Detecting and Monitoring Large-Scale Drought Effects on Forests: Toward an Integrated Approach

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Introduction

Although drought is recognized as an important and overarching driver of ecosystem change, its occurrence and effects have been difficult to describe over large geographic areas (Hogg and others 2008, Panu and Sharma 2002). In forests, drought contributes to tree stress and mortality through the direct impacts of reduced moisture and high temperatures (Anderegg and others 2013, Wang and others 2012), and through indirect pathways such as increased disturbance from insects or fire (Martínez-Vilalta and others 2012, Mattson and Haack 1987, Meyn and others 2007, Raffa and others 2008, Schowalter and others 1986, Trouet and others 2010). Detecting drought effects on plant species demands detailed knowledge of where those species occur, but with few exceptions, only coarse vegetation maps are available for broad areas (Allen and others 2010). Long-term monitoring is helpful, but longer term assessments struggle with causal attribution. Numerous meteorologically based drought measures have been constructed to depict moisture deficits in agricultural contexts, but they may not accurately portray the effects of those deficits on forests, grasslands, or other natural vegetation types, where the constituent species may have diverse drought responses (Mishra and Singh 2010, Vicente-Serrano and others 2012). Furthermore, in order to examine those responses, meteorologically based approaches must make an inference about the impact of a given level of moisture deficit on the plants. Remote sensing-based measures are also available that exploit known differences in reflected radiation among stressed and unstressed vegetation (Peters and others 1991, Peters and others 2002, Zhang and others 2013), yet short-term stress may not be a precursor for ecological impacts that could take multiple seasons or even years to materialize.

Measures available from meteorological station data can be used to infer likely moisture and temperature impacts on trees or other vegetation (Vicente-Serrano and others 2012). When summarized for different time periods deemed relevant (e.g., with respect to tree mortality, multiple consecutive years of severe drought) (Guarín and Taylor 2005, Millar and others 2007), they can better approximate impacts like vegetation loss or cover change. Further assessments can come from direct measurements from remotely sensed or plot data (Ji and Peters 2003, Vicente-Serrano and others 2012, Vicente-Serrano and others 2013, Wullschleger and Hanson 2006, Zhang and others 2013). With

advances in near-real-time meteorological and remotely sensed response technology, it is now possible to generate reasonable coarse-scale forecasts of certain drought effects, such as declines in crop yields (Arshad and others 2013, Hao and others 2014, Luo and Wood 2007). However, finer-scale translation of such expectations for forested areas remains challenging due to a lack of species- and community-specific long-term impact assessments (Carnicer and others 2011, Martínez-Vilalta and others 2012, Michaelian and others 2011). This chapter reviews the status and role of data mining approaches using diverse ancillary data sets that can be brought to bear on monitoring and assessment, and clarifies ways in which they can be leveraged to reduce the uncertainties associated with drought impacts in forested ecosystems.

Fundamental Challenges

Drought can have a range of species- and community-level consequences for forests, many of which are poorly understood (Hanson and Weltzin 2000, Mueller and others 2005). The drought responses that can be systematically monitored at regional scales are only a detectable subset of all those that likely occur or matter, and this introduces uncertainty into monitoring and assessment. Breadth and efficiency are often the practical tradeoffs of having depth of understanding. With such uncertainties, our expectations for broad-scale monitoring are somewhat different from what can be obtained through local field-based observations.

Broad-scale monitoring is intended to describe the scope and relative severity of coarse drought impacts, rather than to quantify effects directly with precision that often depend on local knowledge of topography, weather, or species responses. The coarse-scale expectations of such efforts justify application of relative drought indices instead of actual biophysical measurements such as soil moisture, temperature, or precipitation. In turn, broad-scale drought monitoring produces only relative likelihoods, but such insights may be the most relevant for a particular set of management questions.

To progress as an applied science, broad-scale drought monitoring must confront four fundamental challenges that are described below. Meeting these challenges will improve our ability to comprehend, predict, and address the risks posed to forests by drought.

Challenge 1: Measuring drought in ways that matter for different forests—Our conventional perceptions of drought and its effects have primarily

developed from how drought impacts agricultural production and water supplies (Wilhite and Glantz 1985). Yet the conventional meteorological measures of drought that estimate effects to field or stream may be less than optimal for characterizing drought impacts to forests.

When a broad-scale drought response is detected for forests, its implications are far more complex than mono-specific crop yield reduction or lowered water levels in reservoirs, where there is a clearer expectation of loss. Forests and their constituent species are highly variable in their tolerance of and response to drought, such that no single metric or indicator is likely to capture expected impacts (Martínez-Vilalta and others 2012, Mishra and Singh 2010, Svoboda and others 2004). Unlike annual field crops, most perennials within forest communities are tolerant of one or more years of moderate drought stress, and so scientists contend that multiyear measures of drought are needed (Allen and others 2010, Mishra and Singh 2010, Niinemets 2010, Panu and Sharma 2002, Wilhite and others 2007).

Interpretations of drought responses are especially difficult in areas of high compositional or structural complexity, as the sensitivity of deciduous and evergreen trees, shrubs, and grasses are generally not equivalent (Hanson and Weltzin 2000). Interpretation of drought effects becomes more challenging in areas that have been recently disturbed as these landscapes have vegetation in various stages of successional recovery with dominant species that may differ in their response to drought from one decade to the next (Sousa 1984). Similarly, it can be difficult to make sense of broad-scale drought responses in highly fragmented landscapes where forest, field, and developed areas occur in close proximity (Ewers and Didham 2006, Laurance 2004). We need clearer drought response indicators for these types of landscapes.

The ramifications of drought for species depend on when the drought occurs with respect to species' seasonal phenologies (Anderegg and others 2013). In the Eastern United States, spring and summer growth often responds to winter, spring, and summer temperature and precipitation, but summer and fall drought can shorten the growing season. A number of western tree species depend heavily on winter rains or snowpack to provide a pool of available soil moisture for the subsequent growing season, which is effectively shortened when this pool is reduced (Hanson and Weltzin 2000). The relative importance of heat and moisture stress may differ (Bréda and others 2006,

Mueller and others 2005, Orwig and Abrams 1997) due to fundamental regional differences in the evolutionary climatic environment. Because of these inherent climatic differences, regional patterns of species adaptations affect how meteorological drought is experienced, and how effects are shown (fig. 9.1).

Challenge 2: Establishing context from historical data—In an operational sense, drought is more than heat and dryness (chapter 2). It involves some measure of departure from baseline conditions for a given location and specified time period. Both spatial and temporal aspects of this definition are critical for accurate recognition and prediction of broad-scale drought effects. Extended periods of seasonal and interannual dryness are a normal part of many forest environments, particularly across much of the Western United States (fig. 9.1). Multiyear or decadal averages, as reflected in the term "normal," can mask this climate variability, yet depending on the frequency and intensity of droughts that occur, both species and community attributes may be adapted to climatic extremes as much as, if not more than, any measure of central tendency.

Historical climate data provide both meteorological and biologically relevant context. Long-term paleoclimatological insights help contextualize the duration and intensity of recent drought events (chapter 2), but the relevance of historical drought patterns for contemporary forests and values can be difficult to ascertain where forest structure or composition have changed. From a meteorological perspective, the length of climatically meaningful baselines has been long debated (Lamb and Changon 1981, Livezey and others 2007, Wilks 2013), yet determining the period that is appropriate for understanding forest change may be far more difficult.

Commonly used 30-year baseline conditions may not be representative of the climate that existed when the longest lived trees established or developed. Tree species that produce many vegetative sprouts (as opposed to slower growing seedlings) after disturbance may subsequently have so many saplings that they retain demographic dominance in a site for centuries, regardless of the age of existing stems, and sprouting trees dominate many forest landscapes (Bellingham and Sparrow 2000, Bond and Midgley 2001, Del Tredici 2001, Vesk and Westoby 2004). Moreover, the relevant climate context for old forests may be longer than for adjacent areas affected by disturbance and recent succession. For example, the timing of drought
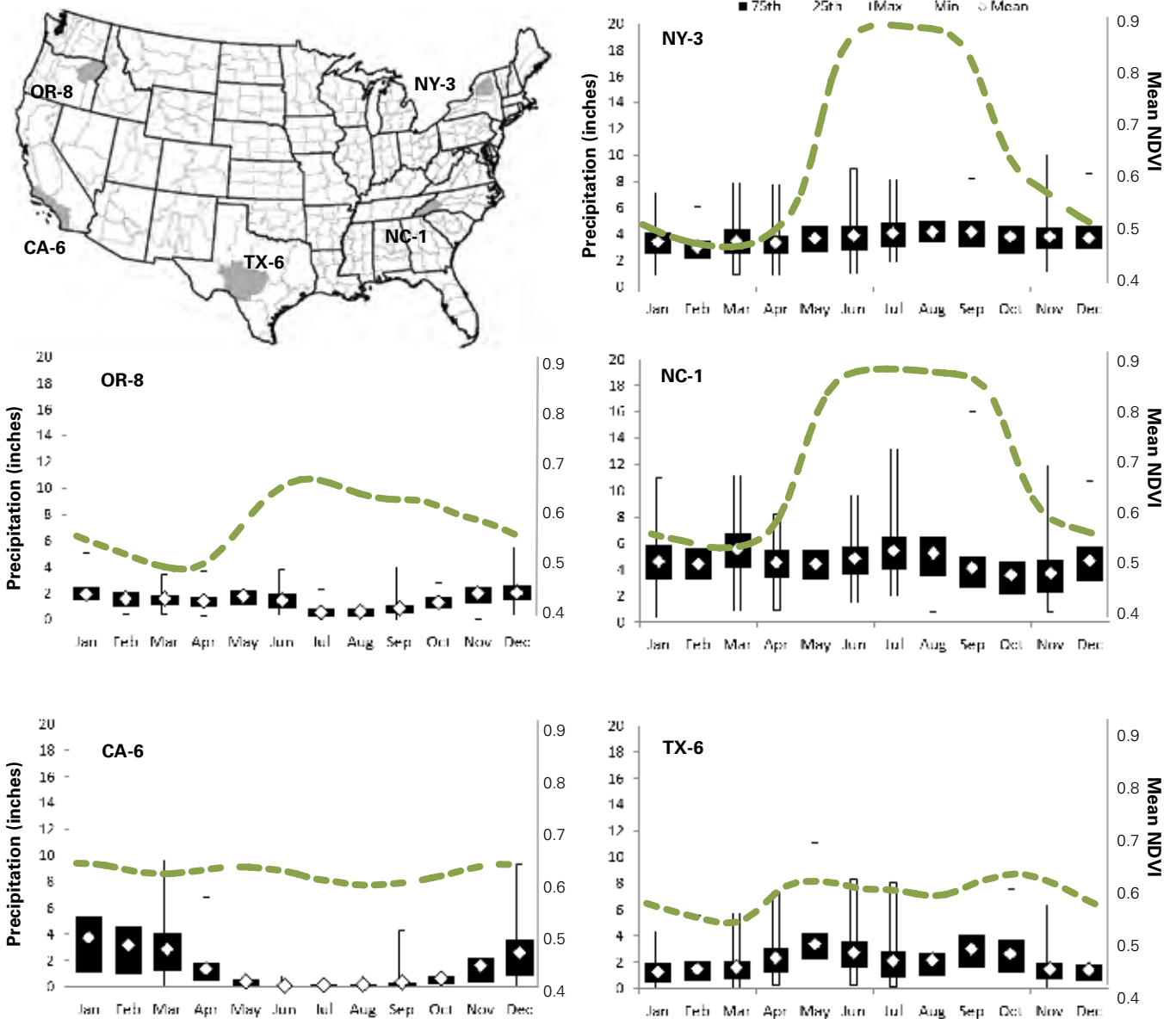
Figure 9.1—Regional differences in normal seasonal precipitation can affect how forests respond to drought. These graphs show historical variability in monthly precipitation for five National Climate Data Center (NCDC) Climate Divisions, 1895–2013, compared to the mean land surface phenology of forested Moderate Resolution Imaging Spectroradiometer (MODIS) pixels in those divisions as measured by the Normalized Difference Vegetation Index (NDVI) for the period 2000–2012. Box-whisker plots show the mean, extremes, and upper and lower quartiles of precipitation. Biweekly NDVI (green line) was derived from a National Land Cover Data (NLCD-2006) conditional filtering of majority forested *ForWarn*-MODIS data that included the following count of randomly selected cells: CA-6, n=110; NC-1, n=480; NY-3, n=474; OR-8, n=571; TX-6, n=247.

episodes during the late 20th century affected the establishment success of white pine (*Pinus strobus)* in old fields of the North-Central United States (Dovčiak and others 2005). Similarly, long-lasting cohorts of ponderosa pine (*Pinus ponderosa*) established during favorable climate windows in the Southwestern United States during the early 20th century (Savage and others 1996). Although forest changes caused by drought-associated mortality may be rapid (Mueller and others 2005, Wang and others 2012), we may need a long climatic perspective to make sense of observed changes over the lifespan of these forest dominants.

The relevance of past forest responses to drought for understanding those of the present is sometimes questionable, as the structure and composition of many forests has changed over the last century in response to logging, invasive insects, diseases and plants, fire exclusion, and livestock grazing (Norman and Taylor 2005, Nowacki and Abrams 2008). Increases in stand density and a decline in drought-tolerant species such as pines, oaks, and chestnut can make forests less resilient today than they were decades ago to drought or drought-associated disturbances such as fire (chapter 7). This potential shift in the implications of a given drought erodes the predictive capacity of efforts that rely only on meteorological data.

Trends in climate can pose serious problems for developing meaningful baselines (Wilks 2013). Such gradual transitions may reflect the progressive effects of a drying climate, and that rate of change is difficult to detect without long-term monitoring or broad-scale plot data (Woodall and others 2009). Mesophytic species may be expanding in importance from fire management, which could increase forest vulnerability if severe drought returns (Nowacki and Abrams 2008). Forests may be more vulnerable because of the increased water needs of denser stands or more mesophytic, less drought-tolerant species composition (Allen and Breshears 1998, Guarín and Taylor 2005, Savage 1997). While meteorological data provide insights into where meteorological trends are occurring (fig. 9.2), our knowledge of long-term trends in forest susceptibility is more limited.

Our primary broad-scale insights into how forests respond to drought comes from satellite observations, yet high-resolution satellite data have only been available for a third of the time that meteorological data have been collected on a wide scale. This shorter observation window limits what we can learn from historical

drought responses as shown through comparison of growing-season drought duration during the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite period with prior baseline periods (fig. 9.3). In this example, drought duration was derived from monthly National Oceanic and Atmospheric Administration (NOAA) National Climate Data Center (NCDC) Climate Division data (Guttman and Quayle 1996). Satellites that pass overhead frequently, such as Terra and Aqua that carry the MODIS sensor, can be used to identify short-term stress and longer term recovery or type conversion; however, their coarser resolution makes them less useful for monitoring species-specific stress in mixed stands over broad areas than less frequent, but higher resolution data. Derived products from satellite observations can help characterize similarities and differences among droughts, as observations coarsely quantify how forests are affected by drought and drought-associated disturbances.

Challenge 3: Capturing diverse drought effects—As an indicator for a suite of other potential drought impacts, vegetation stress monitoring is efficient, even if it does not predict specific individual tree responses. Such efforts only capture a fraction of drought-induced effects to forests, but those aspects that can be monitored can be strong indicators of system dynamics overall. For example, morphological adaptations, such as deeper rooting, are nearly impossible to quantify from either a remote-sensing or field-based perspective, but defoliation or canopy stress can be readily monitored.

It is difficult to translate community-level observations to species- or population-level responses when the constituent species in a region vary in their susceptibility and tolerance to drought (Bigler and others 2007, Floyd and others 2009, Hanson and Weltzin 2000, McDowell and others 2008, McDowell and others 2011). Individual species drought responses can be wide-ranging, divergent, or delayed (chapter 3) (Archaux and Wolters 2006). Community-level responses include reduced productivity and altered composition or structure largely through selective mortality (chapter 4) (Archaux and Wolters 2006). Drought can also have secondary effects on the population dynamics of insects and diseases (chapter 6) (fig. 9.4), or on the occurrence, attributes, or consequences of wildfire (chapter 7), since stressed trees are often more susceptible. Drought stress induces ponderosa pine to leave stomates open at night, increasing exposure to ozone and other airborne pollutants (Grulke and others 2004). Grulke (2011) reported that drought stress increases
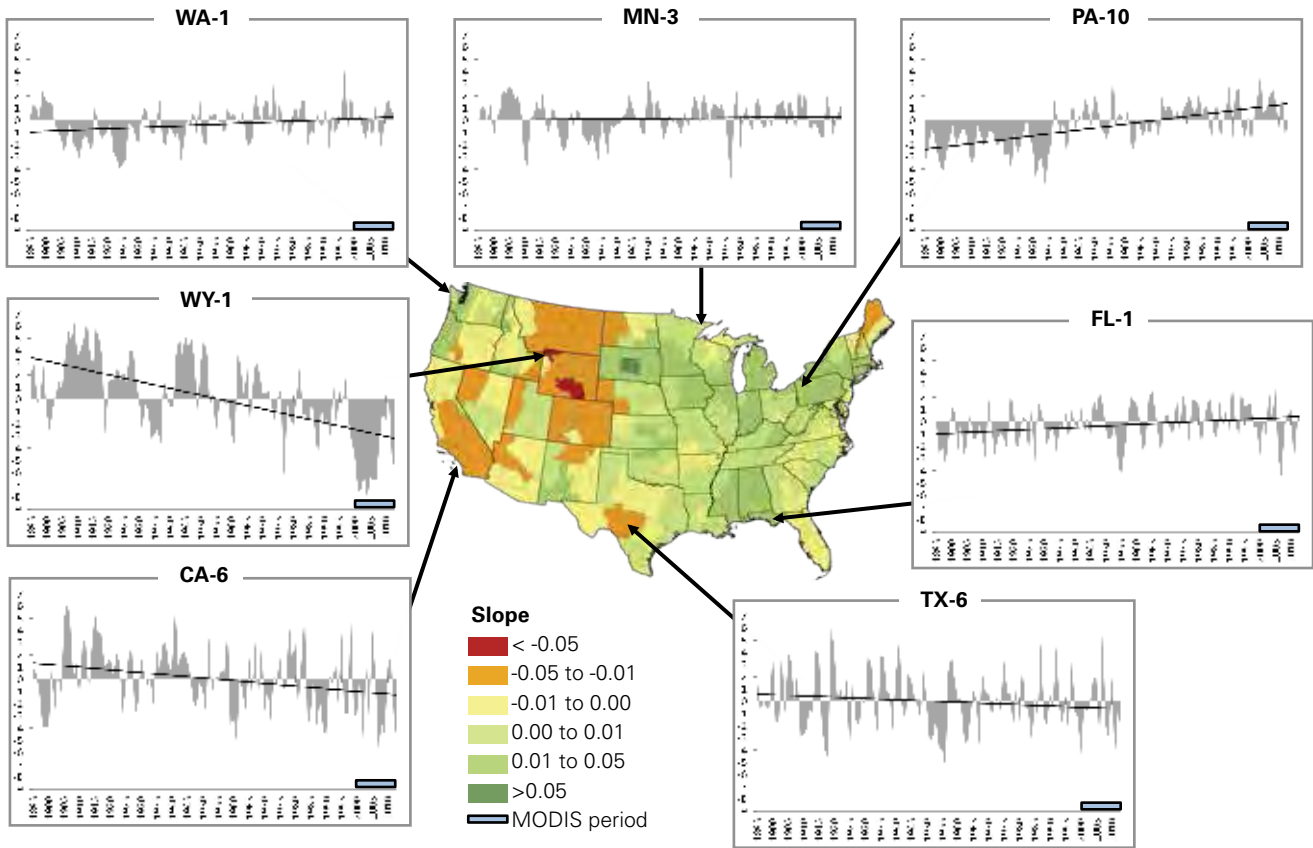
Figure 9.2—Long-term trends (black line) in the mean April–September Palmer Modified Drought Index (PMDI), 1895–2013, by National Climate Data Center (NCDC) Climate Division for the conterminous United States. Selected climate divisions are shown. The representativeness of the Moderate Resolution Imaging Spectroradiometer (MODIS) period relative to the past is suggested by the blue bar in the lower right of each inset graph.

SEVERE DROUGHT
PMDI < -2.0

MODERATE DROUGHT
PMDI < -1.0

Growing season drought duration departure in years

-5 -4 -3 -2 -1 0 1 2 3 4 5

Longer drought
during prior period
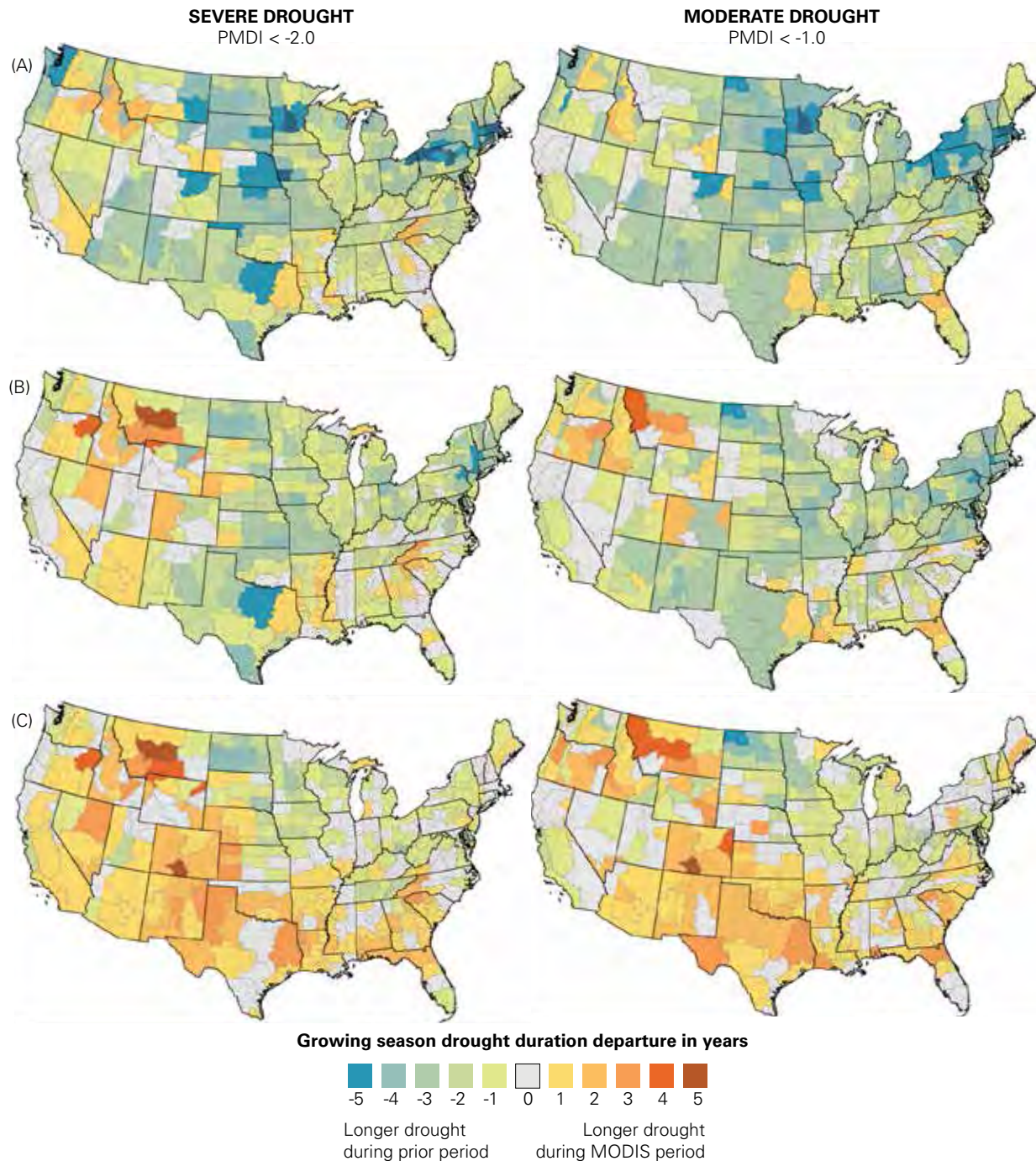
Longer drought
during MODIS period

Figure 9.3—Annual departure, by National Climate Data Center (NCDC) Climate Division, of mean April–September Palmer Modified Drought Index (PMDI) drought duration for the Moderate Resolution Imaging Spectroradiometer (MODIS) period (2000–2013) compared to historical drought duration for three baseline periods: (A) 1900–1999, (B) 1950–1999, and (C) the 14 pre-MODIS years, 1986–1999. Differences at two levels of drought severity are shown: severe drought (PMDI <-2.0) and moderate (PDMI <-1.0).
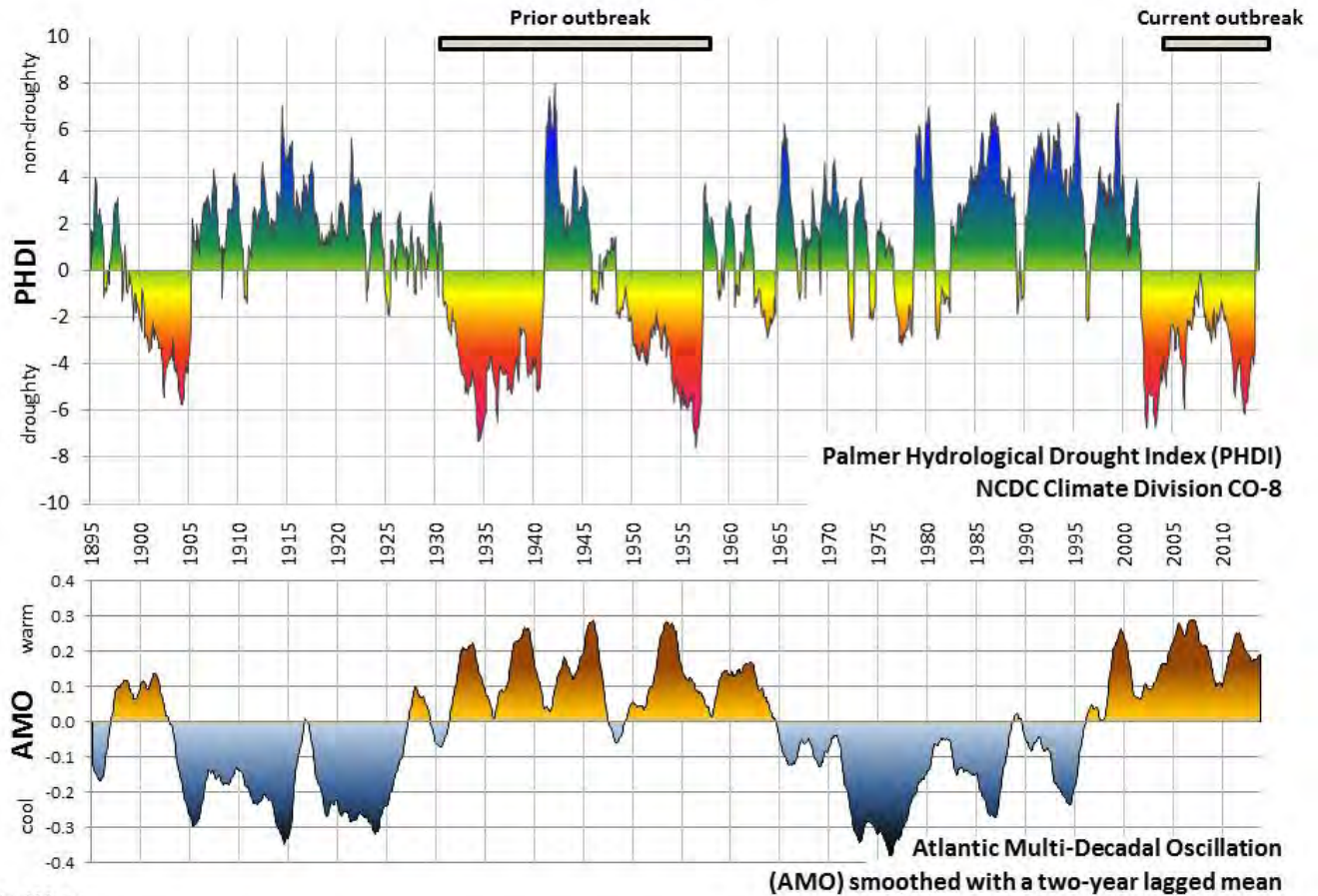
Figure 9.4—Variation in regional Palmer Hydrological Drought Index (PHDI) for northwestern Colorado and its relationship to outbreaks of the spruce beetle (*Dendroctonus rufipennis*). Regional drought is strongly influenced by hemispheric-scale variation in sea surface temperatures, particularly the Atlantic Multi-decadal Oscillation (AMO).

susceptibility to many pathogens that may be emerging with climatic change. While community-level response may not represent all impacts of concern, it provides the spatial pattern of likely effects across the landscape.

Variation in community-wide growing season stress may be the easiest drought-sensitive indicator to measure using remote sensing technologies. High-frequency observations can detect drought progression or near-real-time stress or mortality from wildfire or insects and disease (Hargrove and others 2009). From programmatic high-frequency datasets, measures of temperature and moisture-sensitive phenomena can be derived such as change in the onset of spring and fall and the duration of the growing season. These community-level measures of observed land surface phenological changes can be related to the responses of individual species and seasonal disturbances such as wildfire.

Some drought effects are difficult to recognize or track without ancillary information. The drought responses of different vegetation types are known to vary (Lobo and Maisongrande 2006, Sims and others 2014), so knowing the vegetation composition within particular remotely sensed grid map cells is critical for understanding both drought response and multiyear drought effects. Tree mortality can be delayed for years, and reduced vigor can invite second-order effects (Bigler and others 2007). This potential lag in response makes attribution more difficult without long-term datasets and modeling. Impacts from disturbance such as wildfire, insects, and diseases can be difficult to attribute to drought, since these are often a natural part of forests. With complex drivers in play, ancillary datasets can improve interpretations and predictions.

Conceptual models provide a graphical means of communicating these complex direct and indirect interactions. Figure 9.5 shows two example conceptual models for drought: a basic model of the direct relationships between drought, other drivers of forest disturbance, and their impacts (fig. 9.5A), as well as a more detailed model of the indirect relationships between drought and other landscape-level processes in the Interior West (fig. 9.5B). Within such models, contingencies can be structured as management options that can mitigate or prevent undesirable drought-associated effects. For example, in California's Yosemite National Park, where tree mortality has been associated with drought, drought susceptibility may have increased due to a fire management history

that has resulted in uncharacteristically dense stand structures that affect competition and water stress (Guarín and Taylor 2005). Thus, silvicultural methods such as mechanical thinning or fire may be viable options for improving stands and reducing the likelihood of drought-related tree mortality.

Challenge 4: Making drought-effect monitoring more applied—Broad drought-monitoring efforts capture changes to vegetation rather than impacts to individual trees. Detection of local effects is inferential due to the coarse nature of broad-scale observations. Local forest managers are usually aware when drought and drought-associated stresses are affecting their forests, yet recognizing and tracking drought effects becomes more difficult over States or regions. When large areas are affected by drought, the broad-scale need is often to identify those areas that are hardest hit and to prioritize areas for response. Such decisions can be greatly informed by relatively straightforward measures derived from systematic drought monitoring efforts.
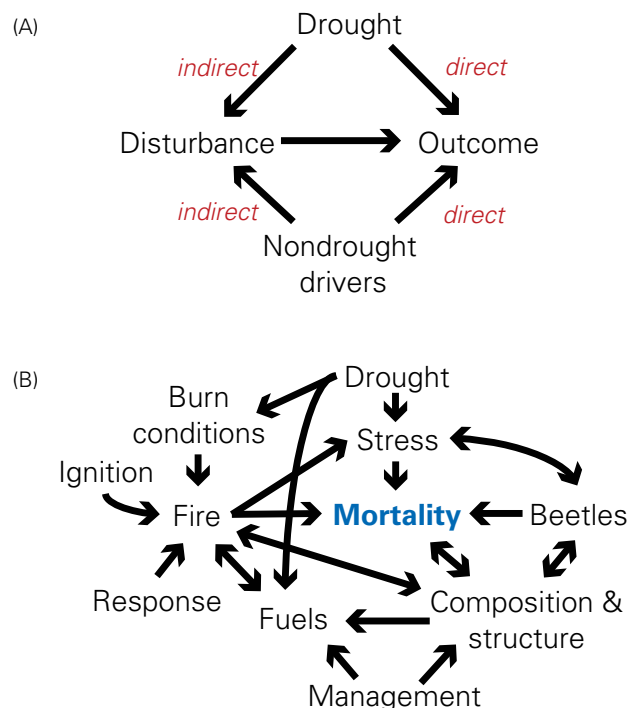

Figure 9.5—Conceptual models show how outcomes can result from direct and indirect climate effects or from unrelated nondrought drivers, such as land use change, management actions, or succession or other biological processes (A). For specific environments such as the dry forests of the Interior West, causal models can organize and communicate more explicitly the complex interconnectedness of landscape processes such as drought, fire, beetles, and management on tree mortality (B).

Near-real-time drought-effect monitoring has been implemented for agricultural and grazing systems that are sensitive to seasonal and short-term drought effects (Brown and others 2008). Efforts have also been developed to improve fire hazard assessments using near-real-time information about the state of drought-sensitive fuels (Schneider and others 2008). These systems are highly applicable to areas with relatively homogenous, drought-sensitive vegetation types, but where land use is mixed, drought-effects monitoring systems are less likely to provide clear information for forest managers. Forests, especially those with an evergreen component, are generally less sensitive to drought than are grasslands or crops. In areas of more fragmented land use, this variable sensitivity makes it far more difficult to interpret drought effects. Geographic patterns in observed stress responses could result from actual differences in drought intensity or they could be from different sensitivities caused by the mix of cover type. Year-to-year changes in land use make interpretation more difficult. Use of ancillary datasets can help to filter out these less reliable areas entirely, or can be used to develop vegetation-specific models calibrated to their drought sensitivities (Lobo and Maisongrande 2006).

Finer resolution imagery can be useful for identifying specific drought responses, particularly for localized areas. While even fine-resolution imagery can harbor a mix of cover types that can hamper interpretations of drought effects, the mixture of grass, shrub, trees, or crops generally decreases at finer spatial resolutions (fig. 9.6). Small inholdings of drought-sensitive vegetation could also be important drought indicators in mixed landscapes, particularly where meteorological station data are lacking.

While local needs often benefit from high-resolution drought monitoring products, these come at a computational cost, which usually involves reduced product frequency (fig. 9.7). To detect and monitor forest drought stress, coarse-resolution products can be effective, but for questions of tree mortality or other detailed impacts, finer resolution research may be necessary. Such local management questions may require local assessments that are calibrated and tempered with information gathered in the field.

Existing Approaches Used for Broad-Scale Drought Impact Detection and Monitoring

Extended periods of extreme drought result from persistent continental- to global-scale climate patterns that affect landscapes and regions. The large extent and contiguity of potential drought impacts helps us identify where drought is occurring because long-term meteorological or stream gauge data are sparse and their use normally requires interpolation. Drought can also be inferred from satellite-based observations of temperature or precipitation, though not without difficulties. Further insights into drought occurrence can be harvested from drought effects to sensitive vegetation as observed from satellites, yet vegetation change can also be caused by factors other than drought, such as disturbance. While these individual approaches for detecting and tracking

(A)	(B)	(C)

|←——— 1000 m ———→|←——— 232 m ———→|←——— 30 m ———→|

Figure 9.6—Mixed vegetation or land cover types that can result from different spatial resolutions, including: (A) 1000 m, (B) 232 m, and (C) 30 m grid cell widths. Products delivered at these resolutions would only provide one value for each unit area above, which typically decrease in diversity from left to right depending on the patch size of the vegetation.
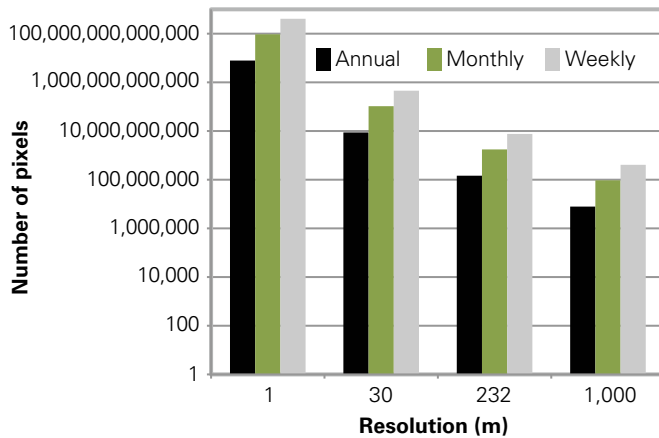
Figure 9.7—Potential tradeoffs between spatial and temporal resolution measured in terms of the number of pixels per year needed to cover the conterminous United States with a remotely sensed product set of a given frequency and spatial resolution. Standard vegetation products from Landsat are at 30-m resolution, while products from Moderate Resolution Imaging Spectroradiometer (MODIS) are 232-m resolution, and products from Advanced Very High Resolution Radiometer are 1000-m resolution.

drought have limitations, integrated monitoring systems can combine their particular strengths (Lawrimore and others 2002, Steinemann 2003, Svoboda and others 2002, Svoboda and others 2004, Tadesse and others 2005). It should be noted, however, that none of these integrated systems specifically focus on drought stress in forested ecosystems.

Meteorology-Based Measures of Drought

Primary meteorological measurements are not themselves the strongest predictors of drought effects. Various combinations of mostly temperature and precipitation measurements have been formulated into indices that are designed to provide drought-specific interpretations (table 9.1). These indices can be calculated directly at the locations of meteorological stations, producing a point-based map, or from gridded datasets (e.g., interpolated station data or reanalysis files). Although all of the indices in table 9.1 estimate the degree of moisture deficit in some context, they are typically associated with a particular class of drought—meteorological, agricultural, or hydrological drought (chapter 2). Some indices, such as the Surface Water Supply Index (SWSI), have distinctive formulations that are clearly applicable to one drought class (hydrological drought, in this case). For other indices, however, these class associations appear to derive from subtle differences in how the indices operate through time. For instance, the Palmer Hydrological Drought Index (PHDI) rebounds less quickly from moisture surpluses

or deficits than the similarly calculated Palmer Drought Severity Index (PDSI), which is generally considered a meteorological drought index (Palmer 1965). Likewise, the related Palmer Z-index (considered an index of agricultural drought) is more responsive to short-term moisture anomalies than either the PHDI or PDSI.

Most of the indices in table 9.1 are, like the PDSI, calculated using a water-balance approach between precipitation and potential evapotranspiration (PET). Indeed, many of the indices in table 9.1 represent direct modifications of the PDSI in response to perceived limitations. For instance, Heddinghaus and Sabol (1991) introduced Palmer Modified Drought Index (PMDI), a revised version of the PDSI. Their revision addressed one of the major areas of criticism regarding the PDSI: the determination of wet and dry spells. The PMDI yields a continuous measure that is less volatile than the PDSI, such that it can accurately capture a linear combination of temperature and precipitation effects across broad geographic regions (fig. 9.8).

A notable departure from the PDSI and other water-balance-based indices is the Standardized Precipitation Index (SPI). The SPI characterizes moisture conditions during multiple, well-defined time windows; it is also considered more consistent across geographic space. Nonetheless, it only uses precipitation data, which could be an important limitation in the face of increasing recognition that high temperatures exacerbate drought impacts on forest mortality (Allen and others 2010, Breshears and others 2005, McDowell and others 2008, Mitchell and others 2014, Vicente-Serrano and others 2013, Williams and others 2013). The Standardized Precipitation Evapotranspiration Index (SPEI) incorporates temperature into the water-balance equation via PET, but also follows the multi-temporal implementation of the SPI. The SPEI has outperformed the PDSI for monitoring drought impacts on "vulnerable systems" (i.e., for capturing impacts on indicator variables such as streamflow, soil moisture, forest growth, and crop yields), and appears to be better than the SPI at capturing drought conditions during the summer, when drought monitoring is arguably most critical (Vicente-Serrano and others 2012).

Ultimately, no meteorology-based drought index—regardless of its specific strengths or limitations—is appropriate in all circumstances. For national- or regional-scale analysis of drought, no single indicator is likely to be sufficient (Steinemann 2003). The U.S. Drought Monitor (DM), developed by the National

Table 9.1—Major meteorological (i.e., weather-station-based) drought indices used in the United States and elsewhere

Index	Key citation(s)	Type[a]	Foundation	Components/inputs	Remarks
Palmer Drought Severity Index (PDSI)	Palmer (1965)	M	Water balance model	Precipitation and temperature; Accounting done with five parameters: precipitation, evapotranspiration (ET) potential evapotranspiration (PET), soil moisture loss and recharge, and runoff	Preceded by a number of less sophisticated indices; like many other indices, enabled by the work of Thornthwaite (1948) on modeling PET; the PDSI has often been criticized but has been widely accepted despite its limitations
Palmer Hydrological Drought Index (PHDI)	Palmer (1965)	H	Water balance model	Precipitation and temperature; calculated during an intermediate step when computing PDSI	Very similar to the PDSI; uses same water balance model, but rebounds less quickly from a moisture deficit or surplus than the PDSI
Palmer Moisture Anomaly Index (Z-index)	Palmer (1965)	A	Water balance model	Precipitation and temperature; also calculated as an intermediate step when computing PDSI	Reflects departure of weather in a particular month from the average moisture climate for that month, regardless of conditions in prior or subsequent months; more responsive to short-term moisture anomalies that the PDSI or PHDI
Crop Moisture Index (CMI)	Palmer (1968)	A	Water balance model	Precipitation and temperature; uses weekly means	Also developed by Palmer; effective at measuring agricultural drought during the growing season; like the Z-index, focuses on short-term moisture conditions
Keetch-Byram Drought Index (KBDI)	Keetch and Byram (1968); Burgan (1988)	M	Water budget model	Precipitation and soil moisture	Forest Service product; developed for wildfire managers in the Southeastern United States, but implemented as a stand-alone drought index by Burgan (1988); values (hundredths of inches) range from 0 (no soil moisture depletion) to 800 (completely saturated soil)
Surface Water Supply Index (SWSI)	Shafer and Dezman (1982); revised by Garen (1993)	H	Available surface water including snowmelt	Measurements for snowpack, precipitation, streamflow, reservoir storage	Statistical properties poorly understood; difficult to compute; mostly used for western United States river basins (i.e., places where snowmelt strongly influences streamflow)
Soil Moisture Anomaly Index	Bergman and others (1988)	A	Water balance model	Uses PET (Thornthwaite 1948)	Developed for global-scale climate monitoring; values change at an intermediate rate somewhere between the CMI (fast) and the PDSI (slow)
Palmer Modified Drought Index (PMDI)	Heddinghaus and Sabol (1991)	M	Water balance model	Same inputs as PDSI. Still uses X1 and X3 terms, but in a slightly different fashion (see next box)	Operational modification of the PDSI; modified rules for index response during wet and dry spells; prevents sudden flipping from positive to negative index values (and vice versal; modified index is continuous and likely to be normally distributed
Standardized Precipitation Index (SPI)	McKee and others (1993)	M	Precipitation probability	Precipitation only; standardized departure with respect to a rainfall probability distribution	Typically calculated for multiple time windows (e.g., 1, 3, 6, 9, and 12 months); main criticism is that it only includes precipitation
Soil Moisture Percentiles	Andreadis and others (2005)	H	Available soil moisture	Modeled soil moisture values	Modeled values from precipitation and soil information, which across regions or continents may lack detail/accuracy
Standardized Precipitation Evapotranspiration Index (SPEI)	Vicente-Serrano and others (2010)	M	Water balance model	Precipitation and temperature	Multi-scale (i.e., incorporates multiple time windows) like the SPI, but also includes temperature via PET (calculated using the Thornthwaite method)

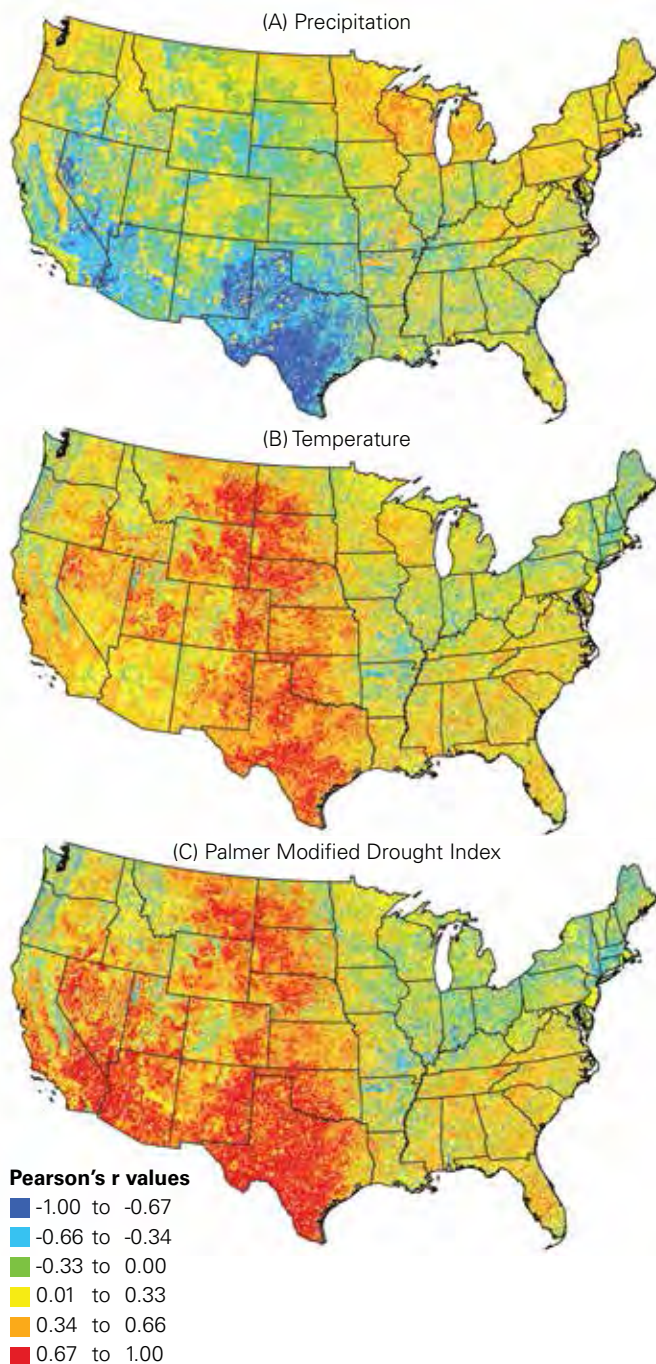[a] Type: M = meteorological, H = hydrological, A=agricultural.

Figure 9.8—Correlations (Pearson's r) between mean March–September Moderate Resolution Imaging Spectroradiometer (MODIS)-based *ForWarn* Normalized Difference Vegetation Index (NDVI) and National Land Cover Data Climate Division mean monthly March–September for (A) temperature, (B) precipitation, and (C) Palmer Modified Drought Index (PMDI), 2000–2012, based on 250,000 random points sampled with a 1-km buffer.

Drought Mitigation Center (NDMC) with cooperation from the U.S. Department of Commerce and U.S. Department of Agriculture (Svoboda and others 2002), and the related North American Drought Monitor (NADM) (Lawrimore and others 2002), were designed to integrate six key and numerous supplementary indicators—some from station data, others via remote sensing—to estimate drought severity, albeit subjectively. The PDSI and the SPI are key indicators in the U.S. and North American Drought Monitors, while the Crop Moisture Index (CMI), the Keetch-Byram Drought Index (KBDI), and the Surface Water Supply Initiative (SWSI) are among the supplementary indicators (see table 9.1).

Strengths and weaknesses of meteorology-based indices—The primary strengths of meteorology-based indices are that precise monthly meteorological data are widely available for most portions of the United States, and regional data extend back in time a century or more to provide a relatively consistent climate context. Individual monthly temperature station records in the Global Historical Climatology Network (GHCN) date to as early as 1701 (Lawrimore and others 2011). Observations from 69 countries and territories were available by 1880. A fairly robust station network was in place for the continental United States (and Hawaii) by the late 1800s (Menne and others 2012).

Satellites are comparatively expensive to manage and to maintain a calibrated and continuous record (Lawrimore and others 2011, Mendelsohn and others 2007, Menne and others 2012). However, the low spatial density of meteorological stations necessitates the use of spatial interpolation, which, despite significant methodological advances in recent decades (Daly and others 2002, Daly and others 2008), can fail in heterogeneous terrain and microclimates. The GHCN daily dataset has data from more than 80,000 weather stations worldwide, but about two-thirds of the stations only record precipitation, and not temperature (Menne and others 2012). By comparison, the GHCN monthly mean temperature dataset provides data for 7,280 stations from 226 countries and territories, plus ongoing monthly updates for more than 2,000 stations (Lawrimore and others 2011). The continental United States has one of the greatest temperature station densities, both historically and currently of any World region (Menne and others 2012). GHCN stations represent only about 10 percent of all weather stations available in the United States (Daly and others 2008), although missing data are still an analytical impediment.

Another issue is that the formulations of most meteorology-based indices are biased in favor of crops that are harvested after a single growing season. Few of these indices carry much information about historical conditions, and when they do, it is on the order of months rather than years. For example, the SPI considers a 12-month history; the SPEI is the longest, with a 24-month "memory." Trees are more resilient to drought effects, making it necessary to track antecedent moisture conditions over the prior several years (see fig. 9.4). Few researchers have devised and regularly employed drought indices that include multiyear prior conditions of the sort needed when gauging forest impacts. Koch and others (2013a, 2013b, 2014, 2015) have used a set of drought indices consisting of 1-, 3-, and 5-year histories for an annual chapter in the last four national reports issued by the U.S. Department of Agriculture, Forest Service, Forest Health Monitoring program.

Fundamentally, with a meteorology-based approach to characterizing drought, impacts are inferred rather than measured directly. Anderegg and others (2013) argued that we have yet to link any meteorology-based drought measure to forest damage or mortality at broader spatial scales. Drought indices are not designed to predict levels of drought damage or mortality in forests or any other vegetation type—just moisture deficit, in an abstract sense. This problem is universal, regardless of the selected drought index or the spatial and temporal coverage provided by stations for the area of interest. Impacts on vegetation due to drought conditions can only be inferred, since vegetation responses are not measured by stations.

Nevertheless, Mitchell and others (2014) highlighted a possible way to employ meteorology-based indices to identify geographic areas where drought-induced tree mortality is most likely. They looked at 41 different forest die-off events across Australia (in different forest types over a period of about 80 years) and found 3 things they had in common: (1) water deficits, (2) maximum temperatures outside of 98 percent of the observed range in drought intensity, and (3) the presence of at least 1 heat wave (3 consecutive days above the 90th percentile for maximum temperature). While these specific threshold values may not translate to new locations—Australian ecosystems are more water-limited than many U.S. forest ecosystems— the concept laid out by Mitchell and others (2014) is worth further research. Toward this end, moisture and temperature extremes for the United States are reasonably well documented from weather station data or from spatially interpolated products such as the gridded maps produced by the PRISM Climate Group at Oregon State University (Daly and others 2002, Daly and others 2008).

Remote Sensing-Based Measures of Drought Impacts

Various remote sensing-based indices have been proposed and utilized to detect drought occurrence and severity (table 9.2). The continuous gridded nature of these remotely sensed indices is an innate advantage over the meteorological indices shown in table 9.1, which are derived from dispersed meteorological stations. This advantage is counterbalanced, however, by the relatively brief observational history that any particular class of satellite sensors provides. New orbital sensors have substantially different characteristics, yet may not share overlapping periods of operation to calibrate with the sensors that they are replacing. The decade-or-more service lifetimes of MODIS and Advanced Very High Resolution Radiometer (AVHRR) are considered long records for remote sensing platforms, yet they are short with regard to tree lifetimes and forest successional dynamics.

In contrast to meteorology-based measures of drought, remote sensing indices measure certain impacts of drought to vegetation and disturbance directly (Deshayes and others 2006). Sensors integrate vegetation conditions across the entire grid cell at the resolution of the sensor, averaging across vegetation types and plant species. Because of these basic distinctions from ground-based measurements, and because these indices represent an emergent vegetation property, the trajectory of such integrating measures across seasons has been referred to as Land Surface Phenology (LSP) (de Beurs and Henebry 2004), and interannual differences in the timing and magnitude of LSP have been suggested as potential indicators of environmental change.

Conceived initially by Rouse and others (1973) but popularized by Tucker (1979), the Normalized Difference Vegetation Index (NDVI) has proven to be useful both alone and as a component of other indices, and also as a fertile starting point, since many variants of this index have been devised. Chief among its advantages is the automatic normalization for differences in sun-and-sensor geometry that is provided by the "difference-over-sum" format of its arithmetic construction, a form that has been frequently borrowed for other indices. NDVI is colloquially referred to as "greenness"

Table 9.2—Remote sensing indices for drought detection and monitoring

Index	Formula	Purpose	Strengths	Weaknesses	Reference
Normalized Difference Vegetation Index (NDVI)	(NIR-Red)/ (NIR+Red) National Inventory Report (NIR)	Monitor vegetation condition and health	Self-normalizing across different sun-sensor geometries	Affected by soil color; may saturate at high vegetation densities	Tucker (1979)
Normalized Difference Vegetation Moisture Index (NDMI)	(NIR-MIR)/ (NIR+MIR) Miscellaneous Inventory Report (MIR)	Uses MIR, which is sensitive to leaf moisture	Measures vegetation water relative to chlorophyll	Not all sensor platforms have MIR band	Wilson and Sader (2002)
Ratio to Mean NDVI (RMNDVI)	$((NDVI_i-NDVI_{mean})/ NDVI_{mean}) * 100\%$	Percentage change relative to mean of last **n** years	Depicts current status relative to a multi-year history	Mean greenness may not show sensitivity to drought impacts	Vegscape
Ratio to Previous NDVI (RPNDVI)	$((NDVI_i-NDVI_i-1)/ NDVI_i) * 100\%$	Percentage change relative to this time last year	Depicts current status relative to prior year	Prior year may not be representative of "normal"; seasonal timing may be shifted	Vegscape
Enhanced Vegetation Index (EVI)	$((NIR-Red)/ (NIR+6Red-7.5Blue+1)) * 2.5$	Lower saturation risk	Lessens soil background effect	Atmospheric effects; requires standardization	Huete and others (2002)
Soil-Adjusted Vegetation Index (SAVI)	$((NIR-Red)/ (NIR+Red+L)) * (1+L)$ Correction Factor (L)	Corrects NDVI when vegetative cover is low and soil color is visible	Adds a soil "brightness" correction factor, L; when $L=0$, SAVI=NDVI	Must know amount of vegetation to set L, and this is somewhat circular	Huete (1988)
Vegetation Condition Index (VCI)	$((NDVI_i-NDVI_{min})/ (NDVI_{max}-NDVI_{min})) * 100\%$	Shows current value relative to dynamic range of previous years	Normalizes current value to past range	Shows other disturbances besides drought; Divisor grows with additional history	Kogan (1995)
Mean-Referenced Vegetation Condition Index (MVCI)	$((NDVI_i-NDVI_{mean})/ NDVI_{mean}) * 100\%$	Shows current value relative to mean of previous years	Normalizes current value to past mean	Change from mean of past years is relatively insensitive	Vegscape
MODIS Global Disturbance Index (MGDI)	$(LST_{max, i}/EVI_{post\ LST\ max, i})/ (LST_{max, n-1}/EVI_{post\ max, n-1})$ Land Surface Temperature (LST)	Detects large-scale vegetation disturbances; separate annual and historical formulations	Disturbances cause LST and EVI to exceed normal variability	Requires annual and historical maximum composite LST and EVI data; current year excluded from denominator	Mildrexler and others 2007), Mildrexler and others (2009)

Note: All are calculated on a cell-by-cell basis, often with respect to past values in that same cell. There are many variants of the Normalized Difference Vegetation Index (NDVI) not covered here, including the Normalized Built-up Index (NDBI), the Normalized Difference Water Index (NDWI) and Modified NDWI (MNDWI), the Normalized Difference Soil Index (NDSI), the Modified Soil Adjusted Vegetation Index (MSAVI and MSAVI2), the Transformed Soil Adjusted Vegetation Index (TSAVI), the Anomaly Vegetation Index (AVI), the Crop Moisture Index (CVI), and uncounted others. We treat the modeled multivariate VegDRI and GIDMaPS indices separately as Drought Detection System entries in table 9.3 (Zhang and others 2013).

although Tucker (1979) never used this term himself. A majority of remote sensing indices attempt to track drought impacts on growth by tracking changes in this "greenness" using the logic that observed changes in photosynthetic machinery can be used to infer drought impacts indirectly (albeit more directly than the purely meteorological indices shown in table 9.1). Classical NDVI, however, saturates at high vegetation densities, giving rise to the "Enhanced" and "Soil-Adjusted" variants (table 9.2).

Most of the remote sensing indices rely on changes in "greenness" (sometimes in concert with leaf moisture or land surface temperature) relative to the same value calculated for the equivalent time interval in a previous year or years. This common construction represents an intention to compare a current value with an historical "normal." This "normal" may be the local value at the same time the previous year [i.e., NDVI or Ratio to Previous NDVI (RPNDVI)]; it may be the ratio to mean (or RMNDVI), median, or maximum value from a number of prior years; or it may be scaled to the full dynamic range of the local value (i.e., VCI). Differences in the mechanism used to characterize this normal baseline are responsible for much of the proliferation of variant forms of these basic indices. Indeed, it may be more challenging to quantify the normal, expected trend than it is to monitor the current status. Development of the standard against which drought or greenness departures are measured may represent the most difficult part of drought detection, whether by meteorology-based or remotely sensed impact metrics.

The appropriateness and temporal equivalency of a "same date" comparison strategy across years relies on the stationarity of seasonal progressions in LSP. However, LSP is known to shift dynamically across years (Hargrove and others 2009). The degree of these seasonal phenology shifts will affect the detection sensitivity of drought indices based on such interannual comparisons, yet an earlier-than-normal fall season may be an indicator of drought (Hwang and others 2014). In the spring, where greenup is typically temperature limited, drought could result in either higher or lower values or both depending on what portion of the spring is considered. Such broad swings in detection sensitivity serve to demonstrate the confounded nature of drought impacts with other types of disturbances, including climatic effects (see Challenge 3 above).

Several indices evaluate the current situation relative to the mean of prior years. While the mean may

characterize the entire prior distribution, the goal of a detection index is unlikely to be detection of a shift in the entire distribution itself. Comparisons with multiyear median may be only marginally more sensitive. It may be more effective to detect an onset of drought based on comparisons with maximum historical greenness, but this comparison will show increasing sensitivity as current greenness is compared with ever-higher values from particularly verdant prior years experiencing unusually favorable conditions.

A key need is to translate remotely observed changes in vegetation to actual impacts on the ground, such as tree mortality, annual growth reduction, or changes related to secondary disturbance risks, such as annual fuels for wildfire or insect and disease responses. Because short-term vegetation responses may not necessarily equate to long-term impacts, the multiyear monitoring capabilities that remote sensing provides are critical for detecting substantive lasting change apart from short-term drought responses related to immediate reductions in seasonal greenness.

Limitations of Remote Sensing-Based Approaches: An Illustrative Example

Remote sensing-based methods for drought detection and monitoring are not a panacea. Interpretation of results shown by remotely sensed products may not be straightforward, and interpretations can be complicated by both the technical aspects of the sensor technologies, as well as by the intricacies and interconnections of the ecological processes.

A recent example highlights the magnitude of controversy that is possible surrounding interpretation of forest drought impacts from remote sensing observations. Impressed by global simulation results with the Hadley Center model in particular (Cox and others 2004), the Intergovernmental Panel on Climate Change (IPCC) AR4 report (IPCC 2007) issued warnings suggesting that the rain forests of the Amazon might collapse under climatic change, being replaced by savanna-like vegetation (Nepstad and others 2008). In addition to the radical transformation of the ecosystem and loss of biodiversity, Phillips and others (2009) claimed that massive Amazon tree mortality would temporarily change the forest from a carbon dioxide (CO_2) sink (2 billion tons absorbed yearly) to a carbon monoxide (CO) source (3 billion tons released).

In part to test short-term predictions of decreases in forest photosynthesis following drought, Saleska and

others (2007) examined MODIS Enhanced Vegetation Index from 2000–2006, and reported that Amazon forests actually became greener during the severe drought that occurred in the region in 2005. Myneni and others (2007) found that Amazon forests become greener in the dry season due to an increase in leaf area index. Huete and others (2006) suggested that photosynthesis in Amazon forests might be limited by light availability, and that the observed increase of greenness during the dry season is stimulated by increased sunlight. Huete and others (2006) speculated that the normal dry season may be the forests' most productive time of year because the rain clouds clear up and more sunlight reaches the forest, in the same way that some areas in the United States show positive correlations between drought and NDVI (see fig. 9.8). They also suggested that soil water content was not a limiting factor for Amazon greenness. Saleska and others (2007) concluded that Amazon forests might be more resilient to climate changes than ecosystem models assume.

These counterintuitive findings were immediately challenged by other studies, which concluded that the 2005 drought had no impact on the greenness of Amazon forests. Samanta and others (2011) found "no evidence of large-scale greening of intact Amazon forests during the 2005 drought." They suggested that the previous findings were attributable to artefacts resulting from contamination of satellite-based observations by clouds and aerosols. Zhou and others (2014) showed widespread decline in greenness of Congolese forests over the last decade, even though such forests are probably more drought-tolerant, with their drier conditions and higher composition of semi-evergreen trees.

Recently, Morton and others (2014) showed that the apparent increase in greenness in Amazon forests could be explained by seasonal variations in lighting caused by changes in sun-sensor geometry. They suggested that it is soil moisture rather than light that determines the balance between photosynthesis and respiration in Amazon forests [summarized in Soudani and François (2014)]. These results tip the balance back toward interpretations that the Amazon is very sensitive to rainfall and, as the IPCC report indicated, may be prone to conversion and loss in a warmer, drier future in the tropics.

The emergence of such a surprising amount of controversy might discourage those considering a

remote sensing perspective on drought detection and monitoring. However, tropical forests represent one of the most challenging of all locations for remote sensing work (Asner and Alencar 2010). A combination of complicating factors in tropical forest exacerbates the interpretation of remote imagery in these locations. High tree diversity in Amazonian forests leads to mixed responses from differential plant sensitivity, and there are potential saturation issues for some greenness-based indices. Clouds are nearly ever-present, and aerosols and terpenes may be in high concentration, as are particulates, soot, and smoke from fires. Most importantly, not many long-term ground observations and datasets exist, with few exceptions (Phillips and others 2009). This alignment of challenges may make tropical locations one of the worst-case remote sensing scenarios (Huete and Saleska 2010). More straightforward and direct interpretations of drought might be expected in temperate or boreal locations. An all-data approach, where remote sensing methods are leveraged with other ancillary data streams, including ground-based measurements, may represent the most promising approach for detecting and monitoring drought in these and other, less-challenging locations.

Existing Systems for Drought Detection and Monitoring

Table 9.3 shows 11 existing systems for detecting and monitoring drought, all of which include remote sensing as a fundamental component. The geographic extent that is monitored ranges from single countries to continents to the globe. Systems can be identified that are primarily the product of meteorologists, agricultural scientists, computational scientists, remote sensing specialists, and even political and social policy analysts. Not surprisingly, each system retains and exhibits the approaches, interests, and perspectives of the group producing and operating it. Some have a practical emphasis, while others are more research-oriented. Systems benefiting from the participation of more than a single one of these domain perspectives are likely to be the most useful in the long term. Although the oldest system has been operational for nearly 3 decades, the majority have been initiated within the last 5 years. There is a clear tendency among these newer systems to take a multivariate approach to drought detection rather than relying on one or a few indicators. Many of the drought systems are designed primarily for detecting food and agricultural drought effects, including verification for crop insurance settlements. Some of the tree-based systems are aimed at carbon accounting

Detection system	Operated by	Year started	Spatial extent	Release frequency	Input data
Famine Early Warning Systems Network (FEWS Net)	U. S. Agency for International Development (USAID)	1985	Africa, Asia, Central America, and the Central Tropics	Every 20 days; predictions 6–12 months ahead	Subjective combination of agro-climatology, production, market data, nutrition, and scenario development
Vegetation Drought Response Index (VegDRI)	USGS (Earth Resources Observation Systems) (EROS), Univ. of Nebraska Lincoln, USDA Forest Service Resource and Monitoring Analysis (RMA)	7 States in 2006, CONUS in 2009	Conterminous United States	Weekly	AVHRR and eMODIS NDVI, combined with PDSI and SPI drought indices, land cover, soil water capacity, elevation, ecological setting, using three seasonal Regression Tree models
ForWarn	Forest Service, National Aeronautic Space Administration (NASA) Stennis Space Center (SSC)	2010	Conterminous United States	Every 8 days	Moderate Resolution Imaging Spectroradiometer (MODIS), Modis Vegetation Index Algorithm (MOD13), Vegetation Indices for Operational Drought Monitoring (eMODIS)
Forest Disturbance Mapper (FDM)	Forest Service Remote Sensing Application Center (RSAC)/ Forest Service Forest Health Technology Enterprise Team (FHTET)	2010	Conterminous United States	Every 8 days	Forest type map, USGS map zones, local MODIS downloads
United States Drought Monitor	Forest Service, NOAA, and Univ. Nebraska Lincoln	1999	Conterminous United States	Weekly	Rain, snow, observer reports on wildlife and crop effects
North American Drought Monitor	USDA, NOAA, University of Nebraska-Lincoln (UNL), National Meteorological Service (SMN) Mexico, National Water Commission (CNA) Mexico, Agrifood Canada, Meteorological Service Canada	2002	Canada, Mexico, United States	Bi-weekly	Subjective maps from the three member countries, which may not line up at international borders
Global Drought Monitoring Portal (GDMP)	NOAA NCDC	2012 startup, seeking global participation	Global	Monthly	Thresholded Global Precipitation Climatology Center SPI with up to 24-month history, other metrics where available
Vegscape Vegetation Condition Explorer/ CropScape	USDA National Agricultural Statistics Service (NASS)/ George Mason	2013/ 2011	Conterminous United States	Daily, weekly, bi-weekly composites	MODIS NDVI, Enhanced Vegetation Index (EVI)
Global Agricultural Monitoring (GLAM) Production System/Global Inventory Monitoring and Modeling Studies (GIMMS))	NASA Goddard, USDA Foreign Agricultural Service (FAS)	2001 Terra, 2002 Aqua	Global	Every 8 days	MODIS Terra and Aqua, treated separately
Global Integrated Drought Monitoring and Prediction System (GIDMaPS)	Univ. California, Irvine	2013	Global, 1980–2014, coarse resolution	Monthly	Precipitation and soil moisture from simulations and remote sensing, including Modern Era-Retrospective Analysis for Research and Applications (MERRA), North American Land Data Assimilation System (NLDAS), Global Drought Climate Data Record (GLDAS), and Global Drought Climate Data Record (GDCDR) historical data sets
ALERTS 1.0/ Planetary Skin	NASA Ames, Univ. of Minnesota, National Space Research Institute (INPE) Brazil, Planetary Skin Institute	In development, beta available	Global, 1 km	Biweekly	MODIS NDVI, Land Surface Temperature (LST)

Purpose	Meteorology or vegetation effects	Algorithm	Web site URL
Drought effects on food security	Vegetation, specifically food	Based originally on AVHRR in Northern Africa; has grown beyond a strictly remote sensing system	*www.fews.net*
Monitor vegetation stress to improve preparedness and response	Vegetation	AVHRR and eMODIS VegDRI index from CART; Percent of Average Seasonal Greenness (PASG) ratio is relative to 20-year mean Seasonal Greenness	*vegdri.unl.edu*, *vegdri.cr.usgs.gov*; Web viewer at *vegdri.cr.usgs.gov/viewer/viewer. htm*
Broad forest change detection, tracking, and recovery	Vegetation	% NDVI difference between current NDVI versus given NDVI baseline	*forwarn.forestthreats.org*; Web viewer at *forwarn.forestthreats.org/fcav*
Assist IDS flight planning and map disturbances	Vegetation	Difference of current vs. historical spectral reflectances, followed by calculation of NDMI in Western United States, or NDVI in Eastern United States	*foresthealth.fs.usda.gov/portal*; Web viewer at *foresthealth.fs.usda.gov/portal/Flex/ FDM*
Monitor broad-scale drought impacts	Meteorology/Vegetation (inferred)	Subjectively combine inputs into five Drought Intensity categories	*droughtmonitor.unl.edu*
Monitor broad-scale drought impacts at continental scale	Meteorology/Vegetation (inferred)	Experts balance conflicts from three countries into five subjective Drought Intensity categories	*www.drought.gov/nadm*; Web viewer at *gis.ncdc.noaa.gov/map/drought/NA*
Provide a global snapshot of water scarcity	Meteorology	A combination of existing continental-scale drought systems, with efforts to harmonize at country borders	*gis.ncdc.noaa.gov/map/drought/Global*
Monitor crop vegetation conditions	Vegetation	Compares NDVI change ratio to previous year, to median and to mean NDVI	*nassgeodata.gmu.edu/vegscape*
Monitor global food production	Vegetation	% NDVI anomaly, calculated from historical all-year mean NDVIs	*glam1.gsfc.nasa.gov*
Drought prediction and probability that drought will persist	Meteorology	SPI, SSI, or Multivariate Standardized Drought Index (MSDI), mapped as five levels of wetness and five levels of drought	*drought.eng.uci.edu*
Improve detection, awareness, and decisionmaking	Vegetation	Multi-resolution Global Water Stress Index Algorithm	*www.planetaryskin.org*, *www. planetaryskin.org/rd-programs/ resource-nexus/global-land-change-detection*, viewer at *ourplanetaryskin. org/ps/is/cs/run.php?uid=guest*

Table 9.3—Existing operational and experimental systems for detecting the extent and severity of drought Forest Service Forest Inventory Analysis (FIA), Insect and Disease Survey (IDS), National Oceanic and Atmospheric Administration (NOAA) Historical Climatology Network (HCN) meteorological stations, U.S. Geological Survey (USGS) Stream Gauge network, and SNOwpack TELemetry (SNOTEL) are related networks that, while providing invaluable ancillary information, are not specifically designed to detect or monitor extent, duration, or impact of drought

or global deforestation, while others monitor drought effects on forests, particularly tree mortality.

Integrating Broad Monitoring With Assessment

Remote sensing platforms see everything; this is simultaneously both an advantage and a drawback of these methods. Observing all vegetation types, all disturbances, and all locations synoptically on a regular interval maximizes the likelihood of understanding the local situation. Nevertheless, remote sensing methods also see nondrought disturbance effects, both abiotic and biotic, and these can be difficult to distinguish and disentangle. Local information, history, and expertise can greatly inform the conclusions made from remote data, and may be a requisite for the successful use of remote sensing to detect drought impacts. Remote sensing platforms alone are insufficient for most drought assessment purposes. However, as discussed in the following sections, they can be extremely useful for drought assessment when combined with ancillary datasets.

Land Surface Phenology Datasets

Phenology, the timing of foliage greenup and browndown, can provide one of the earliest indications of drought effects. In particular, comparison of current greenness with historical phenological behavior can show departures from expected trajectories caused by drought (Hargrove and others 2009). However, such phenological differences might be caused by other, nondrought effects, or might be delayed significantly from when original drought events occurred. These operational difficulties mirror the conceptual difficulties in isolating indirect from direct drought stressors (fig. 9.5).

Drought detectability using remote sensing is variable over time and space. Drought response is not just a function of weather, but also of spatial variation in phenological cover types and fractional vegetation cover, which is often imperfectly known. Conifers remain green even while dormant, while deciduous woody plants and grasses can have an extended period of brown dormancy that can mimic drought conditions (Volaire and Norton 2006). Vegetation response to drought is muted outside the growing season, although winter drought can cause needle loss and reduction in net primary productivity in conifers that can theoretically be detected remotely (Berg and Chapin 1994). This disparate responsiveness of land surface phenology can

be isolated, but drought effects become confounded when the composition of a grid cell is mixed. It can be challenging to know when the remote sensing signal is changing due to disturbance or successional recovery and when it is changing from drought.

High-frequency land surface phenology datasets provide a means to interpret drought responses, particularly for reliably drought-sensitive vegetation types. In open-canopy forests, savannas, or forest edges, increased grass, shrub, or herb cover can increase drought sensitivity. Deciduous trees may respond to drought by earlier leaf senescence (Hwang and others 2014). Although senescence can also be triggered by frost (Vitasse and others 2009), an unusually early onset of leaf browning and/or abscission may serve as a season-specific indicator of drought in some forests. High-frequency land surface phenology datasets may provide a number of drought indicators that can distinguish drought responses among cover types.

In high-elevation or mountainous areas, winter variation in snowpack extent and duration provides an important, albeit temporally delayed source of precipitation that can be monitored. At high elevations, limited snowpack has been associated with the early onset of spring green-up (Hu and others 2010), although this may result from warmer temperatures. Winter drought can extend the subsequent wildfire season and can reduce fuel moisture (Littell and others 2009, Westerling and others 2006). Early green-up may also affect drought-associated insects and diseases (Ayres and Lombardero 2000). The delayed effects of snowpack variation are captured in the next growing season by existing phenological datasets that track NDVI and other vegetation indices (table 9.4).

Insect and Disease Surveys

The Insect and Disease Surveys (IDS) aerial survey program (table 9.4), administered by the Forest Service Forest Health Protection (FHP) program could serve as a national-scale source of geospatial data about biotic impacts triggered by drought. In some cases, IDS data also document direct impacts from drought and other abiotic disturbance agents. Under the program, surveyors use aerial sketch-mapping hardware and software to delineate geospatial features (typically polygons) that depict forest health impacts such as tree mortality or defoliation. The surveyors assign disturbance agent codes, as well as certain measures of the intensity of the impact (e.g., trees per acre defoliated), to each feature. The IDS data are compiled

Table 9.4—Ancillary datasets that may be useful for interpretation during drought detection and monitoring

Dataset	Developers/owners	Contents	Value added for drought detection	Reference
National Land Cover Database (NLCD); NLCD 2011 Forest Service Tree Canopy product	USGS, along with the Multi-Resolution Land Characteristics (MRLC) Consortium	16-class Landsat-based 30-m resolution land cover database for the United States; updated every 5 years; Tree Canopy product provides estimated percent canopy cover plus standard error	Shows vegetation and land cover types to assist estimation of drought impacts across areas with variable sensitivity; enables land cover conditional filtering of drought impacts	*www.mrlc.gov/*
Snowpack/ SNOTEL	NOAA	Ground-based remote sensing of snow accumulations	Future drought impacts in areas dependent on snowmelt water	*www.nohrsc.noaa.gov/nsa*
MODIS hotspots showing recent wildfires	NASA, Remote Sensing Applications Center (RSAC) Active Fire Mapping Program	Thermal detection of wildfires at 1-km resolution	Fire may be the final outcome of drought; separates fire effects from extreme drought effects	*activefiremap.fs.fed.us*
Monitoring Trends in Burn Severity (MTBS) and GeoMac	Remote Sensing Applications Center (RSAC) and USGS	Mapped perimeters of past wildfires, with burn severity estimates	Fire may be the final outcome of drought; separates fire effects from extreme drought effects	*www.mtbs.gov, www.geomac.gov*
Active fire maps	Incident Information System (INCIWEB)	Status of active wildfires and large prescribed burns	Fire progression maps show effects of near-real-time drought conditions	*www.inciweb.org*
Historical Insect and Disease Survey (IDS) maps	Forest Health Technology Enterprise Team (FHTET)	Aerial disturbance surveys from aircraft for a portion of U.S. forests	Shows the pattern and landscape position of pest mortality and defoliation events	*www.fs.fed.us/foresthealth/ technology*
Stream depth and flow	USGS Stream Gauge Network	Depth and amount of flow of rivers and streams	Monitor changes in runoff and surface flow downstream of drought areas	*waterdata.usgs.gov*
LANDFIRE Disturbance database	USDA Forest Service LANDFIRE	Vegetation and fuel disturbances 1999-2010	Separate other disturbances and harvests from drought mortality	*www.landfire.gov/disturance.php*
Forest Inventory and Analysis (FIA)	USDA Forest Service	Inventoried forest plots in a statistical design, remeasured every 5/10 years	Shows long-term cumulative effects and mortality of drought	*www.fia.fs.fed.us*
Phenology data, phenoregion maps	USGS, USDA Forest Service	NDVI and other vegetation indices, statistically created maps of multivariate clusters of NDVI through time	Shows departure from normal timing of greenness, maps major vegetation types having similar phenology behavior, empirically determined	*phenology.cr.usgs.gov, forwarn. forestthreats.org,* White and others (2005)

Note: These data sets and systems, while not directly useful in drought detection, may provide useful surrogate information when used conjointly to support core data in a multivariate "big data" approach to drought detection and monitoring. Most of these data sources are restricted in extent to the United States.

on an annual basis, and so they are not sources of near-real-time information.

Meddens and others (2012) noted several additional obstacles to using the IDS data. First, the amount of forest surveyed varies from year to year, and not all forests are surveyed; flights are targeted at areas where disturbances are most likely to have occurred (in response to ground reports), so it is possible that some affected areas are missed. Second, IDS polygons are delineated broadly, and they typically also include healthy trees. Hence, the severity of a disturbance is not reported consistently. IDS observations are recorded by different observers having a wide range of skills and experience, which introduces further variability in the reported severity and extent of a disturbance.

A related obstacle is a lack of standardized causal attribution. Depending on the aerial surveyor, IDS polygons could be labeled as having been caused by drought, or instead, by insect activity driven by drought. Causal attribution is assigned from the air, with limited field validation. IDS data users must consider multiple agents when trying to ascertain the extent of an impact. For instance, when analyzing pinyon and juniper mortality in the Southwestern United States, Breshears and others (2005) combined IDS polygons attributed to various bark beetles as well as drought. To circumvent these ambiguities, IDS data are probably best used to delineate general geographic regions where multiple years of forest damage and/or mortality have been attributed to a complex of biotic and abiotic agents associated with drought (Huang and Anderegg 2012). These regions can then be adopted as the setting for further retrospective analysis into relationships between the agents, using ancillary data sources (Williams and others 2010, Williams and others 2013).

Wildfire Mapping Datasets
Wildfire often causes tree mortality and initiates successional recovery that destabilizes the historical pattern of climate sensitivity of communities within burned areas. Despite being an indirect outcome of drought (Westerling and others 2006), burned areas are likely to provide a less consistent measure of direct drought effects than are adjacent undisturbed areas. Increases in grass or shrub cover after fire may make burned landscapes more climate-sensitive than when they were dominated by dense conifers. Existing wildfire datasets (see table 9.4) can be used to isolate burned portions of the landscape that may differ in their drought response for a more accurate understanding

of the system in post-fire years. As with insect and disease data, burned areas can be selectively masked for regional interpretations of drought responses, or they could be targeted for understanding the cumulative effects of drought and disturbance.

The 2011–12 Texas drought and drought-associated fires illustrate how remote-sensing-based change monitoring can be better interpreted with ancillary wildland fire data. This Texas drought was remarkable (Nielson-Gammon 2012) because of its severity and duration, and because of the extensive area burned during the 2011 wildfire season (fig. 9.9). Where and when they co-occur, drought and wildfire may have additive or redundant effects on reducing NDVI. For two nearby MODIS pixels in figure 9.10, the effects of fire and drought are at least partially additive. The NDVI of these two pixels tracks each other closely for years prior to 2011, suggesting they had quite similar vegetation, and the 2011 drought effects were likely identical given their proximity. However, the immediate reduction from burning and drought clearly exceeded that of drought alone, and this effect persisted through 2012.

Retrospective analyses of drought effects across different vegetation types provide coarse-filter insights into differential responses. For a random sample of MODIS pixels across west Texas, annual variation in NDVI clearly varies by majority vegetation type, as filtered by the National Land Cover Database (fig. 9.11). Shrub- and grass-dominated areas have greater year-to-year amplitude in NDVI, which is consistent with expectations of their greater climate sensitivity than forests. All vegetation types show a general decline that could be an indication of widespread mortality caused by the 2011 Texas drought.

Land Use/Land Cover Datasets
Changes in land use and land cover are typically so fine-scale that they are unlikely to influence more coarse-scale estimates of climate departure. But taken over decades, extensive areas of certain regions have experienced substantive urban and infrastructural development (Riitters and others 2002, Riitters and Wickham 2003). Conversion from forest to nonforest land cover often increases dominance by grass, shrubs, and ruderal or early-successional species that are generally more responsive to drought than are many forests. In areas that have experienced these changes, baselines from long-term, remotely sensed time series may be less desirable than efforts to model effects based on recent land cover over shorter periods. For the
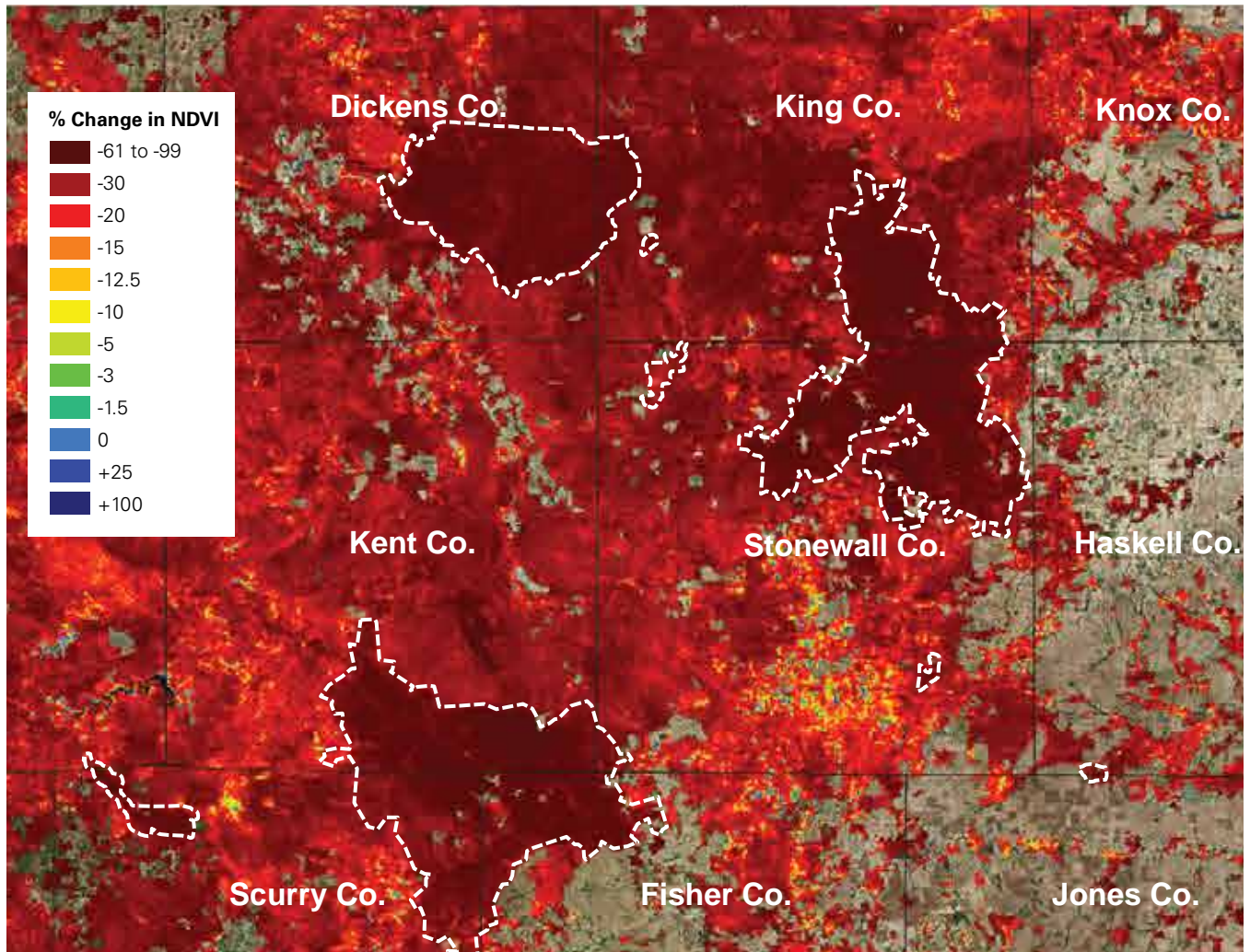
Figure 9.9—*ForWarn* change in Normalized Difference Vegetation Index (NDVI) from the All Year Mean Baseline for the 3-week period ending August 28, 2011, showing the severity of drought and wildfire on nonagricultural lands across northcentral Texas. Wildfire boundaries for 2011 are shown by dashed white lines.
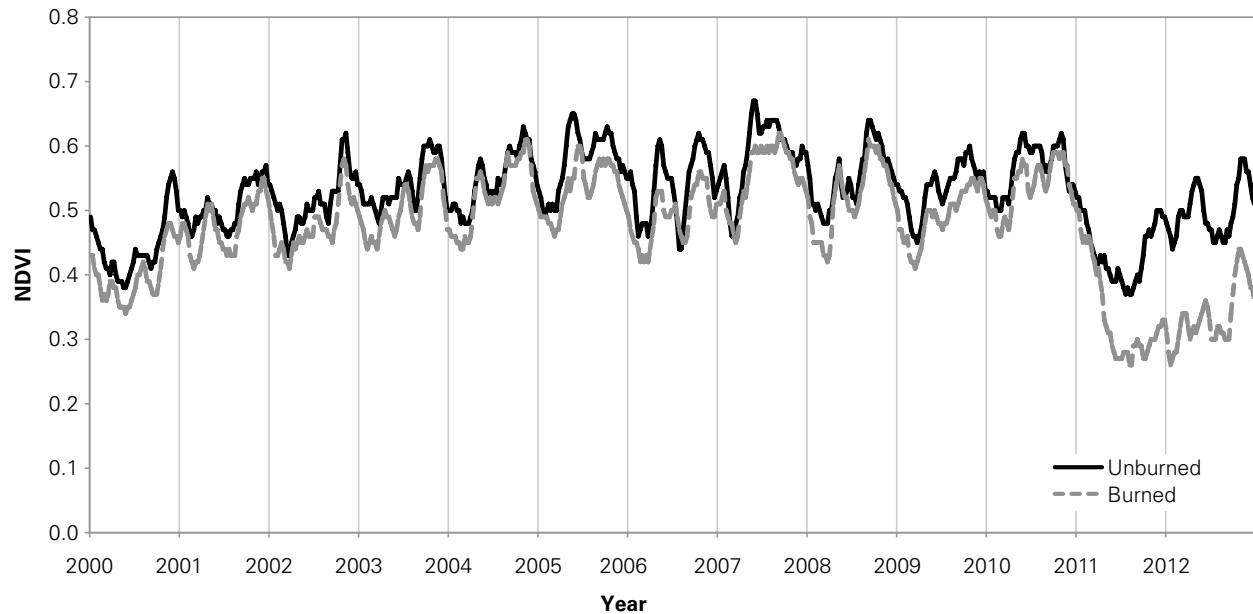
Figure 9.10—A comparison of two nearby woodland *ForWarn* pixels in west Texas on similar sites, one that burned and one that did not during 2011. Note that effects persisted through 2012 on both sites, but that the cumulative effects of drought and wildfire were more pronounced than drought alone. Site locations: unburned site location 31.8295, -100.6636; burned site location: 31.8390, -100.6455.
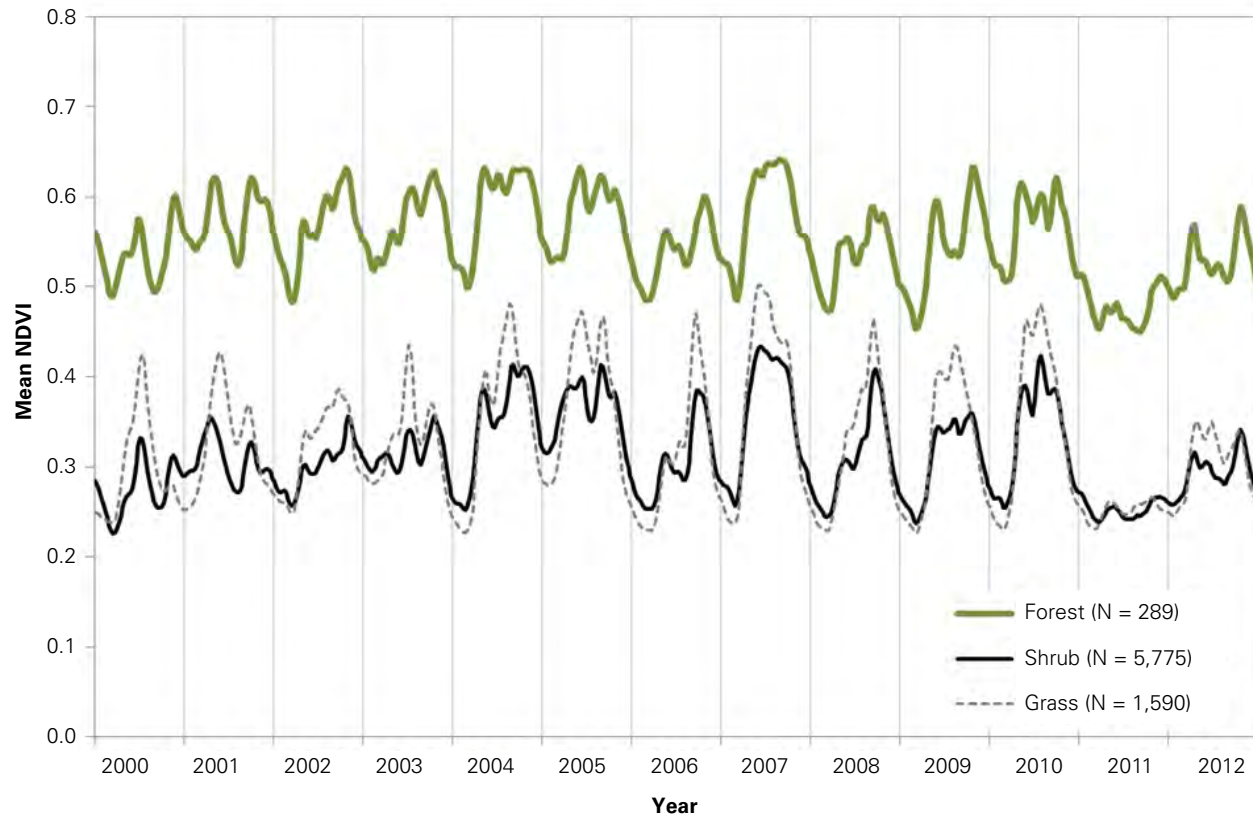

Figure 9.11—Mean NDVI for a random sample of unburned majority forest, shrub, or grass pixels within Texas climate divisions 1, 2, 5, and 6 (west Texas) using the *ForWarn* dataset. Note the extreme decline in NDVI during the 2011 drought that affected all vegetation types.

United States, the National Land Cover Database (NLCD) (see table 9.4) provides complete national coverage for multiple time steps (1992, 2001, 2006, and 2011), allowing analysts to distinguish patterns of land cover change that may be pertinent for interpreting drought response.

More subtle changes in forest management, crop type, or livestock grazing intensity can be difficult to monitor and assess. Crop types and livestock grazing intensity can fluctuate with changes in market prices in ways that confound drought response. Similarly, broad-scale forest restoration that involves stand thinning via mechanical means or prescribed fire has the potential to reduce a forest's sensitivity to drought as grass and shrubs are removed; yet restoration efforts are rarely extensive enough to be widely detected except when they involve wildfire use. Far less logging has occurred over the last decade on most Forest Service lands, suggesting that there was far more drought-sensitive early successional habitat during the 1980s than exists in the 2000s. As large wildfires become increasingly common in the West, extensive areas of forest could become far more drought-sensitive than they were earlier. Certain derived land use/land cover datasets, such as the percent tree canopy cover layer developed by the Forest Service for the 2011 NLCD, may offer limited insight into these landscape dynamics.

"Big Data" Integration: A Contextual Learning Approach to Drought

To understand broad-scale drought impacts, both meteorology-based measures of drought and remote sensing observations need interpretation, and, as we have seen, interpretations are not straightforward. Many ancillary spatial datasets may be useful for selecting, masking out, or simply interpreting different effects that are observed (table 9.4). As noted above, identifying areas that have been affected or not affected by disturbance provides an effective way to isolate direct and indirect drought effects. Comparisons of different vegetation types, whether as specific dominant forest species types, or generally as evergreen, conifer, or mixed forest types, are useful for understanding how drought responsiveness and effects differ on the ground.

At a national scale, conditional filtering of sites based on their drought sensitivity and disturbance history can provide insights into the regional relationships between drought and NDVI (fig. 9.12). While the

MODIS NDVI period is limited to 2000–present, most filtered or masked vegetation types show a strong response of reduced NDVI with increasing drought, with some exceptions. The NDVI response of northeastern hardwood forests runs counter to expectations, perhaps because this area has not experienced the drought and temperature extremes as have hardwood forests of the Southeast (figs. 9.2 and 9.8). With their evergreen attributes, conifers only show some sensitivity to drought stress (fig. 9.12). In contrast, grass and shrublands show as highly sensitive to drought, particularly in areas that have experienced extreme drought during the MODIS period. The sensitivities described here, of course, are with respect to the speed and magnitude of NDVI responses. Such responses are useful to the degree that they reflect actual vegetation impact from realized drought stresses.

Using a random sample of 250,000 MODIS-*ForWarn* grid cells out of the 14.6 million cells in the conterminous United States, we found that 20.4 percent of the continental U.S. forest area was mapped as disturbed by wildfire, insects, or diseases between 2000 and 2012 (estimated using IDS, Monitoring Trends in Burn Severity (MTBS), and GeoMac data; see table 9.4). The drought response of these areas may be misleading for certain analyses, particularly when disturbance or drought occurs nonuniformly during the analysis period. For example, a gradual increase in NDVI associated with post-disturbance succession and recovery may overwhelm any reduction in NDVI caused by drought (see fig. 9.10). By masking out disturbed forests, however, the response of the remaining areas is more likely to relate to direct drought effects (fig. 9.12A).

The majority of the remote sensing indices in table 9.2 scale or proportionalize the absolute changes in greenness into relative terms. Usually the scaling divisor is some metric of total greenness (or range of greenness) in this location. Such formulations suggest a conceptual model (implicit or otherwise) that trees, which are "greener" than grasses, for example, are somehow better able to withstand a particular absolute decrease in greenness than their less-green grass counterparts. Thus, the estimated impact of a drought that causes a uniform absolute decrease in greenness will be reported by such indices as relatively more severe for grasses, since it represents a greater proportion of their total greenness, and relatively less severe for trees.
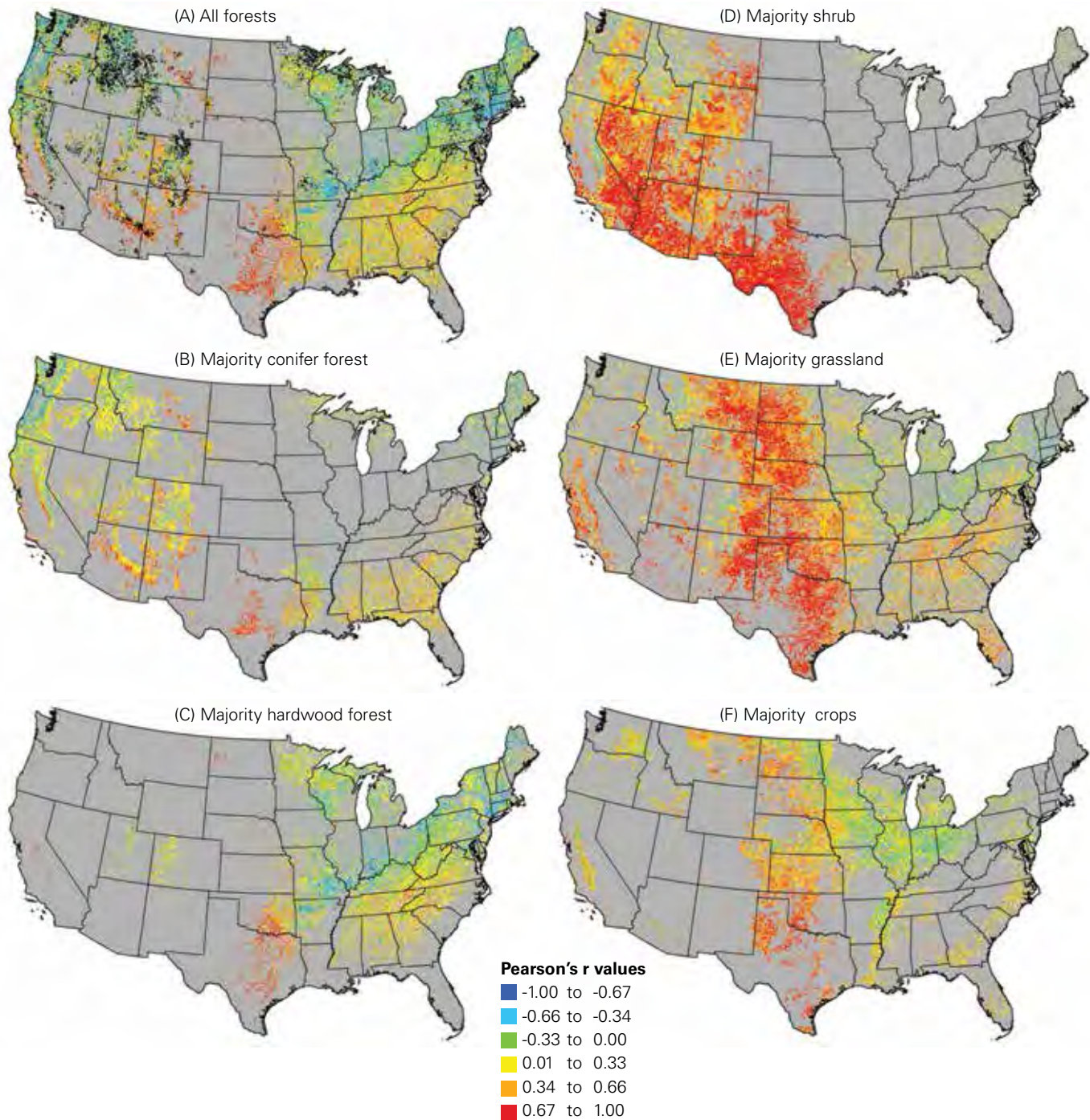
Figure 9.12—Correlations (Pearson's r) between mean March–September Moderate Resolution Imaging Spectroradiometer (MODIS)-based *ForWarn* Normalized Difference Vegetation Index (NDVI) and National Land Cover Data Climate Division mean monthly March–September Palmer Modified Drought Index (PMDI) for majority land cover types derived from the NLCD showing areas of known disturbance by wildland fire or biotic insect or disease in black for (A) all forests, (B) majority conifer, (C) majority hardwood, (D) majority shrub, (E) majority grassland, and (F) majority crops, 2000–2012. Wildland fire was derived from http://www.MTBS.gov (2000–2012) and http://www.GeoMac.gov (2013) (accessed September 1, 2014); insect and disease disturbance was compiled from Forest Service Forest Health Protection (FHP) Insect and Disease Survey (IDS) data. Data shown are based on 250,000 random points, sampled with a 1-km buffer.

Yet such relative sensitivities are diametrically opposite to the differential drought response patterns across vegetation types demonstrated here (Lobo and Maisongrande 2006, Sims and others 2014; see also Challenge 3). Figure 9.12 shows a version of fig. 9.8C that has been filtered by vegetation type. Small stature, low biomass vegetation types like grasses and shrubs are the quickest to show decreases in greenness under drought conditions, but grass and herbaceous perennials can recover quickly following an end to drought. In contrast, when drought leads to tree or shrub mortality, full recovery may take decades. Thus, grasses are a sensitive indicator vegetation type that may be useful as a harbinger of regional drought stress (Sims and others 2014). The NDVI of conifer-dominated forests are relatively unresponsive to drought. For example, at higher elevations, the coastal Northwest, and in New England, NDVI may actually increase as PMDI decreases (fig. 9.12). Weighting the severity of effects by scaling with absolute greenness would seem to be counter-indicated, and also acts to reduce the sensitivity of indices to drought effects on trees.

As noted earlier, remote sensing provides a coarse-filter type approach. Observations are frequent, extensive, and continuous in space, but are not detailed (fig. 9.7), and average across many vegetation types. Sensors are not species-specific and integrate across all vegetation growing in an area to produce a single value. Such integration may actually be advantageous, averaging out noise and measuring land surface phenology as a repeatable, emergent property of the entire vegetated ecosystem. An ideal drought detection approach would leverage both the extent and the temporal completeness of remote sensing approaches, while at the same time utilizing the longer historical record of meteorological records, which offer longer histories than remote sensing platforms. Ironically, the length of the MODIS or AVHRR record is considered long by remote sensing standards, yet it is very short relative to the depth of the climatic records, much less tree lifespans within forests. For even longer comparisons, one must employ other, even more-removed proxies, like tree-ring data (Herweijer and others 2007).

Combining Remote Sensing With Context-Based Learning

The broad spatial coverage and frequent, multiyear temporal sampling are powerful strengths of remote sensing approaches to the analysis of drought effects. It is not possible to do experiments on drought at the landscape scale. The extent is too large to randomize,

to replicate, or to apply droughts as experimental treatments [but see the Walker Branch Throughfall Displacement Experiment near Oak Ridge, TN, described by Hanson and others (2003)]. An inability to apply the classical scientific method does not, however, prevent a remote sensing approach to drought effects from making progress (Hargrove and Pickering 1992). Scientific progress on drought effects at large scales is simply limited to inference, based on what we can see happening. In this, remote sensing of drought is similar to a scientific field like astronomy, in which rich observation without the possibility of direct manipulation is the only avenue for advancement.

We suggest that a filtering approach that carefully considers both vegetative and climatic conditions can leverage the strengths of extensive drought data collected with remote sensing to best advantage. The identification of past situations whose drought outcomes might be informative or discriminating forms the keystone of this approach. A cycle starting with the postulation of an hypothesis, followed by identification and selection of relevant past "natural" experiments, followed by observation of the outcomes that resulted could be expected to produce inferences about the general principles at work, which would, in turn, result in refinement or rejection of hypotheses, beginning the cycle anew.

Such context-based learning, involving the isolation and examination of relevant prior circumstances, would leverage the availability of "big data" volumes of historical observations. Essentially, it is a form of empirical data mining. This type of time sequence approach is sometimes called space-for-time substitution, an approach that has been employed elsewhere in large-scale ecology (Pickett 1989). Figure 9.12 demonstrates the utility of such a filtering approach by showing the differential responses of various vegetation types to drought.

Empowered by ancillary datasets, powerful post hoc opportunistic analyses of drought may be possible when advantage can be taken of past droughts that are embedded within these specific relevant contexts of particular past times and locations. Such observation-based approaches carry with them the dangers of pseudoreplication, or at least an inability to replicate at will (Hurlbert 1984). Nevertheless, a strategy of coarse filtering by vegetation type, antecedent conditions, and drought severity could obtain targeted insights based on the weight of evidence from past outcomes.

Searching an extensive database of observations for the occurrence and review of particularly relevant chronosequences in time and space might be an effective way to make observation-based progress in our understanding of drought effects.

We advocate a data-mining, "big data" approach for detection and monitoring of drought impacts, relying primarily on remote sensing platforms, but also leveraging the longer term meteorological data and ancillary datasets for context-based interpretation. Figure 9.13 shows a conceptual model of how a "big data" approach might be used in developing a system for monitoring drought impacts in forests. This type of circumstantial data harvesting is the method most likely to increase our understanding of the impacts of drought stress on forests. Such a cycle might even advance our scientific understanding of landscape-scale drought effects with greater efficiency than classical experimental approaches (Tilman 1989). The strategy is empirical, allowing patterns to emerge passively from the data, without preconceived notions or hypotheses. Despite their neutrality and passive observational

nature, space-for-time filtering approaches can be highly constructive, as they will generate large numbers of testable hypotheses for the next round of conditional analysis.

Unambiguous establishment of causation (even in a limited pragmatic sense of learning to recognize correlated antecedent conditions) is difficult using these observational methods. Drought impacts are confounded and are difficult or impossible to disentangle without the use of relevant ancillary data (see fig. 9.13). With drought, however, this difficulty in separating proximate from ultimate drivers may not matter. Managers may be satisfied to monitor combined cumulative primary and secondary drought effects, unless they feel that they possess management options that would be effective against one or more of the separated drivers. Managers will want to recognize individual drivers only if they believe that they know how to relieve or mitigate some of the potential drivers. Otherwise, in practical terms, it is the sum total of the cumulative effects that acts to reduce the productivity of their forests.
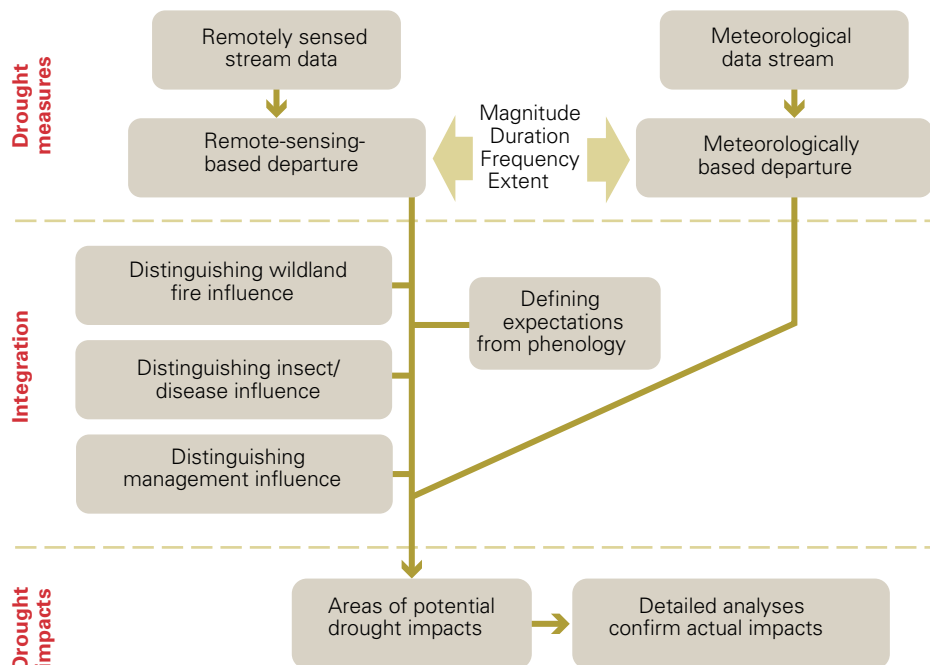

Figure 9.13—Conceptual model of how a "big data" integration approach might be employed in a system for monitoring drought impacts in forests. Fundamentally, areas of potential impacts occur where and when signals from both the remotely sensed and meteorological data streams coincide. Because the remotely sensed data stream documents all kinds of departures from normal vegetation conditions, the integration phase must include ancillary data that can distinguish departures unrelated or only indirectly related to drought. Detailed confirmatory analyses might include, for example, using Forest Inventory and Analysis (FIA) data retrospectively to look for tree growth declines or increases in tree mortality in areas where drought impacts were predicted.

Many of the newest generation of remote-sensing-based drought monitoring systems (table 9.3) are adopting such multivariate approaches. These multivariate approaches mirror appropriately the multivariate nature of drought effects and impacts themselves (as shown in fig. 9.5B). However, we must avoid subjective or quantitative "black box" solutions that infer impacts. We must move beyond such blind methods if we are to increase our basic understanding of complex drought impacts and the processes controlling them. A filtering approach that isolates particular conditions of vegetation and weather before, during, and after drought can, by looking across space, provide needed "experiments" that can yield insights into drought responses under more stringent conditions, isolating particular effects. Combined with ground-based sampling and monitoring data, such a hybrid approach can inform and enlighten our understanding of drought effects on forests.

Embedding Local Monitoring

Large-scale drought monitoring may not be capable of addressing local drought effects with the desired precision, even when the portions of broad landscapes that are likely to be hardest hit can be efficiently identified by large-scale monitoring efforts. Intensive local assessments can fill in the gaps that are not captured by coarse-scale monitoring (fig. 9.13). These efforts may consist of detailed mapping using high-resolution imagery that may or may not be calibrated with plot data or systematic plot inventories to capture changes of concern, such as reduced growth or tree mortality.

The Forest Inventory and Analysis (FIA) program administers an annualized system of field plot inventories. Under this system, first implemented in the late 1990s, plots are remeasured systematically on a cycle ranging from 5 (Eastern United States) to 10 years (Western United States). Thus, in the Western United States, one-tenth of the established FIA plot locations in any given State are sampled each year. These annual samples attempt to be free of geographic bias (Shaw and others 2005), appear to be sufficient for annual time series analysis of forest growth and mortality, and are able to detect relatively low levels of forest change (Shaw and others 2005). However, because of the temporal remeasurement interval, it may be impractical to link a short-term (e.g., single-year) drought event to mortality or any other impact observed on a plot, since the timing of that impact (i.e., exactly when during the several years since the plot was last visited) cannot

be determined (Liknes and others 2012). Long-term trends (i.e., more than a decade) typically must be studied using a combination of annualized and older periodic inventory data between which there may have been methodological differences. In addition, there is roughly 1 FIA plot per 6,000 forested acres, and there are about 130,000 forested plots nationwide. FIA data are probably best suited to analysis of status and trends at broader spatial scales (Shaw and others 2005). Plot density may be insufficient to detect impacts that are patchy in nature, even if they are manifested over a relatively large geographic region (Liknes and others 2012). Unfortunately, drought-induced tree mortality is often patchy (Allen and others 2010).

Despite such limitations, Gustafson and Sturtevant (2013) concluded that a drought-induced tree mortality signal in the upper Great Lakes region could be uncovered using FIA data. Gustafson (2014) similarly used FIA data to construct predictive models of drought-induced tree mortality (based in part on correlation with the NDSI and SPI) in the Northeastern United States. He found that the reliability of these models varied substantially; models for drought-intolerant tree species performed most poorly. Gustafson hypothesized that this may have occurred because long drought periods did not occur in the Northeast during the period when FIA inventories were available.

A major challenge when using FIA data is the inability to ascertain the actual cause of mortality or any other forest health change (Gustafson and Sturtevant 2013). If plots are disturbed, FIA field crews do have the option to assign damage agent codes, and drought is one possible code. However, these codes are reported inconsistently, and, as with the IDS data, field crews may label a disturbed plot according to the primary agent (drought) or the secondary disturbance agent (insect or disease activity). They can also assign multiple agent codes, which might provide some data filtering opportunities. The coarse temporal FIA remeasurements probably lead most field crews to assign secondary damage agents, concealing that these impacts may have been triggered initially by drought.

Ultimately, the best use of FIA data may be for retrospective analyses linking tree mortality and reduced growth to possible explanatory drivers, including drought. For this approach, FIA data might be used in concert with a variety of other data sources, including tree-ring data, remote sensing, meteorological drought index maps, and others. A number of studies

have employed this multivariate approach (Dietze and Moorcroft 2011, Klos and others 2009, Shaw and others 2005, Williams and others 2013). Additionally, through specially commissioned FIA remeasurement surveys, it may be possible to quantify areas experiencing major forest impacts in terms of trees lost and extent of the affected area, as was done by the Texas A&M Forest Service after the exceptional Texas drought in 2011. Final estimates of tree losses and subsequent economic impacts were released within a year (Nielson-Gammon 2012).

Summary

There is much recent interest in understanding how drought effects forests in part because drought and drought-associated forest disturbances are expected to increase with climatic change (Adams and others 2009, Allen and others 2010, Anderegg and others 2012, Breshears and others 2005, Breshears and others 2009, Carnicer and others 2011, Martínez-Vilalta and others 2012, Westerling and others 2006). Yet our ability to systematically and accurately recognize drought effects to forests over broad scales is limited. The most compelling research efforts mostly focus on catastrophic droughts rather than episodic droughts of moderate severity. The collective outcomes of more routine occurrences of moderate drought may be just as important and as impactful as rare, exceptional drought events. In any case, better tools, systems, and indices for dealing operationally with more commonplace drought events of moderate intensity are needed by forest managers and other resource professionals.

Drought is a value-laden term as concerns about particular impacts are implicit in the measures designed and baselines employed. No standard or universal definition is possible or even desirable, given the range of possible effects. Disentangling the various impacts of drought with different measures and ancillary data is part of the extraordinary challenge of dealing with drought effectively. With broad-scale monitoring, it is not possible to cleanly distinguish the effects of drought from the recipients of those effects, as moisture stress is not expressed uniformly across vegetation types (fig. 9.12). The relative composition of vegetation types must be considered in order to gauge the impact of any drought event accurately. In addition to utilizing nonforest species as indicator types that can be used to show what drying or wetting effects trees may be experiencing, it may become possible to utilize the extreme sensitivity of grasses to drought as a means to "standardize" drought intensity universally across all vegetation types, including trees. Understanding drought impacts on trees may require a longer history and a longer period of calculating baselines. Similarly, drought metrics for trees may require a longer, multiyear "memory" of antecedent conditions in order to be useful. New indices specific to trees are needed, because while metrics repurposed from agricultural crop use may work well for forests, these drought indices could be adapted in ways that increase their relevance for forests, in particular. Adaptations might include reformulating drought measures to capture long-duration multiyear drought, targeting drought measures to the sensitive seasons of the year based on phenological insights, or embracing baselines that relate better to the nonequilibrium nature of forested ecosystems.

Taking a broad view, drought effects to forests include direct and secondary effects that must all be addressed to understand each individually and the effects of climate extremes more fully. While wildfire, insects, and diseases can only partially be attributable to drought (fig. 9.5B), a change in drought-sensitive disturbance regimes may be the primary means by which drought alters forests in coming decades. While some drought-sensitive disturbances can be monitored using the same types of systems used for monitoring changes in productivity or mortality, attribution back to drought as the prime mover often requires integration of independent wildfire and insect and disease inventories and datasets.

Because of their inherently multivariate nature, efforts to characterize drought effects on forest landscapes will necessarily involve the integration of information, as knowledge of species, communities, disturbances, and mitigating factors are obtained from a multitude of different programmatic efforts. Interpretation is not inherent in monitoring when indicators are sensitive but coarse, and "big data" help translate observations to effects of specific concern (fig. 9.13). To make large-scale drought monitoring and assessment more accessible, we need an integrating framework for organizing knowledge that efficiently narrows down what is and is not likely to be a drought effect. This knowledge can help prioritize applied efforts for drought mitigation, adaptation, or response more generally.

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