FEATURE

# Satellite and Airborne Remote Sensing Applications for Freshwater Fisheries

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Remote sensing has been pivotal to our understanding of freshwater fisheries, and we review this rapidly changing field with a focus on satellite and airborne applications. Historical applications emphasized spatial variation in the environment (e.g., watershed land use and in situ primary productivity), but improved access to imagery archives facilitates better change detection over time. New sensor platforms and technology now yield imagery with higher spatial, temporal, and spectral resolutions than ever before, which has accelerated development of remote sensing products that more accurately characterize aquatic environments. Free access to imagery archives, cloud computing, and availability of derived products linked to national hydrography databases are all removing historical barriers to its use by fisheries professionals. These advances in remote sensing have allowed new questions to be answered at finer spatial resolutions across broader landscapes and longer time frames, providing a new big-picture perspective to freshwater fisheries conservation and management.



## INTRODUCTION

Remote sensing has revolutionized how fisheries biologists study ecological patterns and processes at broad spatial scales. Remote sensing data have been critical in uncovering the fundamental relationships between fish distributions and their surrounding landscapes (Johnson and Gage 1997), and they have informed conservation needs for freshwater systems that often contain high levels of biodiversity or harbor important recreational and commercial fisheries (Hughes et al. 2006; Wirth et al. 2012). Some derived data sets, defined as data sets secondarily derived from primary remote sensing data such as the National Land Cover Dataset (NLCD) derived from Landsat multispectral data, are now routinely used to understand how land use and land cover influence aquatic habitats and biota (Hughes et al. 2006). Thermal sensors are also widely used to understand temperature influences on fish stocks across aquatic landscapes (Dugdale 2016). The number of potentially useful remotely sensed products of increasingly high spatial and temporal resolution has proliferated in the last decade, and many of these products are not well known in the fisheries community. At the same time, new tools render these data sets more accessible to those without specialized training. In short, the field is changing dramatically. Our goal in this article is to demystify the field of remote sensing for freshwater fisheries biologists by exploring recent applications of airborne and spaceborne remote sensing (as opposed to ground-based or underwater sensors) to freshwater fisheries and highlighting emerging tools that facilitate broader use.

To start, rapid technological advances have produced remote sensors that collect data at higher spatial, temporal, and spectral resolutions than what were collected just a decade ago (Figure 1), and these data are becoming increasingly accessible due to affordable or free, easy-to-use archives and data delivery platforms. This, along with the increasing availability of custom data sets, has improved the ability to match remote sensing data to specific fisheries questions over both space and time (Table 1). For example, many satellite-based sensors collect data at the same location on Earth at a spatial resolution of several meters every few days (see Supplementary File: Table S1). Microsatellite companies, such as Planet Labs (San Francisco, California), process custom orders for high-resolution imagery of specific places on Earth, and many sensors, such as forward-looking infrared sensors, are routinely deployed on aircraft for custom applications (Vatland et al. 2015). Hyperspectral sensors containing hundreds of high-resolution (narrow) spectral bands are becoming more common (versus multispectral sensors with three or four low-resolution [broad] spectral bands), and increased spectral resolution has allowed more precise identification of specific aquatic habitats from imagery, such as identifying wetland vegetation to the species level (Adam et al. 2010).

Concurrently, new policies and capabilities are rapidly overcoming historical challenges to the use of remote sensing imagery: accessibility and cost of imagery archives; expertise needed to process raw imagery and apply it to specific problems; and computer storage and computational power, especially for applications covering large spatial extents (Rose et al. 2014; Turner et al. 2015). For example, since 2008, the U.S. Geological Survey (USGS) and National Aeronautics and Space Administration (NASA) have allowed free access to Landsat archives dating back to 1972, and the U.S. National Oceanic and Atmospheric Administration provides Advanced Very High Resolution Radiometer (AVHRR) data beginning in 1981 (Turner et al. 2015). Similarly, free cloud-based data storage and computing platforms such as Google Earth Engine and NASA Earth Exchange facilitate access to satellite imagery and geospatial archives and have stimulated analytical applications of archived data such as Climate Engine (Huntington et al. 2017) and Global Surface Water Explorer (Pekel et al. 2016).

Using remote sensing for different fisheries applications requires careful consideration of the varying characteristics of remote sensing data and derived products. For many sensors, there is a tradeoff between spatial and temporal resolution, and use of specific imagery should be determined by the spatial and temporal resolution and extent of the question at hand (Figure 2). New products continue to be derived from long-standing satellite missions (e.g., new versions of NLCD from Landsat), and new satellite missions come with their own derived products (e.g., Global Vegetation Index from Sentinel-3). Finally, satellite imagery and derived products continue to be used in various image classification and statistical models that quantify elements of freshwater ecosystems, and these uses have proliferated in the last decade (Palmer et al. 2015; Dörnhöfer and Oppelt 2016; Dugdale 2016).

## A REVIEW OF FISHERIES APPLICATIONS

### Land Cover and Land Use

The most widely used remote sensing data in freshwater systems have been satellite-derived measures of land cover and land use. Landsat-derived NLCD or USGS National Gap Analysis Program land cover data sets (30-m resolution) have been commonly used to link watershed land cover (e.g., coniferous forest) and land uses (e.g., urban, agriculture) to the distribution and abundance of aquatic organisms (Hughes et al. 2006). Freshwater fish ecologists are often particularly interested in riparian vegetation (Figure 3; Macfarlane et al. 2016), which can be difficult to characterize adequately at the 30-m resolution of NLCD (Goetz 2006). Consequently, airborne applications that yield multispectral data at high spatial resolutions (1 m or less) have been used, albeit at smaller spatial extents and with substantial image processing times. For example, Dauwalter et al. (2015) used airborne National Agriculture Imagery Program (NAIP) imagery (1-m spatial resolution) in a supervised, object-oriented classification—whereby the user inputs the classes to be defined using the spectral and textural statistical patterns in an image—to identify woody vegetation in narrow riparian zones in the western United States that was more predictive of Columbia River Redband

Figure 1. Sentinel 2 satellite true color images (10-m resolution) of the Detroit River delta at the confluence with Lake Erie on June 29, 2016 (top panel), and the confluence of the Tennessee River (south) with the Ohio River (north) on February 6, 2016 (bottom panel). Both images were downloaded using Copernicus Open Access Hub.

Table 1. Applications of remote sensing platforms (satellites and sensors) and derived data used to describe freshwater ecosystem components.

| Indirect | Direct | Satellite/ sensor | Derived product | Application | Reference |
|---|---|---|---|---|---|
| **Climate** | | | | | |
| Air temperature | Stream temperature | Terra/Aqua MODIS | Land surface temperature | Model daily stream temperature | Falke et al. (2013) |
| Precipitation | Streamflow | Multiple inputs into REGCM3 climate model | Variable infiltration capacity hydrologic metrics | Winter flood frequency effects on salmonid occurrence | Wenger et al. (2011) |
| **Watershed** | | | | | |
| Elevation | Valley confinement | Multiple sources | National elevation data set | Identify habitat of nonnative species | Wenger et al. (2011) |
| Land use/cover | Converted lands | Landsat Thematic Mapper (TM) | NLCD | Identify effect of land conversion on fishes | Hughes et al. (2006) |
| Terrestrial vegetation productivity | NPP | Terra MODIS | NPP | Predict global patterns in fish species richness | Pelayo-Villamil et al. (2015) |
| | Organic input | Landsat Leica ADS40 | Organic matter export | Predict fish growth from terrestrial organic matter export to lakes | Tanentzap et al. (2014) |
| | Chlorophyll-*a* | AVHRR | NDVI | Predict anadromy from lake productivity | Finstad and Hein (2012) |
| Riparian land use/ cover | Stream buffer vegetation height and composition | Various | Various | Characterize riparian vegetation | Goetz (2006) |
| Vegetation coverage | Solar radiation | Landsat TM and EMT+ | Custom land cover map | Identify wildfire impacts on stream temperature | Isaak et al. (2010) |
| Riparian vegetation | Vegetation structure | Quickbird | Custom vegetation map | Characterize riparian vegetation structure | Johansen et al. (2007) |
| Riparian vegetation | Vegetation type | GeoEye | Custom native and non-native vegetation map | River restoration prioritization | Macfarlane et al. (2017) |
| Woody riparian vegetation | Habitat condition | Airborne multispectral | NAIP | Characterize riparian and trout habitat in desert streams | Dauwalter et al. (2015) |
| In-channel vegetation | Fluvial dynamics | Airborne and SPOT multispectral | Custom vegetation map | Vegetation dynamics | Hervouet et al. (2011) |
| Shoreline development | Number of docks | Airborne multispectral | NAIP | Quantify shoreline development | Beck et al. (2013) |
| **In situ** | | | | | |
| Stream temperature | Thermal habitat | Airborne Therma-CAM SC640 | Thermal infrared | Thermal habitat heterogeneity | Vatland et al. (2015) |
| River altimetry | River gaging | ENVISAT and JASON | Microwave | Satellite river gaging | Van Dijk et al. (2016) |
| Reservoir surface temperature | Thermal habitat and fish growth potential | Airborne TIR; Landsat 5 TM | Thermal infrared; thermal band | Anthropogenic impact to fish growth potential | Budy et al. (2011) |
| River surface ice | Upwelling | RADARSAT-1 SAR; ALOS AVNIR-2 | C-band; multiband | Identify upwelling areas and salmon spawning habitat | Wirth et al. (2012) |
| Aquatic macrophyte | Larval fish habitat | Landsat TM, EMT+ | Enhanced Vegetation Index | Aquatic macrophyte dynamics and fish recruitment | Massicotte et al. (2015) |
| Aquatic macrophyte | Physical habitat structure | Landsat TM, EMT+, MSS | NDVI, normalized difference water index, reflectance | Temporal trends in aquatic vegetation | Zhao et al. (2013) |
| Channel elevation | Channel morphology | Experimental Advanced Airborne Research LiDAR | Elevation | Geomorphic controls on redd distribution | McKean et al. (2008) |

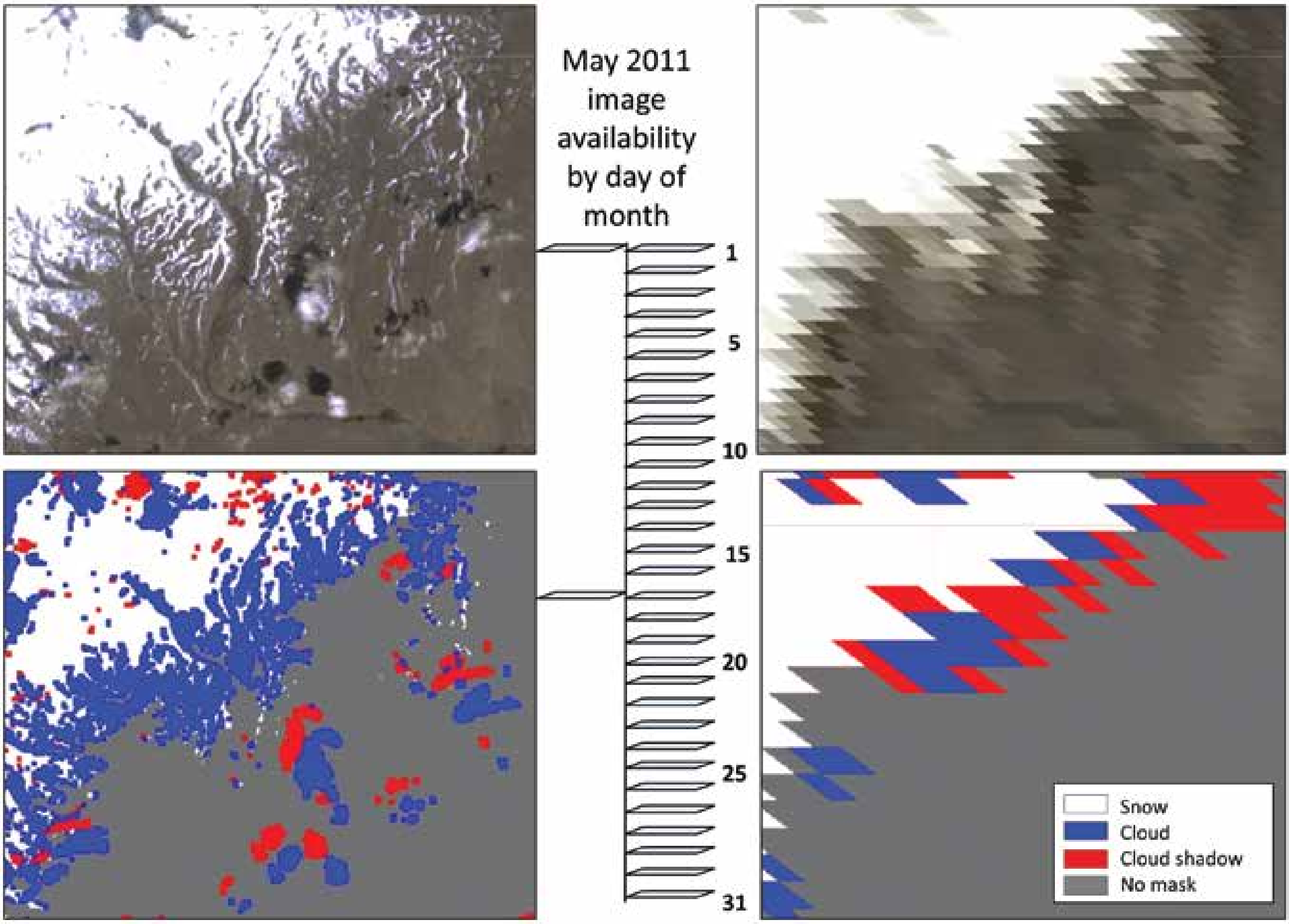


Figure 2. Contrast of spatial and temporal resolution of Landsat 5 Thematic Mapper (left panel: 30-m spatial and ~16-day temporal resolutions) and Terra Moderate Resolution Imaging Spectroradiometer (right panel: 500-m spatial and 1-day temporal resolutions) imagery during May 1, 2011, in upper Salmon Falls Creek watershed, Nevada. Top panels show surface reflectance formatted as natural color images. Bottom panels show derived snow cover data products; bottom left panel is the Landsat image processed using the Fmask algorithm, and bottom right panel is Terra-MODIS based NASA/USGS Land Processes Distributed Active Archive Center 1-km resolution Science Data Set. Note that cloud cover and cloud shadows result in unusable snow cover data (invalid observations) in both data products. Both images were accessed and processed using Google Earth Engine.

Trout *Oncorhynchus mykiss gairdneri* distribution and abundance than field data. Others have used high-resolution NAIP imagery to quantify the number of docks as an index of shoreline development, a known stressor in glacial lakes (Beck et al. 2013).

New hyperspectral imagery has helped to overcome some of the historical limitations of using multispectral imagery for vegetation mapping. Multispectral sensors (e.g., Landsat Operational Land Imager) measure electromagnetic radiation in only a few spectral bands, but hyperspectral sensors (e.g., Earth Observing-1 Hyperion sensor) can measure hundreds or thousands of spectral bands, potentially allowing species-level identification of dominant plants instead of just generalized vegetation types. For example, Hestir et al. (2008) used airborne hyperspectral data at a 3-m spatial resolution to map several invasive aquatic plants in the Sacramento–San Joaquin River delta. Better resolution in future land cover products will yield a more nuanced understanding of how vegetation and land use influence aquatic ecosystems.

In addition to mapping vegetation, remote sensing has been used to inventory and monitor water bodies. Verpoorter et al. (2014) used Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and the NASA Shuttle Radar Topography Mission elevation data to develop a global inventory of lakes that contains geographic and morphometric data. Multiple remote sensing products have also been used to inventory and monitor wetlands over broad areas (Adam et al. 2010). These remote sensing monitoring efforts will be key to tracking changes in freshwater resources over time, as shown by Donchyts et al. (2016), who used 30-m Landsat data to monitor water-to-land and land-to-water conversions globally from 1985 to 2015 due to water use, reservoir construction, sea level rise, and myriad other factors. New satellite missions, such as Sentinel-2 launched by the European Space Agency in 2015, are designed specifically for global monitoring of vegetation, soil, and water.

### Topography and Geomorphology

Watershed topography reflects underlying geology and climate and, in turn, influences hydrology and other aquatic ecosystem components (Johnson and Gage 1997). Historically, watershed topography and elevation were derived from topographic maps, which were created from stereoscopic aerial photo interpretation. Ten-meter resolution digital elevation models (DEMs) derived from older 1:24,000 topographic maps are commonly used to characterize watershed topography and elevation that repeatedly have shown to correlate with fish distributions (Hughes et al. 2006). Small-scale physical features of streams such as unconfined valley bottoms that can be identified using DEMs have also been linked to fish distributions (Wenger et al. 2011). More recently, DEMs are being created using satellite-based sensors. For example, WorldDEM is a commercially available (Airbus Defense and Space, Toulouse, France) global DEM with 12-m spatial resolution (2-m relative vertical accuracy) created from Synthetic Aperture Radar (SAR) data collected by German TanDEM-X and TerraSAR-X satellites. These types of data will be useful in quantifying changes in elevation and topography over time in dynamic landscapes.

High-resolution hyperspectral imagery has also been used to map channel morphology (Leglieter et al. 2004). Marcus et al. (2003) used airborne, 128-band hyperspectral imagery and a supervised image classification to map instream habitat types (e.g., riffles, glides, pools) in Wyoming. Hugue et al. (2016) used multispectral WorldView II data (2-m resolution) in a hydraulic model to map spatial heterogeneity in physical habitat across the Kiamika River, Quebec, Canada. Continued advancement in hyperspectral sensors, such as an increased number of spectral bands, may help overcome some limitations of habitat mapping below surface waters resulting from optical properties, turbidity, and surface turbulence (Leglieter et al. 2004; Hestir et al. 2015).



The three-dimensional structure of terrestrial and aquatic ecosystems can be mapped using Light Detection and Ranging (LiDAR), a form of laser altimetry yielding detailed data (i.e., <0.5 m pixels) on vegetation height and ground elevation simultaneously (Figure 4; Vierling et al. 2008). In a novel application, Kasprak et al. (2012) used airborne LiDAR data to map large wood recruitment potential in the Narraguagus River, Maine, to understand how large wood deficiency may be linked to declining Atlantic Salmon *Salmo salar*. Unlike traditional LiDAR, green LiDAR can penetrate surface water and has been used to map floodplain and underwater stream channel characteristics important to spawning salmon (McKean et al. 2008). Most LiDAR data have been collected from airborne sensors through expensive custom orders. However, spaceborne LiDAR sensors now exist, such as on NASA's ICESat mission (2003–2010), and data from those sensors have been used to develop a global DEM (70-m resolution) and other products; the second ICESat-2 mission is planned for 2018. Continued deployment of LiDAR sensors on space missions will increase the spatial coverage, resolution, and accessibility of LiDAR data that are typically collected from airborne platforms for specific applications.

## Climate

Many remote sensing platforms collect weather and climate data important to aquatic ecosystems. For example, the AVHRR instrument aboard the Polar-Orbiting Operational Environmental Satellite collects multispectral data twice daily to characterize cloud cover, surface temperatures (water and land), vegetation, snow, and ice. Satellite data often serve as inputs into other modeling systems, such as general circulation models (also called global climate models) that predict air temperature and precipitation. Climate data can be used along with soil, vegetation, and topography as inputs for hydrologic models, such as the variable infiltration capacity model (Liang et al. 1994).

Water temperature strongly influences aquatic ecosystem structure and function, including the physiology of ectothermic organisms. Until recently, air temperature was commonly used as an imperfect surrogate for stream and lake temperatures that did not exist across broad scales (e.g., Wenger et al. 2011). However, stream temperatures are now being accurately predicted across broad spatial domains from in situ observations and remotely sensed covariates using statistical models. For example, land surface temperatures measured by Moderate Resolution Imaging Spectroradiometer (MODIS) thermal sensors have been used to model daily stream temperatures (1-km resolution) across the John Day River basin, Oregon, an important river system for temperature-sensitive and imperiled salmonids (Falke et al. 2013). The NorWeST stream temperature dataset (Isaak et al. 2016) includes mean August stream temperatures every 1-km across much of the western United States as predicted from topography, vegetation, and climate (data from the NASA Shuttle Radar Topography Mission, Landsat, and third-generation regional climate modeling, respectively), and the data set has been used to predict future cold-water refuges for fish (Falke et al. 2015; Isaak et al. 2015).

Surface water temperatures are increasingly being measured directly using airborne and spaceborne infrared sensors (Dugdale 2016). For example, Tonolla et al. (2012) linked the dynamics of fish distributions in floodplain areas of the Oder River, Germany, to thermal gradients and patches quantified using airborne forward-looking infrared. This technology has also been used to characterize salmon and trout habitat (Vatland et al. 2015) and map fish growth potential in reservoirs (Budy et al. 2011). Spaceborne thermal sensors have been used to document global increases of 0.045°C ± 0.011°C/year in large lake surface temperatures, with higher warming rates at higher latitudes (Schneider and Hook 2010).

Ice is a prominent feature of aquatic systems in cold climates. Seasonal coverage, type, and thickness of ice can be measured using SAR because ice produces a unique backscatter signature in radio and microwave signals (Duguay et al. 2015). Spaceborne radar data have been used to predict Chum Salmon *O. keta* spawning habitat based, in part, on areas of groundwater upwelling as indicted by persistent ice-free areas (Wirth et al. 2012) and identify Broad Whitefish *Coregonus nasus* overwintering habitat based on pool depth in ice-covered rivers (Brown et al. 2010).

Hydrology plays a central role in stream ecosystems, and remote sensing has long been used for hydrologic modeling. Climate data, along with other remotely sensed data, are inputs for macroscale hydrologic models (Liang et al. 1994) that are then downscaled to estimate ecological flows in small streams where they have been used to link the frequency of winter high flows to the distribution of fall spawning salmonids (Wenger et al. 2011). In Rocky Mountain streams designated as critical habitat for Bull Trout *Salvelinus confluentus*, flow intermittency was predicted using snowpack persistence into the summer as measured from Landsat imagery (Sando and Blasch 2015).

## Primary Productivity

Primary productivity influences freshwater fish production and is typically estimated using in situ measurement of biogeochemical properties. Remote sensing can improve the spatial and temporal coverage of water quality measurements by linking in situ measurements with several types of remote sensing data. In an early example, Carpenter and Carpenter (1983) used statistical models to link Landsat Multispectral Scanner System (MSS) data to in situ turbidity and algal pigment data in several Australian lakes. Satellite data were then used with the model to predict the water quality parameters lake-wide over several time periods. Other models have been developed to estimate primary productivity (both surface and profile estimates) in Estonian lakes using Envisat Medium Resolution Imaging Spectrometer data (Kauer et al. 2015).

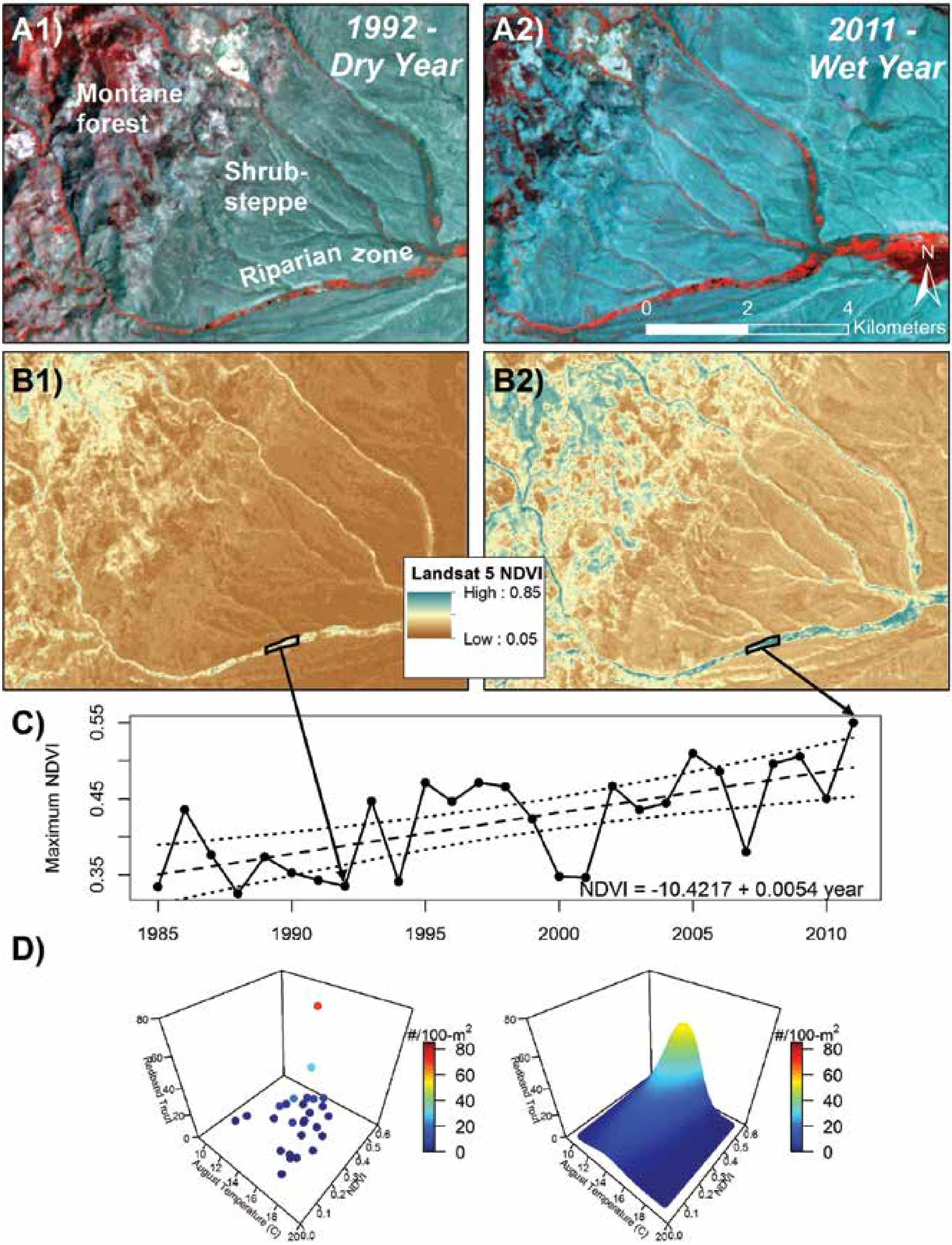


Figure 3. (A) Landsat 5 Thematic Mapper false-color images and (B) NDVI for dry (1992) and wet (2011) years showing interannual differences in riparian vegetation productivity during mid-July in upper Salmon Falls Creek watershed, Nevada. (C) Landsat NDVI significantly increased ($P < 0.001$) from 1985 to 2011 in a riparian exclosure in the watershed. (D) Redband Trout *Oncorhynchus mykiss gairdneri* have higher densities at stream sites with higher riparian NAIP NDVI values in Salmon Falls Creek where stream temperatures are suitable as shown by quantile regression.

Productivity of aquatic systems has also been inferred from estimates of terrestrial primary productivity. In Norway, good predictions of lake productivity (as chlorophyll-*a*) were obtained from a model that included terrestrial Normalized Difference Vegetation Index (NDVI) data from the Polar-Orbiting Operational Environmental Satellites–AVHRR sensor as well as other factors; NDVI is an indicator of active photosynthesis and plant vigor computed from multispectral data (Pettorelli et al. 2005). Lake productivity was then shown to influence sea migration behavior in Arctic Char *S. alpinus* (Finstad and Hein 2012) and competitive dominance between Arctic Char and Brown Trout *S. trutta* (Finstad et al. 2011). Tanentzap et al. (2014) used Landsat-derived NDVI as a measure of vegetation density to show how forest cover alteration influenced terrestrial organic inputs into a boreal lake, the productivity of aquatic food webs, and the growth of age-0 Yellow Perch *Perca flavescens* near lake–stream interfaces. Gross and net terrestrial primary productivity (GPP and NPP, respectively) are now being estimated directly from satellite data, and there have been studies linking MODIS-derived estimates of terrestrial NPP to freshwater fish species richness across the globe at a resolution of 1° (Pelayo-Villamil et al. 2015).

Satellite data have also been pivotal in investigating dynamics of aquatic macrophytes. Massicotte et al. (2015) found that larval Yellow Perch recruitment in fluvial Lake Saint-Pierre along the U.S.–Canada border was associated with aquatic vegetation mapped using Landsat-derived Enhanced Vegetation Index data, which helped overcome logistical constraints with in situ vegetation sampling. Zhao et al. (2013) also used Landsat data to assess the spatial and temporal changes in aquatic vegetation, and thus fish habitat, due to human activities in Taihu Lake, China.

### Water Use

With increasing pressure on water resources, there have been focused efforts to document ecological responses to hydrologic alteration (Poff and Zimmerman 2010). This requires two foundational steps often dependent on remote sensing: mapping natural flow regimes and quantifying hydrologic alteration. Flow regime classifications are based on climate, topography, and soils measured from remote sensing products (Leasure et al. 2016). These same data have also been used in indices of hydrologic disturbance and more directly as predictors for model-based estimates of natural flow conditions (Carlisle et al. 2010). These models are often constructed using dozens of predictors representing various aspects of climate, land cover, soils, and hydrology derived from remote sensing and other data sources.

Human withdrawals of freshwater impact aquatic ecosystems and fisheries, but quantifying water withdrawal and streamflow alteration across large regions has been challenging (Carlisle et al. 2010). However, new evapotranspiration models using land surface temperature derived from thermal infrared Landsat data are being used to evaluate and improve irrigation efficiency, monitor water rights, negotiate interstate water-sharing agreements, and determine water allocations, all of which have the potential to help prioritize water conservation and management to balance instream flow and fisheries needs with societal needs (Anderson et al. 2012).

### Disturbances and Disasters

Disturbances and disasters can strongly affect freshwater habitats and biota. Wildfire can influence watershed and riparian vegetation and result in debris flows that alter stream habitat and fishes (Rieman et al. 2010). Wildfire risk predictions based on remotely sensed topographic, vegetation, and canopy structure data have been used in decision support tools for Bull Trout that inform fire fuel and riverine connectivity management to facilitate population persistence (Falke et al. 2015). Remotely sensed wildfire data are available from several U.S. interagency programs: the Active Fire Mapping Program (fsapps.nwcg.gov/afm), the LANDFIRE program (landfire.gov), and the Monitoring Trends in Burn Severity Program (mtbs.gov).

Floods also influence freshwater ecosystems, and radar and multispectral data have been used to map flooding (reviewed by Klemas 2014). Alsdorf et al. (2000) used Space Shuttle SAR data to document daily water-level changes in the Amazon floodplain of 2 to 10 cm per day. In another application, Landsat, Satellite Pour l'Observation de la Terre (SPOT; Spot Image, Toulouse, France), and RapidEye (Planet Labs, San Francisco, California) data were used to measure connectivity of floodplain lakes to the Saskatchewan River, Canada. Lakes closer to the main channel had limnological characteristics similar to the river itself, whereas less-connected lakes were more influenced by local climate and environmental characteristics (MacKinnon et al. 2015).

## EMERGING TOOLS FOR FISHERIES APPLICATIONS

### New Sensors and Platforms

Long-running Earth observation programs continue to be a priority and provide invaluable data continuity for study of changing environments. Landsat's multidecadal data continuity is a key reason for its wide use (Turner et al. 2015). The joint NASA/USGS Landsat program launched Landsat 8 in 2013, and Landsat 9 is projected to launch in 2023. Continuity missions are also in place or planned by the lead agencies for MODIS (Suomi NPP and VIIRS; jointmission.gsfc.nasa.gov), Sentinel 2A and 2B (Sentinel 2C and 2D; sentinel.esa.int), and SPOT (PROBA-V; proba-v.vgt.vito.be/en). New R-series missions for the Geostationary Operational Environmental Satellite (GOES; goes-r.gov) program will provide higher resolution weather data to improve weather forecasting (a new GOES-R satellite was launched in November 2016). Even some airborne programs were designed for data continuity, such as NAIP imagery, which provides periodic coverage (~3-year frequency) of the United States at a high spatial resolution (1 m).

Advanced sensor technology facilitates freshwater investigations that were not previously possible. Spaceborne hyperspectral sensors are becoming more common after the recent success of the Hyperion sensor (220 spectral bands, 30-m spatial resolution) aboard the NASA EO-1 satellite. Airborne hyperspectral sensors, for example, have been used to map instream habitats, depths, and large wood in streams (Marcus et al. 2003). Likewise, advancements in LiDAR technology, including both spaceborne LiDAR and airborne green LiDAR, are increasing availability of high-resolution topographic data, including state-of-the-art freshwater bathymetry data (McKean et al. 2008). In addition, Earth is now orbited by a fleet of commercial satellites with specialized sensors that have targeted spectral bands, submeter resolution, and daily return times that should prove useful for unique applications (e.g., WorldView, GeoEye, QuickBird).

Innovative new remote sensing platforms such as microsatellites and unmanned aerial vehicles (UAVs) are also opening new possibilities. UAVs provide cost-efficient, high-spatial-resolution data with low-altitude flights at spatial extents not possible with field surveys. This was demonstrated by using UAVs to map nuisance green algae on the Clark Fork River, Montana (Flynn and Chapra 2014). UAVs have also been used in combination with SPOT satellite imagery to study postflood revegetation processes in French rivers (Hervouet et al. 2011). Small startup companies

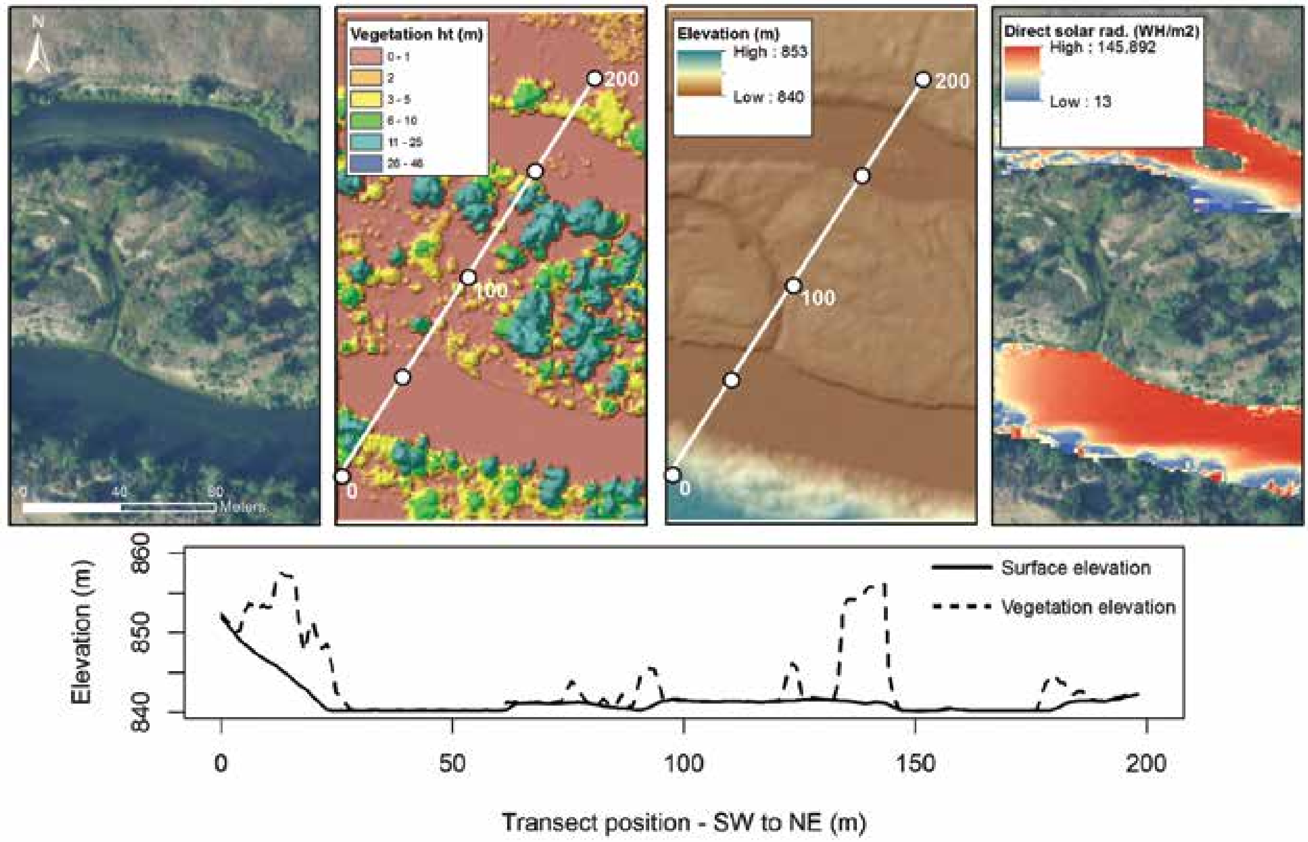


Figure 4. Top panels (left to right): Aerial imagery, airborne LiDAR vegetation height (first laser return minus last laser return) and ground elevation (last laser return), and solar exposure on surface water showing spatial variation in vegetation height (reflecting vegetation type and structure), hillslope and floodplain topography, and stream shading for the Boise River, Boise, Idaho. Bottom panel: Transverse profile of vegetation and floodplain elevations from LiDAR data. LiDAR data resampled to 3-m spatial resolution.

are developing microsatellites with lower development times and costs when compared to traditional satellites. The smallest satellites, nanosatellites, may be less than 10 kg with costs as low as US$1 million, compared to larger satellites that can be over 1,000 kg and $500 million.

### Future Data Products

Global and regional-scale change detection (e.g., land cover and climate) will continue to be a focal point for freshwater fisheries. For example, global changes in forest cover over several decades were measured at a 30-m spatial resolution using Landsat archives (Hansen et al. 2013), and future changes to land use and climate are expected to influence fisheries in different ways (Radinger et al. 2016). As programs like Landsat continue to accumulate longer time series, more change detection products will become available. Recent versions of the NLCD now even include summaries of land cover change over time. In parallel, new water temperature and hydrology models are being developed with remotely sensed measures of vegetation, topography, and climate. As mentioned earlier, the NorWeST project is developing spatial predictions of stream temperatures every 1 km across large portions of the United States (Isaak et al. 2015). USGS Geospatial Attributes of Gages for Evaluating Streamflow (GAGES II) was an effort to develop models of streamflow at that same scale but using data from streamflow gages and not remote sensing platforms (Carlisle et al. 2010).

Stream networks are now represented in geospatial hydrography databases with unique identifiers for stream segments (confluence-to-confluence reaches) and hydrologic units. These databases provide standardized frameworks for archiving stream- and lake-related information that is often derived from remote sensing data. The National Hydrography Dataset Plus (NHD+; horizon-systems.com/nhdplus) and the National Watershed Boundary data set (nhd.usgs.gov/wbd.html) data sets are used in this way. For example, the StreamCat data set contains information on land cover, runoff, soils, and other watershed attributes for specific stream segments in the NHD+ data set (Hill et al. 2016). These databases are often the foundation for large-scale aquatic assessments and planning frameworks (Williams et al. 2007; Esselman et al. 2011).

### Data Access and Acquisition

Though remote sensing data archives are now more accessible through platforms like USGS Global Visualization Viewer (GloVis), USGS Earth Explorer, and the European Space Agency's Copernicus Open Access Hub, contemporary imagery and derived products are often now available in near real time. Terra/Aqua MODIS, Landsat Operational Land Imager, and Sentinel data are available within 24 h of acquisition. The Active Wildfire Mapping Program uses MODIS data for near-real-time wildfire mapping. Other innovative applications include continually updated species distribution maps like Yale University's Map of Life (mol.org) and population models like Stony Brook University's Mapping Application for Penguin Populations and Projected Dynamics (MAPPPD) project (penguinmap.com) that use the most recent and near-real-time remote sensing data.

Cloud-based storage and automated processing of remote sensing data overcome key historical limitations: data storage, computing power, and software licensing. This drastically increases access to data at spatial and temporal scales relevant to fisheries. Free, cloud-based platforms such as NASA Earth Exchange and Google Earth Engine allow individuals to access, manipulate, and analyze petabytes of imagery with only a desktop computer and an Internet connection. These platforms are behind big data applications like Deltares Aqua Monitor that offer near-real-time monitoring of surface water gains and losses globally with 30-m spatial resolution (Donchyts et al. 2016).

## DISCUSSION

Despite new developments, several challenges remain. Many commercial satellites and almost all airborne platforms can still be cost-prohibitive for landscape-scale applications (Turner et al. 2015). Manipulation of raw data requires some remote sensing expertise, and there will still be a lag in development of some derived products useful for freshwater applications. Freshwaters in general are optically complex, and sensors designed for oceanographic purposes yield data that are spatially and spectrally too coarse for use in inland waters because aquatic vegetation communities need to be differentiated at higher spatial resolutions than the broad spatial gradients typical of off-shore algal communities. Use of multi- and hyperspectral imagery in riverine habitats can be complicated by bottom reflectivity, water column optical properties (e.g., turbidity), and surface turbulence (Marcus et al. 2003). Similar factors influence bathymetry and benthic substrate measurement accuracy in lakes (Dörnhöfer and Oppelt 2016).

Other challenges include the need for in situ data across broad scales for validating remote sensing products (Schaeffer et al. 2013). The void in in situ data highlights the need for closer coordination between the fisheries and aquatic resources communities and remote sensing community. Progress *is* being made, however, as exemplified by the Wabash River in Indiana where a spectral and biogeochemical database is being developed to facilitate remote sensing of water quality in large rivers (Tan et al. 2016). Here, spectral measurements are taken at the same time as in situ measurements of primary production, organic matter, and nutrients so that models can be developed to understand how water quality changes with hydrology and other factors using remote sensing data.

Most freshwater fisheries studies using remotely sensed data have emphasized spatial rather than temporal variability in the environment. This is because derived data products and summaries are only updated once or twice a decade, even though the underlying remote sensing data are collected much more frequently. However, increased availability and accessibility of imagery archives has expanded our understanding of how temporal variability in terrestrial and aquatic landscapes influences freshwater ecosystems (Figure 3; Tonolla et al. 2012). The rapid availability of remote sensing data could also drive near-real-time applications of remote sensing for regulatory compliance (e.g., temperature exceedance, illegal fishing), threat response (e.g., wildfire), and recreational fisheries management (e.g., biologically based seasons).

Remote sensing clearly has advanced the knowledge of freshwater fisheries across broad landscapes, and we highlighted these advances to make its application more accessible to fisheries biologists and managers (Text Box; Table 1). More platforms and better sensors will continue to improve the spatial, temporal, and spectral resolution of remote sensing data and products derived

### A ROADMAP: PRACTICAL GUIDANCE FOR USE OF REMOTE SENSING DATA

With rapid advancements in remote sensing, the sheer volume of information, raw data, and derived products can be overwhelming. NASA's Applied Remote Sensing Training Program (arset.gsfc.nasa.gov) offers online or in-person training and covers a variety of topics that include introductory material, and most data delivery platforms (e.g., Google Earth Engine) have some sort of training tutorial. Here are a few simple steps to get started:

Step 1: Identify Question: Identify a research or management question that can be addressed with available remotely sensed data and limited project resources. Know the available data options when developing your question, and know how others have used remote sensing data for similar questions. Tables 1 and S1 are good starting points.

Step 2: Data Acquisition: Review available data sets suitable for your question, paying particular attention to spatial resolution, spectral characteristics, temporal availability, postprocessing requirements, and costs. You must balance trade-offs between these factors when selecting a data product. For example, four-band NAIP data (1-m resolution) requires approximately 500 times as much storage as seven-band Landsat data (30-m resolution) along with a commensurate increase in processing time. Many data sets are available for free, so start with those if possible. Data are easily accessible from Google Earth Engine, NASA Earth Exchange, and USGS Global Visualization Viewer GloVis and Earth Resources Observation and Science.

Step 3: Data Processing and Storage: Some data sets require significant postprocessing. For example, satellite images often require cloud removal and atmospheric correction to calculate a reliable vegetation index. A digital elevation model must go through several processing steps to delineate streams or watersheds if existing hydrography frameworks are insufficient. This requires time, expertise, software, computing power, and data storage. These steps are often worthwhile, and sometimes necessary, to get a quality data set. However, services may be available to automate processing (Google Earth Engine, USGS StreamStats, Geodata Crawler), and there are often free data products that meet your needs (NHD+, NorWeST, NLCD, BioClim, LANDFIRE, GAGES II, and StreamStats).

Step 4: From Data to Information: Once you have acquired and processed a remotely sensed data set, you still need to extract and summarize the data for your question. Some fisheries research questions require different spatial scales of measurement. For example, assume that you have a raster of NDVI values for your study area, but your research question relates fish abundance to riparian vegetation upstream of your sample sites. For every site where you measured fish abundance, you need to delineate the upstream riparian zone and summarize NDVI values within those areas (e.g., mean, minimum, SD). Services are now becoming available to automate these steps (USGS StreamStats, Geodata Crawler). There are also efforts to map stream networks and archive fisheries-relevant information about particular stream segments and hydrologic units (NHD+, USGS GAGES II). Thus, existing geospatial data sets may already contain the data summary you need.

from them. In short, these advances will continue to help answer new questions at finer spatial and temporal resolutions across larger landscapes, continue to provide the big picture to fisheries management and ecology, and be a tool used more frequently by fisheries biologists and the broader natural resources community.


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## SUPPLEMENTARY FILES

Available: www.tu.org/rem-sens-fish

Table S1: Examples of commonly used commercial and governmental (civilian) spaceborne satellites and sensors used in natural resources applications of remote sensing.

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