of a drought’s “landfall” to be the last instance when a cluster covers less than 100,000 km$^2$ over land (i.e., the same threshold used to define landfall). If the cluster disappears while still over land, we record the cluster’s disappearance as the end of the landfall.

We use the two-sample Kolmogorov-Smirnov test to quantify whether there are differences in the characteristics of Landfalling droughts before and after landfall and whether the land and ocean phases of Landfalling droughts behave differently from other droughts. (Note that because the distributions of drought cluster areas, monthly growth rates, and monthly intensification rates are log-normal, we take the base-10 logarithm of the distributions before applying the Kolmogorov-Smirnov tests.)

We conduct these analyses globally and for five regions: western North America (170°W to 100°W, 15°–55°N), eastern South America (68°–10°W, 47°S to 0°), southwestern Africa (33°W to 25°E, 45°S to 0°), eastern Oceania (133°E to 180°, 48°–12°S), and eastern Asia (100°E to 180°, 15°–55°N). These regions are chosen to span all continents and cover areas that have both high exposure and vulnerability to landfalling droughts (Figure 2) (e.g., eastern instead of western Australia due to higher population density).

2.5. Physical Drivers of Landfalling Droughts

We use droughts that make landfall over western North America as a testbed for identifying possible physical drivers of Landfalling droughts. For these analyses, we use monthly data from ERA-Interim, including the vertical integral of northward and eastward water vapor fluxes, mean sea level pressure, geopotential height at 500 mbar, and $U$ and $V$ components of wind at 10 m and 500 mbar. We calculate mean anomaly composites of these variables during the months when we observe Landfalling droughts in transit toward western North America. Further, we use the monthly time series of the Niño 3.4 index (Rayner et al., 2003) from 1981–2018 to explore relationships between the interannual variability of Landfalling drought events and El Niño–Southern Oscillation (ENSO).

We also use the results from Herrera-Estrada et al. (2019), where subdaily vertically integrated moisture fluxes and daily vertically integrated water vapor, precipitation, and evaporation from ERA-Interim are used to drive the Dynamic Recycling Model (DRM; Dominguez et al., 2006; Martínez & Dominguez, 2014). The DRM estimates the fraction of the precipitable water and precipitation over a given region that originates from evaporation within that region and what fraction originates from other specified regions upwind. Using these existing model runs, we calculate the anomalies in the precipitation that originates over the Pacific Ocean and falls over western North America during the months in which Landfalling droughts occur.

3. Results

3.1. Identification of Landfalling Droughts

From 1981 to 2018, we identify an average of 37,672 total drought clusters globally (reanalysis range: 24,814–48,115). Of the clusters that lasted at least 3 months, 2,470 (range: 2,018–2,908) reached a maximum area of at least 100,000 km$^2$ and existed only over the oceans, while 1,723 (range: 1,549–1,817) reached a maximum area over land of at least 100,000 km$^2$. In this latter category, 53% of clusters (range: 49–57%) originated, developed, and ended completely over land; 31% (range: 27–35%) either originated over both ocean and land simultaneously or originated over land and disappeared over the ocean; and 16% (range: 15–17%) were Landfalling droughts that originated over the ocean and subsequently reached the continents.

Figures 1a and 1b show the distributions of number and size of drought clusters globally. We observe higher spatial coherence in ERA-Interim’s representation of moisture anomalies, yielding fewer, larger clusters. Conversely, CFSR/CFSv2 shows larger spatial heterogeneity in $P - E$ anomalies, producing more, smaller drought clusters. Figure 1c shows the robustness of the number of Landfalling droughts identified across
data sets and how that number varies in response to the land area threshold used to define landfall (see section 2). CFSR/CFSv2 identifies more Landfalling droughts at smaller land area thresholds compared to ERA-Interim, but the three data sets converge for high threshold values above 100,000 km². Figure 1d shows the robustness to the maximum land fraction allowed at genesis (see section 2). The number of Landfalling droughts increases by a factor of 1.26 to 1.37 as we increase the maximum land fraction at genesis from 0% to 10%. Thus, allowing some fraction over land at genesis increases the number of Landfalling droughts that are identified and the range of values observed between the reanalyses.

For the rest of this study, we use the more stringent definition of Landfalling droughts (i.e., that 100% of the cluster must start over the ocean, and landfall occurs when the area over land reaches at least 100,000 km²). This stricter definition yields higher robustness across data sets (Figures 1c and 1d) and also allows more consistent comparisons of the ocean phase of Landfalling droughts with Ocean-only droughts (by limiting the number of land grid cells included in the Landfalling droughts).

### 3.2. Spatial Distribution of Landfalling Droughts

Figure 2 shows the spatial distribution of Landfalling drought clusters ($n = 832$ across data sets, between 1981 and 2018). Landfalling droughts affect most of the Americas and Oceania, as well as regions in southern Africa, northern Europe, southern and eastern Asia, and Antarctica (Figure 2a). Among the regions with particularly high frequency of Landfalling droughts are Antarctica (up to an average of 0.28 clusters/year across data sets), Chile (0.27 clusters/year), Argentina (0.24 clusters/year), New Zealand (0.24 clusters/year), the western United States (0.20 clusters/year), and eastern Australia (0.17 clusters/year). Likewise, the highest
exposure occurs over southern South America (1.4 months/year), southeastern Asia (1.4 months/year), Antarctica (up to 1.2 months/year), eastern South America (1.1 months/year), and Oceania (1.0 months/year) (Figure 2b). The largest mean extents of Landfalling drought clusters occur over areas of Canada, the U.S. southern Great Plains, southeastern Asia, and Oceania (Figure 2c). The Landfalling droughts in these regions exhibit high intensity, as do those in several other regions, particularly in Southeast Asia (Figure 2d). Because the reanalysis grids range from 0.5°–0.75°, the prevalence of Landfalling droughts over small land regions—including many islands—may not be captured. However, we expect our results to hold for the world’s land areas that extend at least 100,000 km².

Figure 2. Spatial distribution of Landfalling droughts’ characteristics (1981–2018). (a) Average number of Landfalling droughts per year. (b) Average number of months per year affected by Landfalling droughts. Average extent (c) and intensity (d) of the Landfalling drought clusters that covered each grid cell. Average number of Landfalling droughts per year that originated over each ocean grid cell (e) and that occupied each ocean grid cell from the month following genesis until landfall (f). Hatching represents regions without two thirds agreement of Landfalling drought between the reanalyses (see section 2).
Over the ocean, we find the highest frequency and exposure of Landfalling droughts across the Southern Ocean and the northeast, southeast, and west Pacific Ocean, although the Indian and Atlantic Oceans also exhibit areas of high frequency and exposure (Figures 2a and 2b). Much of the Pacific Ocean exhibits high mean intensity, along with the largest extents found in the global oceans (Figures 2c and 2d). Over the tropical Pacific, high intensity co-occurs with high exposure and low frequency (Figures 2a–2d), suggesting prevalence of prolonged, intense drought clusters that eventually make landfall.

The four metrics in Figures 2a–2d are spatially correlated (Table 2). For example, we find that the regions that are most affected by Landfalling droughts also tend to have the highest exposure to larger and more intense events. Over land, the highest correlations are between “Landfalling drought frequency” and “average exposure to Landfalling droughts” ($r = 0.89$) and between “Landfalling drought frequency” and “average intensity of Landfalling droughts” ($r = 0.72$).

Landfalling droughts can originate almost anywhere over the global oceans, although they tend to appear more frequently closer to the continents (Figures 2e and 3a). While there is high variation in the areas of Landfalling drought genesis both spatially and across data sets, the most active genesis regions appear to be in the tropical and southern Pacific Ocean, the tropical Atlantic and Indian Oceans, and the Southern Ocean (Figures 2e and 3a). Likewise, the regions through which Landfalling droughts most frequently “transit” between genesis and landfall are the northeastern, southwestern, and southeastern Pacific Ocean; the central Atlantic Ocean; the southern Indian Ocean; and the Southern Ocean (Figure 2f). Few clusters whose centroids originate south of 60°S travel northward (Figure 3a), causing Antarctica to have some of the highest Landfalling drought frequencies (Figure 2a).

Figures 3a and 3c show that there is variation in the location and trajectory of individual drought clusters across data sets. However, Figure 3b shows that there is some degree of agreement across the data sets on how many Landfalling drought clusters are present globally in any given month. These differences are discussed further in section 4.

Figure 4a shows the distributions of four characteristics for all Landfalling droughts that made landfall between 60°N and 60°S ($n = 587$ across data sets, between 1981 and 2018), where most of the world’s population resides. We find that the median drought cluster takes 5 months to make landfall, travels a distance of 1.380 km from origin to landfall, has a size of 1.23 million km$^2$, and covers a maximum area over land of 377,000 km$^2$ (roughly the size of Norway). We find that these characteristics show some sensitivity between reanalyses (Figure 4a) and to various methodological choices in the definition of Landfalling droughts (Figures 4b and 4c). These sensitivities are discussed further in section 4.

### 3.3. Comparison of Characteristics Across Drought Types

The ocean phase of Landfalling droughts is significantly ($p < 0.001$) larger (220%; Figure 5a), faster growing (253%; Figure 5b), more intense (4%; Figure 5c), and more rapidly intensifying (9%; Figure 5d) than Ocean-only clusters. Similarly, the land phase of Landfalling droughts is significantly ($p < 0.001$) larger (435%; Figure 5a), faster growing (285%; Figure 5b), more intense (30%; Figure 5c), and more rapidly intensifying (28%; Figure 5d) than Land-only drought clusters. Further, Landfalling drought clusters are significantly ($p < 0.001$) larger (430%; Figure 5a), faster growing (69%; Figure 5b), and more intense (8%; Figure 5c) after making landfall. While there is some heterogeneity, these patterns generally hold across regions (Figure 6).

This robustness suggests the possibility of distinct physical controls on Landfalling droughts. For example, land surface processes (e.g., Seneviratne et al., 2010) may amplify the size, intensity, and growth rate once Landfalling droughts move from ocean onto land. Moreover, the mechanisms responsible for the onset of Landfalling droughts over the oceans (see section 3.4) can create large moisture anomalies such that Landfalling droughts develop to be larger throughout their duration, regardless of whether they are over the ocean or land.

### 3.4. Physical Drivers of Landfalling Droughts

We select western North America for a more detailed analysis of the physical drivers of Landfalling droughts, since past studies have identified patterns of atmospheric conditions and moisture transport associated with long-lasting droughts over the region (e.g., Herrera-Estrada et al., 2019; Swain et al., 2014, 2016, ...
We find that Landfalling droughts appear to result from a decrease in moisture flux from the ocean to the adjacent continent (Figure 7). Droughts that make landfall primarily over the subtropical north Pacific east of 160°W and over the midlatitudes of the northeast Pacific west of 160°W (Figure 7b). The spatial pattern of these clusters (Figure 7b) is closely matched by the composite of \( P - E \) anomalies accumulated during the months when Landfalling droughts are in transit (Figure 7c).

Previous work shows that hydrological extremes in western North America are highly modulated by atmospheric pressure and circulation patterns over the Pacific Ocean, affecting the tracks of atmospheric rivers and other storm systems (Gao et al., 2015; Gonzales et al., 2019; Hagos et al., 2016; Swain et al., 2016, 2017) or blocking storm systems over the region altogether (Swain et al., 2014, 2016, 2017). We find that drought clusters that make landfall in western North America are associated with areas of anomalously high sea level pressure and 500 hPa geopotential heights over the high latitudes of the central north Pacific and the midlatitudes of the northeast Pacific (Figures 7g and 7h). These high-pressure anomalies are likewise associated with anticyclonic circulation anomalies, both at the surface and aloft (Figures 7g and 7h). These atmospheric circulation anomalies are in turn linked with anomalous increases in moisture transport over the ocean both toward western North America north of 50°N and away from western North America in the subtropics, along with anomalous decreases in moisture transport over the midlatitudes adjacent to western North America (Figure 7d).

We also analyze the DRM data from Herrera-Estrada et al. (2019), which estimate the precipitation that originates as evaporation over the Pacific Ocean and falls over western North America. During the months with Landfalling drought occurrence (Figure 7a), the distribution of anomalies in precipitation that originates from the Pacific Ocean and falls over western North America is weighted toward negative values (Figure 7f), providing further evidence that Landfalling droughts are associated with decreased moisture transport from the ocean onto adjacent land areas. Overall, these results suggest that the migration of moisture deficits from ocean onto land is associated with moisture flux anomalies induced by anomalous atmospheric pressure patterns that promote descending air masses, anticyclonic circulation, and the poleward deflection of moisture transport (as identified in Swain et al., 2014, 2016, 2017).

### 4. Discussion

Droughts are often classified based on their spatiotemporal characteristics, including “flash droughts” (e.g., Mo & Lettenmaier, 2015, 2016) and “megadroughts” (e.g., Ault et al., 2016; Cook et al., 2015; Williams et al., 2020). Categorizing droughts based on their spatiotemporal characteristics has helped the scientific community isolate specific patterns and mechanisms related to the different types of droughts (Parry et al., 2012; Seager & Hoerling, 2014; Sheffield & Wood, 2011). Distinguishing “Landfalling droughts” from other types of droughts may help to further elucidate causal mechanisms.

The robust identification of Landfalling droughts (Figures 1c and 4) suggests that the ocean’s role in drought development is not limited to atmospheric teleconnections with remote SSTs. In fact, we find no strong, significant correlations \( (r > 0.2, p \text{ value} < 0.05) \) between the occurrence of Landfalling droughts and the Niño 3.4 index (Figures 3b and 7a). The findings that Landfalling droughts exhibit characteristics that are

| Table 2  | Spatial Correlation of Landfalling Drought Characteristics |
|----------|-----------------------------------------------------------|
| Metric   | Average exposure to Landfalling droughts                  | Average extent of Landfalling droughts | Average intensity of Landfalling droughts |
|          | Land | Ocean | Land and ocean | Land | Ocean | Land and ocean | Land | Ocean | Land and ocean |
| Landfalling drought frequency | 0.89* | 0.70* | 0.77* | 0.10* | 0.13* | 0.12* | 0.72* | 0.45* | 0.56* |
| Average exposure to Landfalling droughts | —   | —     | —     | 0.06* | 0.34* | 0.28* | 0.69* | 0.48* | 0.59* |
| Average extent of Landfalling droughts | —   | —     | —     | —     | —     | —     | 0.43* | 0.61* | 0.54* |

*Note. Pearson correlations between the maps in Figures 2a–2d over land, ocean, and both land and ocean grid cells combined. The metric names correspond to the map labels in Figure 2. \( p < 0.01. \)
Figure 3. Spatial and temporal robustness of Landfalling droughts. (a) Unit displacement vectors between the clusters' centroids during genesis and the centroid of the land area covered during landfall for every Landfalling drought identified between 1981 and 2018 across the three data sets ($n = 832$). Dots represent the clusters' centroids during genesis. Yellow and purple dots show Landfalling drought clusters that match across three and two data sets, respectively, while black dots correspond to clusters that are only identified in one data set. Two clusters are matched across data sets if they occurred within 3 months of each other and their centroids at origin are within 500 km. The arrow colors represent the data set to which each drought cluster belongs. (b) Running count of Landfalling droughts through time for each reanalysis together with the Niño 3.4 index. (c) Temporal variability of the fraction of Landfalling droughts in each data set that are matched—in at least one of the two other data sets—with a Landfalling drought, an Ocean-only drought, or a drought that started partially over land.
statistically distinct from both Land-only and Ocean-only droughts suggests the potential for some distinct causal mechanisms. Deeper understanding of these mechanisms may help identify model development priorities for seasonal forecasting (Roy et al., 2019; Wood et al., 2015) and climate change projections (Herrera-Estrada & Sheffield, 2017).

Given that half of Landfalling droughts take at least 5 months to reach land, extending operational drought monitors (e.g., U.S. Drought Monitor; Svoboda et al., 2002) to identify and track moisture deficits over the oceans could provide new information to improve seasonal forecasts and early-warning systems (Wood et al., 2015). In the case of western North America, detection of moisture deficits over the northeast Pacific Ocean combined with indicators of persistent anticyclonic atmospheric pressure anomalies could serve as an early warning of Landfalling drought potential. SSS has also been identified as a predictor of winter precipitation over the southwestern United States (Liu et al., 2018), reinforcing the predictive potential of ocean moisture deficits. Further, we hypothesize that our results can translate to other regions because anticyclonic atmospheric patterns are common drivers of droughts around the world (Sheffield & Wood, 2011). Future studies may expand on how the characteristics of these patterns differ in other regions and potentially identify additional physical drivers of Landfalling droughts.
4.1. Sensitivity Analyses

The total frequencies of Landfalling droughts (Figure 1c) and their aggregate statistical characteristics (Figure 4) show high consistency across data sets, increasing confidence that Landfalling droughts are a coherent drought category. However, there is low agreement in the identification of specific Landfalling droughts between reanalyses (Figure 3). We find that the reanalyses have different representations of the spatial heterogeneity of $P - E$ anomalies (Figures 1a and 1b) and that differences in monthly estimates of $P - E$ are mostly driven by differences in precipitation (Figure S3). The uncertainties in representation of the hydrological cycle (e.g., Beck et al., 2020; Chen et al., 2019) likely contribute to the challenge of matching individual Landfalling droughts across data sets (similar to how different reanalyses yield variable representations of atmospheric rivers; Gonzales et al., 2019). Thus, efforts to incorporate Landfalling droughts into operational drought monitoring must account for uncertainties in the representation of the hydrological cycle (particularly precipitation).
In this study, we employ a 20th percentile drought threshold and a 12 month accumulation period for $P - E$ anomalies when identifying drought clusters. Lower percentile thresholds will isolate regions of extreme drought conditions and omit regions under moderate drought. Some regions under extreme drought may experience temporary recovery, which may be misinterpreted as a full recovery if the percentiles rise above the low threshold, preventing us from accurately tracking the continuation of drought over a region through time. Therefore, choosing lower percentiles will result in fewer Landfalling drought clusters (Figure 4b). Lowering the percentile threshold also leads to smaller clusters (since the adjacent areas exhibiting less extreme conditions will be ignored), and to shorter distances between genesis and landfall (Figure 4b).

Shorter accumulation periods for $P - E$ anomalies yield time series with higher variability and clusters of shorter duration. Lowering the accumulation period also results in shorter durations between genesis and landfall and larger maximum extents over land (Figure 4c). Longer accumulation periods will miss shorter and less intense droughts but are more likely to identify moisture anomalies that persist through time (even if there is intermittent recovery).

### 4.2. Choice of Drought Metric

We use percentiles of cumulative anomalies of $P - E$ because they are (i) normalized, nonparametric measurements of moisture availability, (ii) consistent over land and ocean, (iii) flexible in accounting for...
Figure 7. Atmospheric conditions linked to drought landfall over western North America. (a) Annual distribution of drought clusters that make landfall over western North America along with the Niño 3.4 index. (b) Composite of all drought clusters that make landfall on western North America between 15°N and 55°N. (c) Composite anomalies of normalized 12 month cumulative precipitation minus evaporation for the months shown in a. (d) Composite anomalies in the magnitude of vertically integrated moisture fluxes shown together with the vectors of absolute moisture fluxes for the months shown in a. (e) Aggregate regions over the Pacific Ocean and western North America considered for the calculations of moisture transport shown in f. (f) Distribution of anomalies in precipitation that originates from evaporation over the Pacific Ocean and falls over western North America as calculated by the Dynamic Recycling Model during the months shown in a. (g) Composite anomalies of sea level pressure, together with the vectors of 10 m wind anomalies, for the months shown in a. (h) Composite anomalies of 500 hPa geopotential heights, together with the vectors of 500 hPa wind anomalies, for the months shown in a. All calculations shown for ERA-Interim data.
Figure 8. Comparisons between $P - E$, soil moisture, and sea surface salinity. Pearson correlations between 12 month cumulative anomalies of $P - E$ from ERA-Interim with (a) monthly anomalies in volumetric soil water down to 1 m from ERA-Interim (January 1981 to December 2018), and monthly anomalies in observations of sea surface salinity from (b) ESA CCI (January 2010 to November 2018) and (c) the Hadley Center (January 1981 to December 2018). Hatching represents $p$ values $> 0.05$. 
different accumulation periods, and (iv) reflect moisture balance constraints over land. Further, \( P - E \) exhibits significant \((p < 0.05)\) Pearson correlations with soil moisture over land, and with SSS over the oceans (Figure 8). Soil moisture and SSS are more direct measurements of moisture availability over land and oceans, respectively, because they capture additional physical characteristics (e.g., soil type) and processes (e.g., advection). However, the challenge of combining soil moisture and SSS to seamlessly track droughts that span land and ocean—along with relatively short and incomplete observational records—are important limitations to their use in Landfalling drought analysis.

Other drought indices such as SPI, PDSI, and SPEI also have the advantage of consistency over land and oceans and have been used in drought clustering analyses (Diaz et al., 2020; Zhan et al., 2016; Zhou et al., 2019). The primary advantage of these drought metrics is that they can be calculated over longer time periods using temperature and precipitation observations, thus capturing more severe drought events that are not included within the reanalyses' temporal range. However, SPI only includes precipitation, ignoring the contribution of evaporation entirely. PDSI and SPEI include estimates of potential evapotranspiration (PET) and allow for PET models of varying complexity (subject to data availability). Still, the use of simple PET models in PDSI and SPEI can cause biased drought estimates (Sheffield et al., 2012). In comparison, our \( P - E \) metric incorporates estimates of actual evapotranspiration over land calculated by the land surface model in each reanalysis and is therefore constrained by reanalysis soil moisture. Our estimates of \( P - E \) thus include more information about moisture availability over land than can be captured by SPI, PDSI, or SPEI.

5. Conclusions

In this study, we identify a new type of large-scale drought that originates over the ocean and migrates onto land. We find that these Landfalling droughts account for \(~16\%\) of all large-scale droughts over the continents. Although they generally affect land regions near the ocean, Landfalling droughts can extend farther inland. While there is uncertainty in the precise identification of any individual Landfalling drought across reanalysis data sets, there are several robust characteristics. For example, the number of Landfalling droughts, the median time and distance to landfall, and the maximum area covered over land are all equal or similar across the reanalyses. Further, we find robust differences compared with Land-only and Ocean-only moisture deficits, including larger areas, higher intensities, and higher growth rates.

Focusing on droughts that make landfall over western North America as a case study, we find that migration of moisture anomalies from the Pacific Ocean onto the continent appears to be driven by reduced moisture transport from the ocean associated with anomalous high-pressure systems off the western coast of North America. One interpretation for these results is that these high-pressure systems over the ocean create large areas favorable for the development of moisture anomalies. The migration of Landfalling drought clusters then results from the evolution of moisture anomalies within these large-scale areas. The degree to which the spatiotemporal dynamics of Landfalling droughts within these high-pressure systems are random or if there are specific physical mechanisms that cause them to make landfall requires further investigation.

Because Landfalling droughts are larger, more intense, and grow and intensify faster than droughts that develop only over land, the mechanisms governing their origin, growth, and displacement are critical for understanding the drought risks faced by communities and ecosystems worldwide. In particular, deeper understanding of the mechanisms that control the development of moisture deficits over the ocean and their subsequent displacement onto land—including the role of atmosphere-ocean variability—could offer the ability to extend and improve early-warning systems, which would in turn yield substantial humanitarian and economic benefit.

Data Availability Statement

Data are freely available online: ERA-Interim (at https://www.ecmwf.int), CFSR/CFSv2 (at https://rda.ucar.edu), MERRA-2 (at https://disc.gsfc.nasa.gov/), ESA CCI’s SSS (at http://cci.esa.int/), Hadley Center’s SSS (at https://www.metoffice.gov.uk/hadobs/en4/), and ENSO indices (at https://www.esrl.noaa.gov). The code for the clustering algorithm is found online (at https://github.com/julherest/drought_clusters).
Acknowledgments
We thank Danielle Touma and three anonymous reviewers for their feedback. We acknowledge funding support from the U.S. Department of Energy and Stanford University.

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