CHAPTER 6

Precise Mapping of Disturbance Impacts to U.S. Forests Using High-Resolution Satellite Imagery

Steven P. Norman
William M. Christie

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INTRODUCTION

Aerial mapping of forest disturbances has contributed to monitoring efforts in the United States since aircraft were first used to detect wildfire and insect mortality after World War I. In the century since, routine aircraft patrols with field examinations have successfully documented disturbances with increasing effectiveness. There remain conspicuous discrepancies among States, jurisdictions, and forest types, however, and this is further complicated by shifting mapping methods over time (e.g., Housman and others 2018).

Satellite-based remote sensing provides a complementary approach for aerial surveys as it brings efficient, cross-jurisdictional standardization to change detection. Systematic observations from satellite data taken over months to decades provide substance for programmatic forest monitoring, and this approach gives us a rigorous understanding of status and change over time using the satellite data archive.

Until recently, integration of satellite-based remote sensing with field and aircraft efforts was impeded by data processing constraints, given the large and unwieldy datasets involved. With the rise of cloud computing such as Google Earth Engine (hereafter referred to as EE), data access and image processing are no longer constraining (Gorelick and others 2017, Hanson and others 2013). Other game changers have been the opening of satellite data archives for free use (Wulder and others 2012) and the launch of new satellites with higher resolution than existed before. Imagery from the Sentinel-2 satellites in particular has nine times more spatial detail than Landsat and about 600 times more detail than Moderate Resolution Imaging Spectroradiometer (MODIS) imagery. Mapping forest change at this more precise resolution gives insights into the pattern and texture of disturbances that are helpful for accurate mapping and interpretation. Despite these technological advances, causal attribution can still be challenging, so field observations are needed to resolve insect defoliation or when multiple causes contribute to tree stress or mortality.

This chapter reports on the broad patterns of forest anomalies across the conterminous United States for 2020 as detected from remote sensing. A prior effort used the summer persistence of anomalies in 240-m MODIS imagery across this same extent (Norman and Christie 2020). Leveraging the computational power of EE, this current effort summarizes conditions over that same area using forested 10-m grid cells. As hexagons have been proposed as a standardized unit for forest reporting (Potter and others 2016), we demonstrate how these precise gridded observations can be filtered and summarized into coarser reporting units.

METHODS

Imagery from the European Space Community's Sentinel-2 satellites were accessed using EE to produce national maps of the Normalized Difference Vegetation Index (NDVI) for summer 2019 and 2020. Data were corrected for surface reflectance and filtered for clouds. The NDVI captures canopy vegetation vigor and has wellunderstood limitations (Norman and Christie 2020). Compared to some other vegetation-sensitive indices, Sentinel-2's NDVI relies on the 10-m resolution red and infrared bands—a resolution which approximates the footprint of a single large canopy tree. We used a maximum NDVI value compositing technique to select the best imagery available for a designated period of time, and this minimized the influence of clouds and shadows that lower NDVI (Spruce and others 2011).

Growing season NDVI was defined as the maximum NDVI observed over a 2.5-month period for 2019 and 2020. For areas east of the 100th meridian, the compositing period was May 15 to July 31, which is generally the best season for detecting early spring defoliators and when summer NDVI reaches its phenological high in the East (Norman and others 2017). For the West, we used the highest NDVI between July 15 and September 30 to reduce the influence of variable spring timing and mountain snowpack. We acknowledge that local phenological factors and the timing of some disturbances before or after these dates could interfere with some mapping objectives, but for this national-scale effort, our primary objective is to have a transparent and standardized methodology.

We calculated 1-year absolute change in summer NDVI (dNDVI) by comparing the 2019 and 2020 maps. The 1-year baseline ensures that the detected changes are recent as it avoids persistent effects from prior years. A shortcoming of using the 1-year baseline is that in areas with sequential year disturbances such as year-on-year defoliation, the 2020 dNDVI may mischaracterize impacts when 2019 was also anomalous. A 1-year baseline provides the most clarity for industrially logged regions, as multiyear artifacts accumulate there and these obscure other disturbances (Norman and Christie 2020).

In EE, we distinguished likely forest from nonforest using the 2016 National Land Cover Database (NLCD) (https://www.mrlc.gov/). While the NLCD product is at 30-m resolution and its cover type designation is outdated where severe fire or logging activity occurred immediately prior to 2019, this was the best nationally consistent land cover source available.

For our national overview, we used EE to summarize forest-only changes below a threshold of -0.1 NDVI, and we summarized these in hexagons of 834 km^2. This nationwide NDVI departure threshold was chosen because declines that are less are more likely to have minor or ephemeral impacts to the canopy. Based on observations in the Eastern United States where thresholding is challenging due to the dominance of mixed deciduous cover, this threshold usually captures growing season canopy stress from moderate to severe fire and wind and insect defoliation, as well as tree mortality. This effort gave us approximately 9,810 hexagons for the conterminous United States with each having 8.34 million 10-m Sentinel-2 grid cells. We calculated the percentage of each hexagon with forest and the percentage of forest cells departed at or below the specified threshold. For our finer scale assessment, we relied on the same 10-m Sentinel-2 NDVI change product and the same

NLCD forest mask. This seamless approach allowed us to visualize regional and fine-resolution patterns of departures efficiently using the *HiForm.org* script in EE.

RESULTS AND DISCUSSION

At the national scale, broadly coherent patterns of growing season change generally conform to ecological or climatological regions. The central and southern Interior West exhibit more NDVI departure than the northern Interior West or Pacific Northwest coast (fig. 6.1). Across the East, the Southeast Piedmont and Coastal Plain show more NDVI departure than most of the Northeast, but there are pockets of stronger departure such as in northern Michigan, northeastern New England, and southern Pennsylvania. There is additional variability among hexagons within each broad region. Together, these multistate and hexagon-scale patterns suggest stress at the regional and landscape scale for 2020.

Even at this coarse hexagonal resolution, regional causes of disturbance can be inferred. In particular, the coherence of the Interior West's summer NDVI departure and that of much of New England is generally consistent with the U.S. Drought Monitor for late September 2020 (https://droughtmonitor.unl.edu/Maps/MapArchive.aspx). The areas of moderate departure across the Southeast's Coastal Plain and Piedmont region, Maine, and portions of the Pacific Northwest are consistent with where intensive forest harvesting occurs, which along with drought ranks as a leading cause of summer NDVI variability for the conterminous United States (Norman and Christie 2020, Norman and others 2016).

As the national hexagon map is assembled from 10-m source imagery, we see local patterns and textures of disturbances by zooming in. With this precision, we also gain further insights into the local causes of forest NDVI departure. Figure 6.2 includes the U.S. Department of Energy Savannah River Site, and it shows prominent patterns of linear streaks, rectangular blocks (in dark blue indicating recovery and red indicating extreme decline), and separate amorphous areas (in light yellow indicating low NDVI change). The streaks were caused by spring 2020 tornadoes, and the blocky areas of disturbance and recovery are from recent logging. The yellow areas likely represent areas of low-severity prescribed fire or thinning that had a minor effect on the overstory canopy. The extent, shape, edge attributes, and intensity or texture help us interpret these patterns, often with a high degree of certainty even when ancillary data such as storm tracks and treatment dates are not utilized. These ancillary datasets can serve a confirmational role, but the drop in NDVI can result from more than one cause, such as wildfire and beetles, beetles and logging, wind damage, and prescribed fire.

Situated in the northern Lower Peninsula of Michigan, figure 6.3 shows a large, amorphous area of moderately severe disturbance caused by *Lymantria dispar dispar* (formerly known as European gypsy moth) defoliation. This 2020 outbreak was documented by field observations, and this map is particularly adept at showing

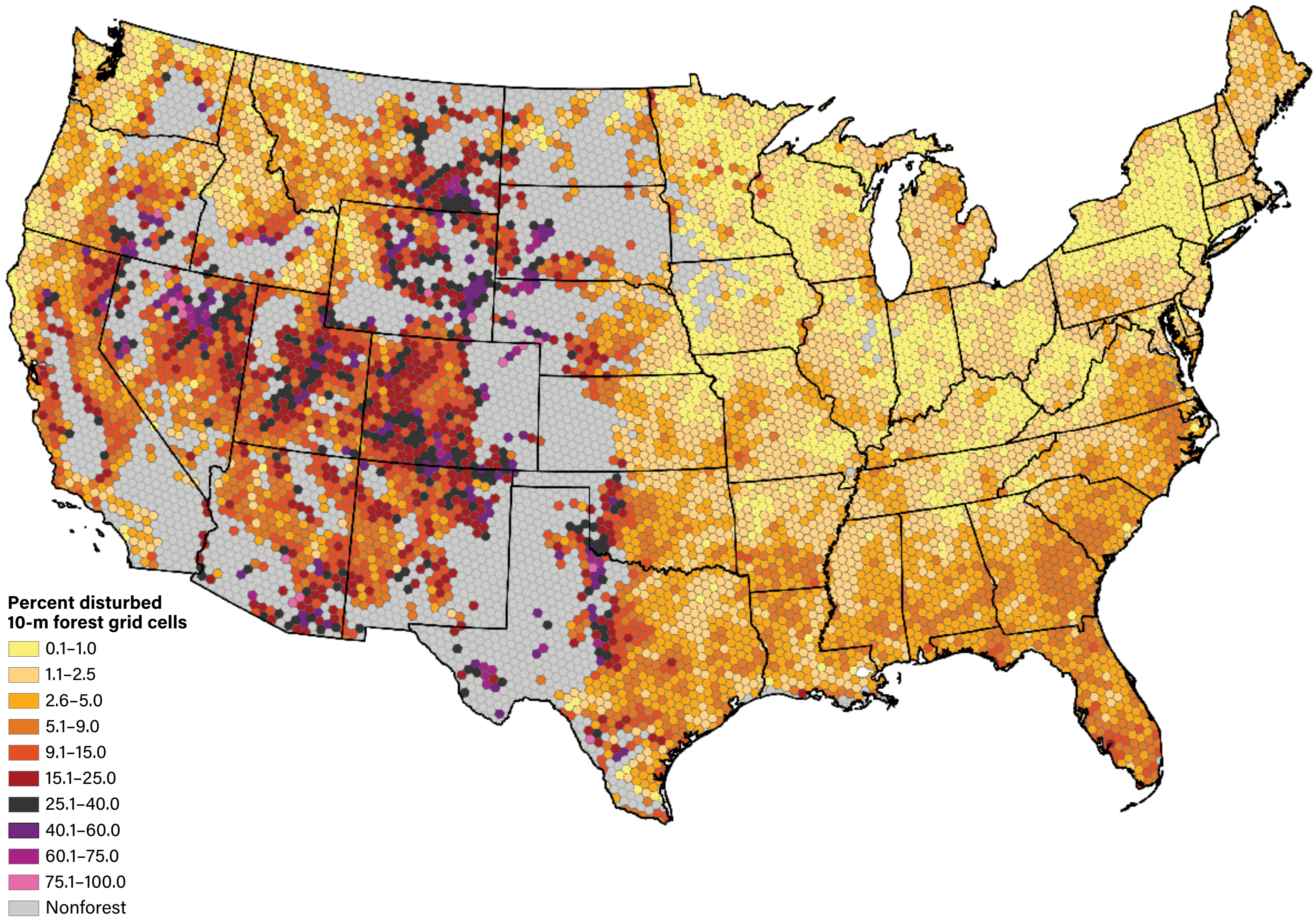

Figure 6.1—Percentage of 10-m forest grid cells within 834-km² hexagons that were disturbed below a threshold Normalized Difference Vegetation Index (NDVI) departure of -0.11 from the 2019 to the 2020 growing seasons for the conterminous United States. Grey hexagons have little to no forest cover.

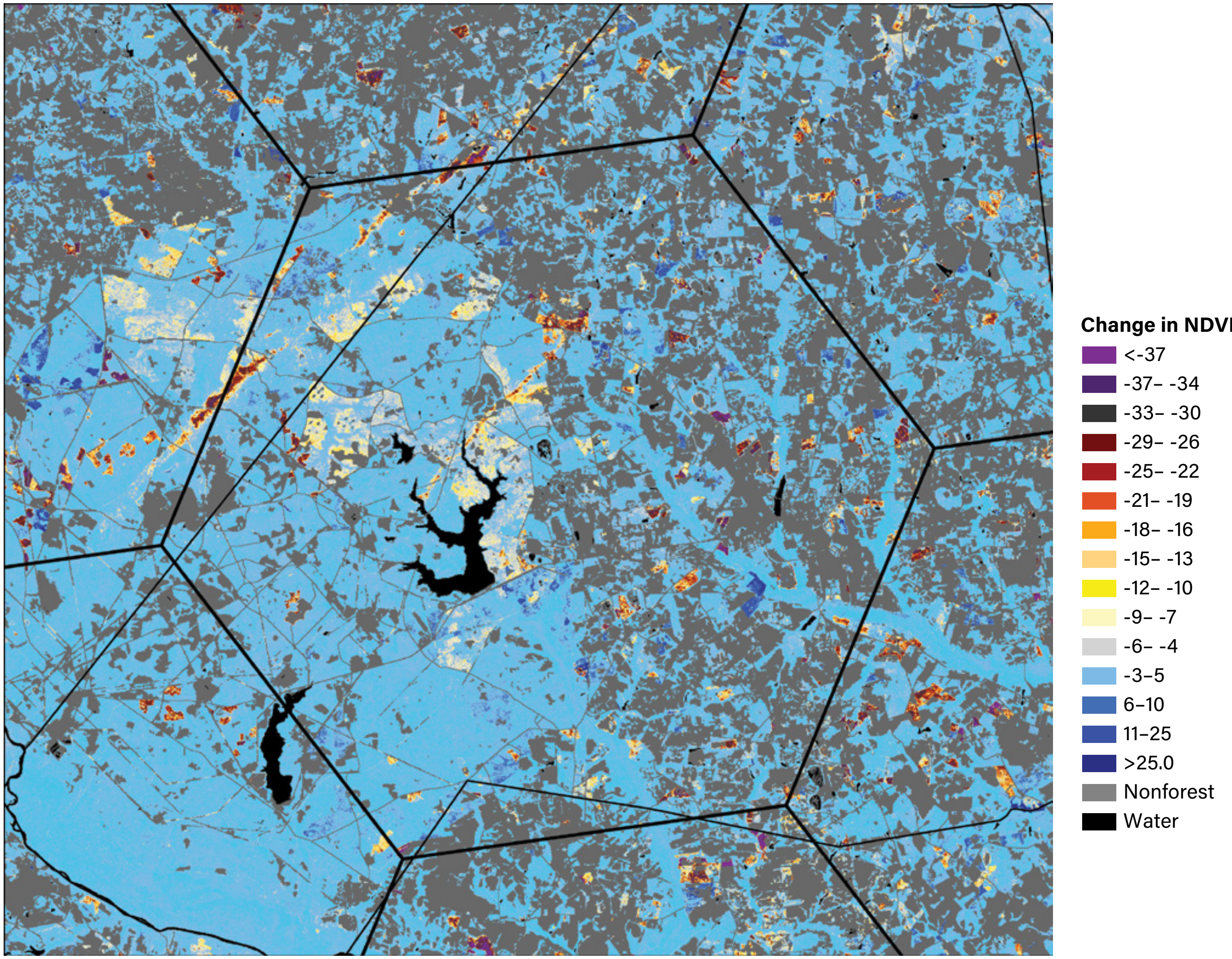

Figure 6.2—Forest disturbances near the U.S. Department of Energy Savannah River Site, SC. Areas in yellow to red show the severity of recent disturbances, while light blue shows forests with no change. Dark blue is recovery from earlier disturbances.

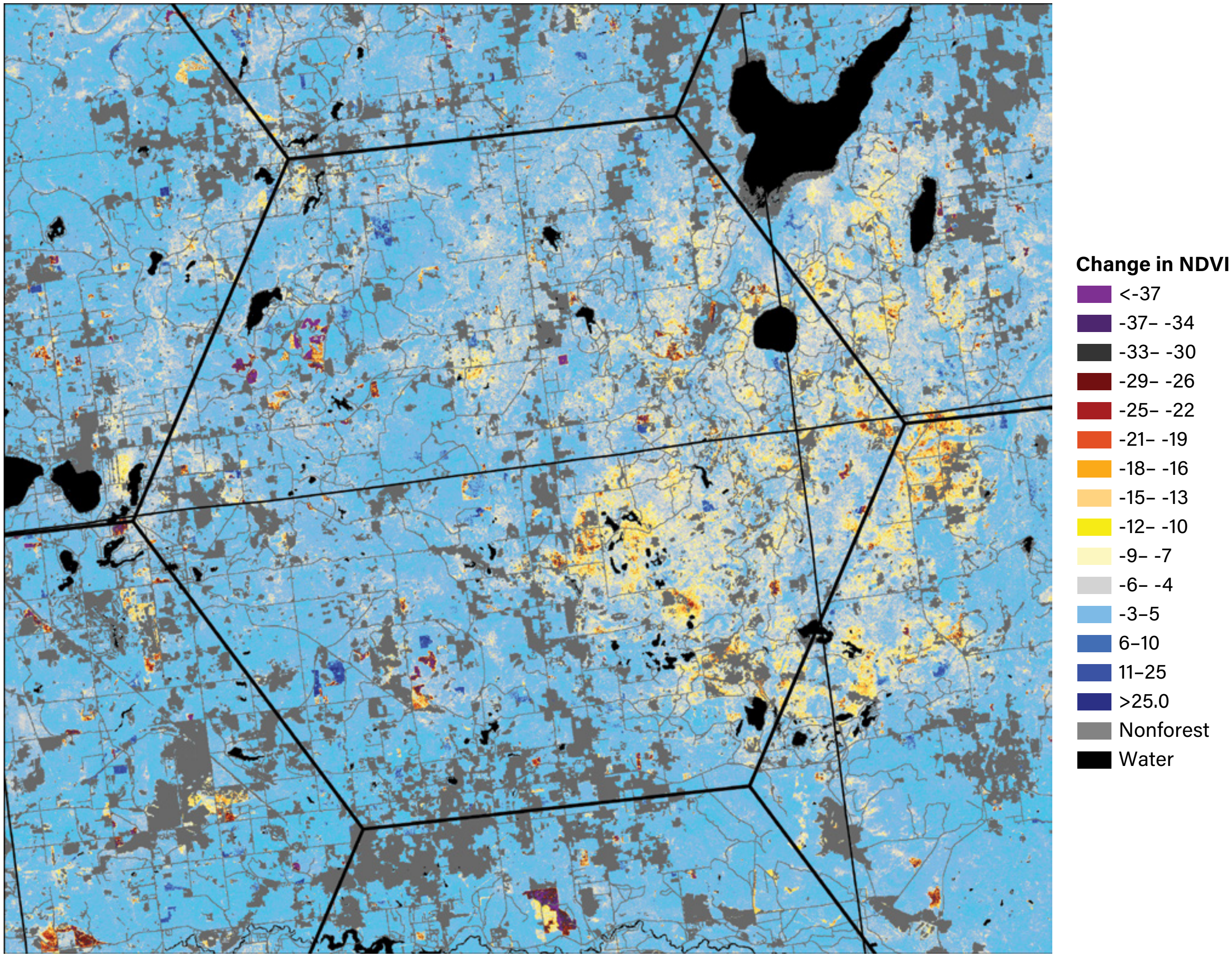

Figure 6.3—Change in Normalized Difference Vegetation Index (NDVI) in northeastern Michigan. Areas in yellow to red show the severity of recent disturbances, while light blue shows forests with no change. Dark blue is recovery from earlier disturbances.

subtle differences in defoliation intensity. As recurrent gypsy moth defoliations can occur over multiple years, impact assessment may need to be calculated using a baseline year that had no defoliation as part of a local exploration process. Such multiyear impacts are difficult to accurately map as is gradational intensity without the benefit of remote sensing.

Just east of Portland, OR, and south of the Columbia River Gorge, figure 6.4 shows relatively few acres of late summer NDVI decline, but these are readily mapped using 10-m NDVI change imagery. The area of the September 2017 Eagle Creek wildfire now in post-fire recovery is shown in dark blue at the top of the figure, while areas of local NDVI declines shown in yellow at the southern and eastern edge of that fire are likely from delayed mortality from insects. It is notable that there has been gradual migrating NDVI decline near these sites each year since the fire. Also note the extreme NDVI declines from logging near the western edge of the hexagon in purple that lie amid areas of NDVI recovery in dark blue. The co-occurrence of similarly shaped rectangular blocks of decline and recovery is indicative of industrial logging.

Figure 6.5 shows change in NDVI for a high elevation (8,000–12,000 feet) subalpine spruce-fir forest in the San Juan National Forest in Mineral County, CO. Both figure 6.1 and the status of the late summer 2020 U.S. Drought Monitor suggest that the primary cause of this broad NDVI departure is drought. This is particularly likely here because in 2020, most areas showing NDVI departure marginally fall under the definition of forest due to prior mortality. The June 2013 West Fork Complex burned the eastern portion of the hexagon in figure 6.5, and while this area has had limited mapped insect activity recently, significant mortality occurred during the last decade. Inspecting these areas more closely in EE using background imagery, nearly all the NDVI departures in yellow and the majority of the NDVI departures in red on figure 6.5 are those areas of prior mortality. As drought-sensitive grass is not the intended target for mapping, a more recent and higher resolution forest mask would isolate recent tree impacts from nonwoody drought responses here.

Tools for Disturbance Assessment

With technological advances improving the accessibility of satellite data, analytical needs shift toward disturbance assessment. That is, detections may or may not be real disturbances, and when they are, analysts need to know exactly what caused them. In practical terms, attribution comes down to likelihoods based on the weight of the evidence available.

In many cases, the most likely cause of a disturbance is suggested by available ancillary datasets. Thanks to numerous independent governmental efforts, we generally know where drought, major storms, large wildfires, and extensive insect defoliations are occurring before their precise impacts are mapped (Norman and Christie 2020). Assessment refines the disturbance footprint, maps severity, and tracks the disturbance's duration or recovery over time. Where disturbances appear unexpectedly, the

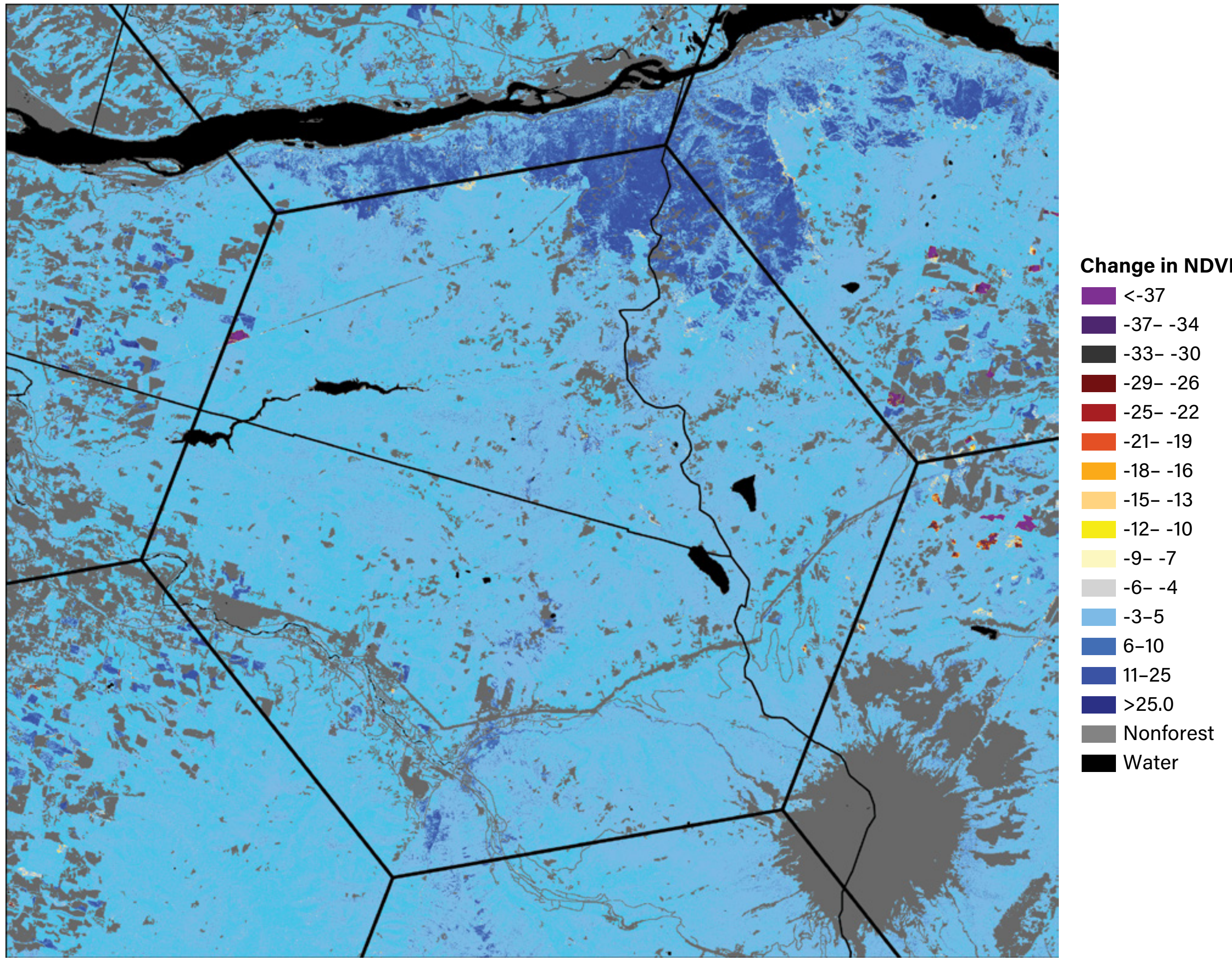

Figure 6.4—Change in Normalized Difference Vegetation Index (NDVI) east of Portland, OR. Mount Hood lies just outside this hexagon at lower right. Areas in yellow to red show the severity of recent disturbances, while light blue shows forests with no change. Dark blue is recovery from earlier disturbances.

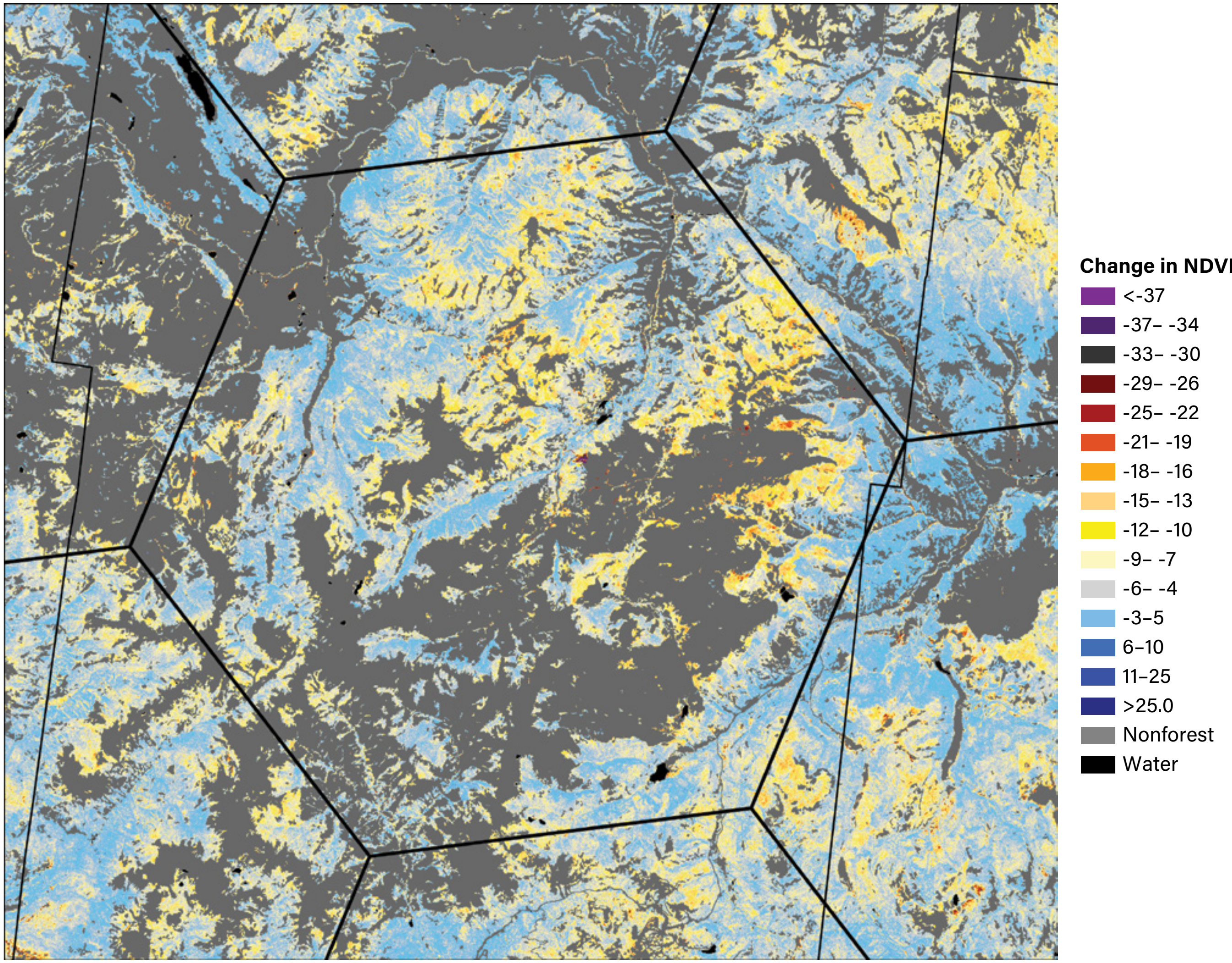

Figure 6.5—Change in Normalized Difference Vegetation Index (NDVI) for a high-elevation (8,000–12,000 feet) portion of the San Juan National Forest in Mineral County, CO. Areas in yellow to red show the severity of recent disturbances, while light blue shows forests with no change. Dark blue is recovery from earlier disturbances.

spatial and temporal attributes of the disturbance become critical for attributing cause.

The field of landscape ecology has devised numerous ways to characterize the spatial attributes of landscape features, and these are useful for characterizing the processes that give rise to them (Costanza and others 2019, Gustafson 1998). Critical attributes include extent, shape, edge, texture, and intensity. The precision of these measures is reduced by coarse-resolution imagery such as MODIS, particularly in heterogeneous forests with diverse cover or fragmented landscapes.

Fine-resolution imagery is more likely to reveal these disturbance attributes accurately, but texture, shape, edge, and intensity also reflect vegetation susceptibility. In mixed stands, disturbances that preferentially affect one species can create spotty or dispersed textures, while fragmented land use and a homogenous forest type can create aggregations. The underlying patterns of susceptibility from exposure or host vulnerability can result in shapes that would not otherwise occur, which means that pattern interpretation needs to reflect both this underlying condition and the diagnostic characteristics of a particular disturbance. Situational context is key.

The behavior of remotely sensed measures over time can also be useful for attributing cause. Algorithms such as LCMS (Landscape Change Monitoring System), LandTrendr (Landsat-based detection of Trends in Disturbance and Recovery), and VerDET (Vegetation Regeneration and Disturbance Estimates) evaluate multiyear responses using time series data, and these temporal patterns are often indicative of general classes of disturbances (Cohen and others 2018, Hughes and others 2017, Kennedy and others 2018, Schroeder and others 2017). For near-real-time evaluations, weekly streaming MODIS satellite data are particularly adept at documenting onset timing, progression, and duration in particular (Hargrove and others 2009). Recurrent observations within and across growing seasons at any grid resolution can help distinguish ephemeral defoliation from actual tree mortality (Norman and Christie 2020).

Indicators

Most indicators in common use by remote sensing analysts are informal, but a more standardized approach is critical for communication and machine learning approaches that could someday support attribution efforts. As shown below, four spatial indicators include extent, shape, edge character, and texture and intensity. Three temporal indicators are the seasonal onset date, the speed of development or weekly progression, and the duration of the impact. These indicators can differ among disturbances (as shown in tables 6.1 and 6.2):

1. **Extent** (local, landscape, regional)—Extensive disturbances often suggest a weather or phenological cause, although the manifestation of the anomaly is often confined to susceptible vegetation types. Extensive disturbances result from drought, hurricanes, spring freezes, and derechos, but delayed spring green-up, an early leaf senescence, and variation in snowpack can create similarly broad-scale anomalies at certain times of year.

Table 6.1—Common spatial indicators for assessing the causes of Normalized Difference Vegetation Index (NDVI) decline that link pattern with process

Cause	Extent	Shape	Edge	Texture and intensity
Drought	Broadly regional extending across multiple counties or States	Amorphous	Gradational, usually over tens to hundreds of kilometers	Depends on the sensitivity of vegetation types to drought stress
Tornadoes	Local to landscape depending on storm track	Strongly linear patch, in a consistent direction as storm tracks	Moderately sharp, with steep wind speed gradients over hundreds of meters	Generally highly intense along the midline with lateral reductions with reduced wind speed
Hurricanes	Multicounty or multistate, particularly from more intense storms	Broad impacts often with narrowing breadth inland as wind speeds fall	Generally decreasing inland; sharp-edged only with differences in cover type, such as at flood plains or harvest boundaries	Valleys show strong post-storm decline from flooding; damage intensity varies by hardwood/deciduous type
Freezes	Multicounty to regional consistent with extreme low temperatures	Broadly evident but locally constrained by elevation and topographic position	Gradational regionally but locally abrupt with cover, topography or the freeze line	Usually low intensity; textural impacts vary with cover type and terrain
Downbursts /hail	Local to landscape	Often oblong and directionally consistent with storm tracks	Gradational to fuzzy except where core impacts persist	Usually has an epicenter of concentrated impact surrounded by lower impact areas
Defoliating insects	Local to landscape	Amorphous	Gradational	Often with areas of concentrated high impact in areas of modest decline; rash-like
Bark beetles	Local to landscape	Gap to patch sized; clustered	Sharp or gradual	Can show a leading edge of progressive migrating decline or highly textured variation; sometimes rash-like
Diseases/ pathogens	Local	Spotty; constrained by affected host distribution	Sharp or gradational	Depends on the density of the affected host and size of the infestation
Prescribed fire	Local, confined to management units	Usually limited to a distinct management unit or confined by roads or streams	Usually gradational, often with minimal detectability; severe patches are often sharp-edged	Variable; usually of lower intensity with fewer discrete patches than area wildfires
Wildfire	Local to landscape	High-intensity patch shape often conforms to topography	Usually soft or gradational due to operational backfires or managed edges	Variable severity is common with high-intensity patches conforming to topography
Thinning	Local, confined to a management unit	Patchy	Gradual to sharp depending on the intensity	Strong fine-scale textural variation; sometimes rash-like
Logging	Local, confined to a management unit	Patchy	Very sharp where canopy patches are removed	Generally extreme with variation from exposed soil or persistent slash
Landslides	Highly localized	Patchy and linear, especially with downslope flow	Very sharp	Depends on size and severity; extreme where bare rock or soil
Flooding	Occurrence is generally confined to waterways or valley bottoms	Linear or branching along valley networks	Generally sharp, conforming with the topography	Microtopography affects depth and overstory canopy affects the apparent intensity

Table 6.2—Common temporal indicators for assessing the cause of Normalized Difference Vegetation Index (NDVI) decline that link pattern with process

Cause	Onset date	Development speed	Duration
Drought	Regionally specific; sometimes only evident during drought-sensitive seasons; affects snowpack and the timing of spring and fall phenology	Usually gradual; behavior is sensitive to phenology, particularly that of grass	Usually seasonal; duration is often consistent with meteorological drought, but mortality can create a multiyear legacy
Tornadoes	Spring or early summer when these storms occur	Rapid	Multiyear with mortality
Hurricanes	Late summer or fall when these storms occur	Rapid	Seasonal to multiyear
Frost	Mid- to late spring when this weather occurs; in spring, often manifest as a delayed or slowed spring; in fall manifest as early senescence	Rapid	Weeks; severe frost damage can extend through the entire growing season
Downbursts/hail	Anytime during the growing season; usually spring or summer	Rapid	When severe, effects can persist through the remaining growing season
Defoliating insects	Region and defoliator-dependent; early spring through mid-summer	Gradual, over a period of weeks	When severe, effects can persist through the remaining growing season
Bark beetles	Region- and insect-specific; mortality can be year-round in the Southeast	Rapid to gradual over a period of weeks	Multiyear with mortality
Diseases/pathogens	Recognition can depend on the host tree's seasonal leaf phenology	Often gradual; the outbreak can evolve over several growing seasons	Multiyear with mortality
Prescribed fire	During the region's prescribed fire season; winter prescribed fires may not emerge until spring	Rapid	Multiyear; often only visible soon after the event
Wildfire	Normally emerge during the region's wildfire season	Rapid	Multiyear with mortality
Thinning	Anytime	Rapid to gradual over a period of weeks to months	Multiyear with mortality
Logging	Anytime	Rapid to gradual over a period of weeks to months	Multiyear with mortality
Landslides	Anytime; usually triggered by a heavy rain event	Usually rapid unless actively expanding	Multiyear with mortality
Flooding	Anytime; usually triggered by a heavy rain event	Rapid	Weeks to months

2. **Shape** (amorphous, linear, blocky, conformal)—Shape is particularly useful for isolating intense weather events such as tornadoes and downbursts. At high resolution, shape often depends on the susceptibility of the available vegetation or land cover type as much as the physical attributes of the disturbance itself, and this is particularly complicated in mixed deciduous-evergreen forests.

3. **Edge** (sharp, gradual, conformal)—Natural disturbances such as wind, hail, and insect defoliations often have gradational edges because the stress grades naturally, but severe fire patches can be as abruptly edged as clearcut logging units. Fragmented landscapes often have conformal disturbance edges due to how different cover types respond.

4. **Texture and intensity** (uniform, patchy, rash-like)—These attributes reflect both the behavior of the disturbance and the vulnerability of the vegetation involved. In heterogenous mixed evergreen-deciduous forests, textural variation in intensity can reflect topography and host density. In homogenous forests, it can reveal unfolding disturbance processes, such as local epicenters of spreading beetle mortality.

5. **Onset date** (winter, spring, summer, fall)—Onset date provides important evidence when analysts know when different disturbances emerge locally. Many insect defoliators are diagnosed by when they erupt. Importantly, the canopy effects of some disturbances that occur during the fall, winter, or early spring may not be detected by remote sensing until leaves emerge, and this delay in manifestation can limit the usefulness of onset date.

6. **Speed of development** (rapid, gradual)—Most severe forest disturbances occur suddenly, but some evolve over the course of weeks, such as progressive pine beetle mortality or the gradual logging of a unit. After windstorms, the manifestation of a disturbance can be slow to show up even when the event is rapid, possibly because downed canopies take time to brown.

7. **Duration** (weeks, season, multiyear)—Disturbance duration is particularly useful in eastern hardwood forests for distinguishing among ephemeral defoliations or minor damage from hail, wind, or frost effects, and tree mortality. In some cases, severe canopy damage can occur that is only detectable for a few weeks due to compensatory growth, and this limitation may only be overcome through field examinations.

The grid resolution of remote sensing products can affect how clearly these first four indicators—extent, shape, edge, and texture and intensity—can be recognized. Meanwhile, the temporal frequency of imagery can affect how precisely we can resolve onset date, speed of development, and duration. As a result, daily coarse-resolution imagery such as 250-m MODIS may best document temporal behavior, while high-resolution imagery that is 10 m or less can most reliably show shape, edge, and textural variation. A precise understanding of spatial pattern is most important in areas with complex terrain, cover types, or mixed species as that helps isolate what caused NDVI departures.

High-resolution imagery can even be important for attributing cause to extensive disturbances such as drought, given the different sensitivities of cover types (Norman and others 2016).

CONCLUSIONS

Cloud-based remote sensing provides forest monitoring solutions for near-real-time tracking purposes and as part of a broader forest monitoring program. The flexibility of cloud-based analyses allows efficient use of high-resolution imagery, such as Sentinel-2, for national-scale summary efforts while retaining the fine spatial resolution needed to effectively attribute cause. At 10 m, small disturbances that involve just a few trees are often detectable. This use of fine-resolution imagery as the foundation for national assessments efficiently satisfies the local demand for precision and accuracy and the landscape, regional, and national need for context and generalization, all using a common indicator—change in growing season NDVI at 10 m.

The persistent challenge of remote sensing for landscape monitoring is causal assessment. That is, when the purpose of monitoring is to resolve impacts to a known disturbance, the cause is usually established from the start, but when the objective is to systematically track forests more broadly, attribution can be difficult. Our use of a single remote sensing measure reflects the need to capture vegetation dynamics broadly, and this includes disturbance recognition, attribution, quantification of impacts, and recovery.

The science of disturbance attribution can be advanced through use of a standard set of spatial and temporal indicators, such as those shown on tables 6.1 and 6.2. Yet without use of ancillary datasets and aerial or field confirmation, such indicators can only shift the likelihood of different causes, as their attributes overlap. For confirmation of the cause of an NDVI departure observed from remote sensing, storm, fire, and management activity datasets are useful. Field observations are sometimes also critical, such as with the need to resolve which defoliating insect is responsible when multiple species are possible. For precise characterization of disturbance impacts, aerial surveys and field observations are generally required. Local expertise is, therefore, a critical part of monitoring, and advances in remote sensing are best used in support of an integrated monitoring program.

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