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Headwater streams and inland wetlands: Status and advancements of geospatial datasets and maps across the United States

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Abstract

Headwater streams and inland wetlands provide essential functions that support healthy watersheds and downstream waters. However, scientists and aquatic resource managers lack a comprehensive synthesis of national and state stream and wetland geospatial datasets and emerging technologies that can further improve these data. We conducted a review of existing United States (US) federal and state stream and wetland geospatial datasets, focusing on their spatial extent, permanence classifications, and current limitations. We also examined recent peer-reviewed literature for emerging methods that can potentially improve the estimation, representation, and integration of stream and wetland datasets. We found that federal and state datasets rely heavily on the US Geological Survey's National Hydrography Dataset for stream extent and duration information. Only eleven states (22%) had additional stream extent information and seven states (14%) provided additional duration information. Likewise, federal and state wetland datasets primarily use the US Fish and Wildlife Service's National Wetlands Inventory (NWI) Geospatial Dataset, with only two states using non-NWI datasets. Our synthesis revealed that LiDAR-based technologies hold promise for advancing stream and wetland mapping at limited spatial extents. While machine learning techniques may help to scale-up these LiDAR-derived estimates, challenges related to preprocessing and data workflows remain. High-

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resolution commercial imagery, supported by public imagery and cloud computing, may further aid characterization of the spatial and temporal dynamics of streams and wetlands, especially using multi-platform and multi-temporal machine learning approaches. Models integrating both stream and wetland dynamics are limited, and field-based efforts must remain a key component in developing improved headwater stream and wetland datasets. Continued financial and partnership support of existing databases is also needed to enhance mapping and inform water resources research and policy decisions.

Keywords

headwaters; inland wetlands; mapping; streamflow permanence; CONUS; NHD; NWI; remote sensing; field assessments; LiDAR; dynamic modeling; machine learning

1. Introduction

Headwater streams and inland wetlands are freshwater systems providing essential hydrological, biogeochemical, and biological functions supporting healthy watersheds (USEPA 2012). Headwater streams (hereafter “headwaters”) are defined here as low-order stream segments in river networks (i.e., orders 0–3) where zero-order represents non-channelized flows (e.g., swales) and first through third order streams follow the Strahler (1957) stream order method that incorporates non-perennial and perennial headwater stream channels (Vannote et al. 1980; Gomi et al. 2002). Inland wetlands (hereafter “wetlands”) are freshwater wetland systems (e.g., ocean-derived salts are <0.5‰; Cowardin et al. 1979) located within and distal to river floodplains.

While individual headwaters and wetlands are typically small or have low flow volumes, their relative abundance on the landscape coupled with the conditions for high biogeochemical reactivity (e.g., relatively long residence times, anoxic conditions) means they cumulatively have an outsized impact on watershed hydrological and biogeochemical processes (Creed et al. 2017). Headwaters and wetlands exist along a connectivity continuum from frequently and directly connected to infrequently and indirectly connected to other waters (Alexander et al. 2018; Leibowitz et al. 2018). Thus, they variably control the volume and transport of water, solutes, sediments, and other particulate matter to downstream waters, thereby supporting drinking water quality, agriculture water resources, industrial water use, and other aquatic ecosystem services (Creed et al. 2017; Golden et al. 2019). In addition to supporting human uses, headwaters and wetlands provide necessary habitat for wildlife (Hagen and Sabo 2014; Sánchez-Montoya et al. 2016) and are often hotspots for biodiversity (Ward et al. 1999; Finn et al. 2011).

A comprehensive understanding of where headwaters and wetlands are located on the landscape is needed for their protection, restoration, and overall management to optimize the delivery of desired ecosystem services. Headwaters and wetlands remain vulnerable to anthropogenic modification and destruction (Creed et al. 2017). Urban and agricultural conversion and encroachment lead to wetland acreage losses, increased flows from impervious surfaces and exposure to pollutants (e.g., Walsh et al. 2005; Kelly et al. 2017). In addition, shifts in hydrological regimes from a changing climate and anthropogenic alteration of surface and subsurface flows (e.g., groundwater pumping for irrigation or public water supply, tiled or ditch drainage in agricultural landscapes, underground pipes and associated trenches in urban landscapes) will influence the distribution and functioning of headwater and wetland systems (Blann et al. 2009; Foufoula-Georgiou et al. 2015; Bonneau et al. 2017; McKenna et al. 2017).

Headwaters and wetlands represent a substantial portion of the freshwater network within watersheds. Headwaters dominate freshwater riverine systems in both density and length (Larned et al. 2010; Datry et al. 2014). For instance, in the conterminous United States (CONUS), conservative estimates indicate that headwaters constitute over 79% of the freshwater river length and drain approximately 70% of the land area (Colvin et al. 2019). Similarly, while over 50% of historical wetlands have been lost, remaining mapped wetlands are still estimated to cover 44.6 million ha or ~5.5% of the CONUS (Dahl 2011), with high densities in areas such as the Prairie Pothole Region, the Mississippi Alluvial Valley, and the Atlantic and Gulf Coastal Plain ecoregions (Tiner 2003; Keddy et al. 2009; Lane and D'Amico 2016).

Despite concerted efforts to map these aquatic resources and understand their hydrology, spatial extents and dynamics, headwaters and wetlands are often under- and/or misrepresented in existing mapping products (Heine et al. 2004; Brooks and Colburn 2011; Fritz et al. 2013; Vanderhoof and Lane 2019; Fesenmyer at al. 2021). Headwaters and wetlands are often small and/or seasonally dynamic, with inundated area expanding and contracting longitudinally and laterally between seasons and years. For stream dynamics, the timing, magnitude, frequency, and duration of streamflow are typically measured by stream gauges. However, permanent instrumentation is most often placed on rivers and streams further downstream (Poff et al. 2006; Deweber et al. 2014; Krabbenhoft et al. 2022). Thus, quantitative measurement of headwater streamflow regimes is limited (Zimmer et al. 2020; Hammond et al. 2021; Price et al. 2021).

Of the many aspects of stream dynamics and flow, mapping often focuses on classifying the continuum of flow durations in headwaters into three categories: perennial (always flowing except during times of drought), intermittent (flowing seasonally due to base flows or snow melt), or ephemeral (flowing only in direct response to precipitation events). Likewise, many nontidal wetlands also exhibit complex expansion and contraction of wetted area (Niemuth et al. 2010; Vanderhoof et al. 2016) and marked seasonality (Zedler 2003; Bourgeau-Chavez et al. 2016). Yet these processes are often simplified in classifications to permanent (all year), seasonal (less than all year but at least three months), and temporary (less than three months) inundation or soil saturation. In addition, error and uncertainty associated with existing maps of streams and wetlands are often not readily available or are difficult to convey to dataset users.

More spatially and categorically accurate stream and wetland data, along with improved measures of spatial and temporal dynamics, are needed to educate the public on the importance of these systems and inform water-related federal, state, tribal, and local policies and decision-making processes. Such activities and decisions include regulating and permitting actions that affect headwaters and wetlands, prioritizing and planning restoration

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of buffers and habitat, identifying or modeling flood risks, creating or enhancing recreational opportunities, and managing systems for irrigation and drainage (Nadeau and Rains 2007; Douglas et al. 2011; Biggs et al. 2017; Creed et al. 2017; Moomaw et al. 2018). Each of these activities rely on spatial information to inform their decisions. Thus, it is crucial to understand what geospatial datasets and methods are currently available for federal and state decision makers as they manage and understand headwater and wetland extents and dynamics.

Here, we review and synthesize US federal and state geospatial stream and wetland datasets to determine the availability, methods, and resolution of currently available datasets and their associated spatial extents. We aim to close scientific knowledge gaps on the extent and changing conditions of headwaters, streamflow duration, and wetlands. We further identify dataset gaps and limitations and review recent peer-reviewed literature to specifically identify emerging methods that can inform and improve the estimation and representation of (1) headwater and wetland extents, (2) streamflow duration, and 3) integrated stream and wetlands systems. Several reviews have addressed specific aspects of headwater (e.g., channel head identification, Wohl 2018) or wetland mapping (e.g., remote sensing approaches: Tiner et al. 2015; Guo et al. 2017; Mahdianpari et al. 2020a) individually. However, we examine headwaters and wetlands jointly using multiple approaches to better integrate these systems and link them to the geospatial datasets on which US scientists and managers rely. We conclude with a set of research recommendations to advance future headwater streams and inland wetlands mapping to inform federal, state, tribal, and local policy objectives and water programs.

2. Methods

We conducted a search for national stream and wetland mapped datasets in the fall of 2020 by evaluating geospatial data platforms and web pages for each relevant federal agency, developed from a list from usa.gov’s A-Z Index of US Government Departments and Agencies (USAGov 2022). Using links provided within the list, we accessed each agency’s website and used pre-defined search terms (Table 1) to locate datasets related to either headwater stream or wetland mapping. We used both the internal agency search engine as well as using the external Google search engine. We further checked for mapped data sources by repeating searches for parent organizations, if any, of the listed agencies or departments.

We used similar methods to identify state wetland and stream datasets. For each state, relevant agencies or departments were identified, and web pages were evaluated for geospatial data portals to headwater extent and wetland maps. We performed the same search for streamflow duration at federal and state agency websites and recorded relevant datasets. We further searched StreamStats (https://streamstats.usgs.gov) across sample subbasins in each state to identify the streamflow characteristics (e.g., peak flow, low flow, and zero-flow probabilities) and supporting data that were provided. Non-governmental and tribal datasets were not included within the current search. However, we included some within the discussion of emerging technologies that could help federal and state managers supplement and enhance existing governmental datasets.

3. State of the Science: Current Headwater and Wetland Mapping Datasets

The need to comprehensively review the status of federal and state datasets for headwaters and wetlands is clear. In this section, we characterize these datasets, including mapped headwater extents (section 3.1), mapped headwater streamflow duration (section 3.2), and mapped wetland extents (3.2). Potential limitations of these datasets are combined and described in section 4.

3.1 Mapping Headwater Extent

3.1.1 Federal Datasets—One national dataset, the National Hydrography Dataset (NHD), primarily focuses on mapping streams and rivers across the US (Table 2). Led and maintained by the US Geological Survey (USGS) National Geospatial Program, the NHD is considered to have the best available stream/river data for the CONUS and has published inclusion standards. The NHD, along with legacy NHD and NHD value added products, are all derivatives of original USGS topographic quadrangle mapping efforts conducted primarily between the 1940s and 1990s. Those efforts included creating 30×60 minute (1:100,000 scale) and 7.5×7.5 minute (1:24,000 scale) topographic quadrangle maps from stereo orthophotographs, field surveys, and interviews. Digital Line Graphs for hydrography were extracted from these quadrangles to form the basis of the NHD medium resolution (NHD MR legacy; 1:100,000 scale) and the NHD high resolution (NHD HR; 1:24,000 scale or finer) data, including stream segments and streamflow duration classifications (see section 3.2.1). The current NHD (1:24,000 or finer scale) data include over 12 million kilometers of streams and rivers in the CONUS with over 27 million stream reaches or unique features in the geospatial dataset (Figure 1). Further, the US Environmental Protection Agency (EPA) and USGS created the NHDPlus (1:100,000 scale) and NHDPlus HR (1:24,000) datasets. These “Plus” versions of NHD add numerous catchment-related attributes that enhance stream network navigation and analysis, estimate elevation-based catchment areas and stream characteristics for each stream segment, and provide headwater nodes (Johnston et al. 2009).

Apart from the NHD based products, few other federal stream mapping datasets exist, and these ultimately rely on the NHD data (Table 2). The National Wild and Scenic River lines dataset identifies free-flowing river and stream systems that have some scenic, recreational, geologic, fish and wildlife, historic, cultural, or other “outstandingly remarkable value”, and is built off the NHD HR dataset (Wild and Scenic Rivers Act 1968; Public Law 90–542; 16 U.S.C. 1271). The other dataset identified in our search was the National Waterway Network (NWN) dataset, developed by the US Army Corps of Engineers (USACE) which uses a subset of river and stream reaches from the NHD MR and adds information about shipping lanes, river mile markers, ports and locks managed by the USACE.

All of the federal datasets contained supporting documentation and were found to meet Federal Geospatial Data Committee (FGDC) requirements for metadata and reporting standards (e.g., information on the data origin, data quality, reference system, constraints, symbology, and distribution of the data; FGDC 1998). The NHD products (and NWSR) provide information regarding the acceptable level of longitudinal and latitudinal error. For example, the NHD HR dataset states that 90% of defined features are within 12 m of the true position. While the most comprehensive stream dataset, the NHD has known limitations primarily stemming from original cartographic constraints (see section 4.1). Since initial digitization, some portions of the NHD HR have incorporated greater headwater detail (e.g., Indiana) in more recent mapping efforts (see section 3.1.2).

3.1.2. State Datasets—The majority of state stream maps (>53%) are derivatives of NHD (Figure 2). Overall, 138 state-level datasets contained stream mapping information with 80 providing enough metadata to know the map source and resolution (SI Table 1). Of those described datasets, 55% were at the 1:24,000 scale, 28% were at the 1:100,000 scale, while 14 datasets (17%) had a higher resolution than 1:24,000 scale (Figure 2). Thirty-six state datasets provided stream data but did not attribute a data source.

Eleven states developed stream mapping data that increase or modify the spatial detail of the NHD HR (Table 3). Four of those states added or modified stream segments to existing NHD data to create a more consistent NHD HR product either using aerial imagery (e.g., Washington; Table 3) or Digital Elevation Models (DEMs)(e.g., Idaho; Table 3). The other seven states increased the resolution of their stream network using either aerial imagery or DEM flow-accumulation catchment thresholds (Table 3). Except for Iowa, all of the states modified the stream network within the NHD framework. The Iowa stream layer, which was developed by the Iowa Department of Natural Resources, relied on Light Detection and Ranging (LiDAR) derived DEMs, a 9.7-hectare flow accumulation threshold, and 1 m imagery to develop the network (see SI Table 1 for more details).

3.2 Mapping Headwater Streamflow Duration

3.2.1 Federal Datasets—Streamflow duration for CONUS-based datasets focus primarily on permanence classifications (perennial, intermittent, and ephemeral) included within the NHD. These classes were derived from orthophotos, field visits, and interviews during the creation of the USGS topographic quadrangle maps (Hafen et al. 2020). While perennial and intermittent classes are identified through the CONUS within the NHD, ephemeral reaches are typically only included in NHD maps of the western US, especially in the arid southwest. Fesenmyer et al. (2021) counted over 1.4 million km of streams labeled ephemeral in Western US xeric ecoregions (including portions of Arizona, California, Colorado, Idaho, Texas, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming) which accounted for 62% of the total stream length in that ecoregion.

While the NHD provides the only discrete streamflow duration classification, other federal streamflow statistical approaches can also potentially inform classifications. The USGS StreamStats (https://streamstats.usgs.gov/ss/), a map-based web application, provides various metrics of flow for numerous states at a user-defined location of interest (Figure 3). StreamStats streamflow information is typically based on regression analyses derived from stream gauges and landscape, topographic, and/or climate variables for states or regions. The gridded stream network within the application mimics the NHD MR. While included as a federal effort, the analyses are typically conducted at the state level in partnership with state entities. Thus, the type of available flow information varies by state (Figure 3; SI Table 2). Those relevant to non-perennial flows will be discussed in more detail in 3.2.2.

In addition to StreamStats, the USGS Probability of Streamflow Permanence (PROSPER) model provides yearly probability estimates of perennial flow in the Pacific Northwest region (Jaeger et al. 2019) and the Upper Missouri River (Sando et al. in review). The PROSPER model combines existing field observations of wet or dry summer stream conditions with climatic and physiographic variables to train and predict annual probabilities of summer permanence using a Random Forest model (Figure 3, Table 3; Jaeger et al. 2019). The probabilities and associated model outputs were developed for 2004–2016 for the Pacific Northwest and 1989–2018 for the Upper Missouri River Basin. As of March 2022, PROSPER results are available as a tool on the USGS StreamStats web viewer in Oregon, Washington, Idaho and portions of Montana, while the remainder of Montana, North Dakota and South Dakota are currently being implemented (Figure 3, Table 3).

3.2.2 State Datasets—Of 27 states that included mapped streamflow duration classes, 80% were directly extracted from the NHD classes (SI Table 3), while seven datasets contained additional duration information (Table 3). Multiple states used aerial imagery or DEMs to add stream segments to the NHD at a greater spatial resolution (Table 3). However, only Vermont and Idaho developed regression equations to estimate intermittent flow (Vermont: Olson and Brouillette 2006) or perennial flow (Idaho: Wood et al. 2009) and included them in state maps. Michigan estimated baseflows using stream gauges and hydrograph separation on NHD MR reaches; whenever baseflow was zero, the stream was assumed to be intermittent.

USGS StreamStats in the CONUS currently provides state or regional analyses of streamflow information for 41 states (Figure 3), yet a minority of states include metrics that could potentially support flow duration class determinations, such as low flow estimates (21 states), probabilities of zero flows (five states) or probability of perennial flow in Massachusetts. In the StreamStats application, many states provide a high level of detail about the development of their state-specific statistical regressions, links to literature and methodologies, as well as indications of how and when the tool outputs may be appropriately used or applied. See SI Table 2 for the full listing of available streamflow statistics and their associated methodologies available by state.

3.3 Mapping Wetland Extent

3.3.1 Federal Datasets—The National Wetlands Inventory (NWI) Program, led and maintained by the US Fish and Wildlife Service (USFWS), is the definitive high spatial resolution source for mapped wetlands across the US (Table 4). Available throughout all of CONUS, NWI has standardized the mapping, characterization and monitoring of wetlands at fine spatial resolutions via aerial photography and multispectral satellite imagery. Beginning with 1:80,000 scale imagery in the late 1970s, the spatial resolution has increased through time with the Targeted Mapping Unit (the minimum area that can be consistently mapped) of current standards being 0.2 ha using 1 m imagery at the 1:12,000 scale (FGDC 2009). The current NWI (version 2) documents almost 34 million unique wetland vegetation or water features, each with information on wetland vegetation type, permanence, and human alterations. Due to the enormity of the task of national fine-resolution mapping and limited federal funding for the NWI, the inventory is a patchwork of different base map dates (from the 1970s to the present) and different dataset resolutions (1:80,000+ to 1:12,000 scales) (see section 4.1). Much of the current updating work of the NWI is done via collaborative efforts with state and local entities as 67% of the 165 contributors to the NWI are state agencies, tribes, and regional or local governments (USFWS 2021). Updates occur on an ad-hoc basis and are posted to the USFWS's Wetlands Mapper (https://www.fws.gov/wetlands/data/Mapper.html) on a biannual basis.

Although NWI is the only dataset that follows FGDC Wetland Mapping and Classification Standards, several other federal datasets contain some wetland information (Table 4). For example, some USGS NHD mapped areas include wetland features with limited categorical detail (i.e., swamp and marsh). Furthermore, a few Landsat satellite-derived federal datasets with 30 m resolution identify woody and emergent wetland vegetative classes using NWI data for model parameterization and/or calibration (Table 4). These 30m products have been found to generally be reliable indicators of wetland type and change at the county or broader scales (Wickham et al. 2018). The National Oceanic and Atmospheric Administration's (NOAA) Coastal Change Analysis Program's (C-CAP) high resolution product (minimum mapping unit of 0.1 ha) produces 1–5 m wetland landcover classes in select areas using NWI data as an essential model input. USGS's Gap Analysis Program's (GAP) product classifies regional vegetation groups from field reference data, Landsat imagery, elevation data, and biophysical gradients within decision tree models and some of the vegetative groups are primarily affiliated with wetlands (e.g., Eastern Great Plains Wet Meadow – Prairie Marsh). While not including explicit wetland classifications, the 30 m Dynamic Surface Water Extent (DSWE) produced by the USGS has four classes of surface water confidence: open water – high confidence, open water – moderate confidence, partial surface water – conservative, and partial water – aggressive (Jones 2015, 2019). The partial surface water components employ a mixed-pixel approach to identify Landsat pixels that are a mixture of water and vegetation. USGS developed DSWE products for each cloud-free Landsat pass so temporal dynamics can be investigated as well.

3.3.2 State Datasets—Of 69 state-level datasets with wetlands information, the majority (75%) use NWI clipped to the state or as a base layer for updating state maps (SI table 4). Several states amend NWI data with additional state-specific data (Table 4). For example, New Hampshire used 2014 USDA National Agricultural Imagery Program (NAIP) leaf-on true color imagery and ancillary datasets to add a set of hydrogeomorphic-type descriptors (landscape position, landform, water flow path, and waterbody type) to NWI wetlands to estimate likely functions of wetlands. Data resolutions for these datasets are consistently 1:10,000 to 1:24,000 scale.

Only five states have wetland maps not directly linked to NWI (Table 4). Of those identified, two are generated for cities or municipalities (Anchorage, Alaska and Boulder, Colorado) while two represent potential (not necessarily actual) wetlands in Kansas and portions of southeastern Arkansas. Kansas and Wisconsin provide the only examples of a state level dataset that was generated independently from the federal NWI effort (Table 4). In 2018, the Wisconsin dataset was reconfigured to align with the NWI and is now part of the NWI dataset.

4. Limitations in Current Federal and State Aquatic Mapping

4.1 Limitations of Current Headwater and Wetland Extents

Our knowledge and use of stream and wetland extents rely heavily on the NHD and NWI datasets, yet each have specific constraints. Other remotely sensed wetland extents also have specific limitations. These include:

A. Original cartography often underestimates headwater extent.—Field studies from different regions of CONUS indicate that the NHD often underestimates stream headwater extent (e.g., Heine et al. 2004; Brooks and Colburn 2011; Fritz et al. 2013, Fesenmyer at al. 2021). As the NHD family is ultimately derived from original surveys, old cartographic constraints, inconsistencies, and decisions limit some headwaters. For example, historically, ephemeral reaches were not mapped and were only recently added to some western states (Fesenmyer et al. 2021). Figure 4a highlights the additional headwater stream segments included within a LiDAR-derived stream map (Lang et al. 2012) that are not included in the NHD for a catchment in the Delmarva Peninsula.

B. Imagery can miss or misclassify some headwaters and wetlands.—Mapping efforts can be limited by the resolution of the underlying data layers (e.g., aerial photographs, satellite images, elevation datasets). The NHD and NWI rely on aerial imagery, yet linear, narrow stream channels (with median widths <0.3m) and small wetlands (with area <0.2 ha) may not be mapped due to the aerial image resolution (Wohl 2017; Allen et al. 2018: Sahour et al. 2022) or mapping conventions. Likewise, most current satellite-derived US datasets rely on moderate (30m) resolution Landsat imagery so wetlands smaller than 1 ha are likely missed or merged with surrounding wetlands (Muster et al. 2013; Lang et al. 2015; Vanderhoof and Lane 2019).

At any spatial resolution dense cloud cover, tree canopy, and understory vegetation can block passive optical sensors from viewing the earth's surface (Tiner 1990; Lang and McCarty 2008). In deciduous forests, photographic and multispectral imaging are typically timed for leaf-off conditions and are further limited to cloud-free days. However, evergreen or mixed forests can hide small wetlands and streams completely, and trees associated with wetlands and headwater streams may be spectrally ambiguous with those in upland forests (Lang et al. 2020). In addition, the spectral signature (i.e., the variation of light reflectance as a function of wavelength) of surface water overlaps with that of shadows created by trees, stumps, and other structures (Huang et al. 2014; Xie et al. 2014).

C. Headwater and wetland datasets can be spatially and temporally inconsistent.—The combination of uncertainties associated with image resolution, imaging dates (e.g., season, day), update intervals, cartographic conventions/interpretations, classification methods, and continued stream and wetland losses can lead to an uneven patchwork of mapped streams (Figure 4b; Colvin et al. 2019) and wetlands (Tiner et al. 2015; Lane and D'Amico 2016). For example, while NWI has focused more recent updates on areas of greater wetland densities (coasts and the Great Lakes), the NWI base map dates range from the 1970s to the present, with 51% of the CONUS mapped in the 1980's and 35% mapped since 2000 (as of September 2020). Inconsistent spatial and temporal mapping

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across broader areas makes studying, comparing, modeling, and visualizing these systems more challenging (Figure 4b).

D. Seasonally dynamic systems pose a challenge for temporally limited data.—Seasonal headwaters and wetlands, which dry during parts of most years, may not be captured in the underlying imagery depending on the frequency and the timing of imagery collection. Mapping efforts conducted in past decades may not reflect current conditions as climate variation (Hafen et al. 2020), shifts in climate, land use change or management (Szantoi et al. 2020; Wilson et al. 2022) affect the extent, condition, hydrology, and/or existence of headwaters and wetlands.

E. Continual updating of maps is needed but challenging.—Managers of NHD and NWI consistently work, often through partnerships with states and other entities, to provide updates to both datasets. Yet the ability to quickly provide high-quality, high-resolution maps has been constrained by available funds, imagery, methods, and the needed development of additional partnerships.

F. Temporally dynamic systems pose a challenge for static maps.—Static maps fail to highlight innate dynamics of streams and wetlands leading to a public perception of static aquatic systems. While classifications of permanence or seasonality can convey some aspects of headwater and wetland dynamics, current maps fail to adequately convey stream and wetland hydrologic dynamics and the uncertainty surrounding those static maps.

4.2. Limitations of Current Streamflow Duration Measures

Mapped headwater streamflow descriptors rely heavily on NHD classifications, and other non-NHD-based US datasets of streamflow metrics have additional limitations. These include:

A. Streamflow classifications focus primarily on streamflow duration.—Mapped stream dynamics are often focused on streamflow duration, ignoring other potentially important flow regime components of magnitude, frequency, timing, or rates of change. Yet consideration of flow regimes like magnitude or timing can be important to management concerns surrounding pollutants, flood-hazards, or habitat needs.

B. Streamflow duration classes require a discrete separation of a continuous variable.—Flow duration varies year-to-year and among reaches and thus may be difficult to place into separate bins. The misclassification of perennial, intermittent, and ephemeral stream reaches has been particularly troublesome in headwater streams (Nadeau and Rains 2007; Caruso and Haynes 2011; Fritz et al. 2013; Nadeau et al. 2015). Incomplete data, the presence of non-representative conditions during the original survey campaigns (Hafen et al. 2020) or shifts in flow duration from human and climate induced changes since the time of mapping may lead to mischaracterizations. Limiting the duration characterization of a stream reach to one of only three classes is a simplification that may not be preferred by water resource managers for adequate representation on maps. While more classes or

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continuous measures of flow duration do not necessarily lead to fewer misclassifications, the additional data may enable managers to identify key hydrological conditions that might aid some decisions and identify cumulative influences.

C. Many headwaters lack streamflow data and metrics.—A minority of states have low-flow metrics within StreamStats or have permanence probabilities within PROSPER (Figure 2). USGS stream gauges, often used to calculate StreamStats metrics, are biased toward placement on larger perennial rivers (Poff et al. 2006; Deweber et al. 2014; Krabbenhoft et al. 2022), which potentially limits the applicability of calculated values in smaller headwaters. In fact, StreamStats estimates have minimum catchment size warnings to their regression predictions that are often larger than the typical catchment size of headwater streams. For example, when estimating probabilities of zero flow, recommended minimum catchment sizes ranged from 2.6 km^2 in Ohio to 19.2 km^2 in Idaho yet the largest contributing size for channel head initiation across a wide variety of US studies was only 0.79 km^2 (Wohl 2018). Probability models like PROSPER require sufficient permanence data from a range of stream sizes and over periods representing different meteorologic conditions, which are difficult to obtain or do not exist (Jaeger et al. 2019; Jaeger et al. 2021). More data are needed to improve streamflow duration classifications, models, and metrics. Acquiring sufficient data that is updated regularly may require compiling across disparate datasets and using crowdsourcing and citizen science efforts (e.g., Seibert et al. 2019).

4.3 Integrated Stream and Wetland Systems

Headwaters and wetlands are primarily treated separately as different systems within datasets and related tools and analyses, as outlined by the following:

A. The integration of headwater and wetland datasets is limited.—NHD has some waterbodies associated with their dataset, and the latest NWI (version 2) includes features associated with streamlines. However, integration of the detailed systems is challenged by differences in the structure of the datasets, discrepancies, and duplication between various versions of both datasets.

B. There is a lack of datasets and models that incorporate both headwaters and wetlands, and their dynamics.—Current datasets and associated models fail to utilize the most detailed and consistent representation of wetland and headwaters (Figure 4a). Models that include both systems could better represent both water storage, dynamics and incorporate the full suite of potential remotely sensed data (see emerging approaches in sections 6–8) to best quantify streamflow duration classifications. A lack of such integrated models leads to a continued disconnect between disciplines (Golden et al. 2017).

5. Emerging Approaches to Mapping Headwaters and Wetlands

While limitations in current headwater and wetland datasets exist, emerging approaches using LiDAR, other remote sensing platforms, field and remote monitoring, machine learning, and modeling can help to close gaps created by these limitations. Figure 5 provides a conceptual overview of various approaches that contribute to mapping headwaters and wetlands.

5.1 Remote Sensing Approaches to Improve Mapping of Extents and Dynamics

Remote sensing (RS) approaches are of particular interest and can support more accurate and frequent mapping of wetland and stream extent, if resources are available to develop and employ these methods. While it is not currently possible to fully automate the generation of FGDC standard compliant data (i.e., for wetland data having 0.2 ha using 1 m imagery at the 1:12,000 scale; FGDC 2009), several remote sensing approaches may prove useful in reducing manual processing and interpretations. Box 1 provides a primer for the types of remote sensing that are potentially used to map headwaters and wetlands.

5.1.1 LiDAR—The continued development and use of DEMs derived from LiDAR, combined with Geographic Information Systems (GIS) and machine learning statistical methods, will help to improve estimates of headwaters and wetland extents as well as reduce spatial inconsistencies in the data. LiDAR aerial surveys have progressed in spatial and temporal coverage significantly in the past decade. Much of the CONUS now has at least one LiDAR coverage housed within NOAA’s US Interagency Elevation Inventory, which will work towards a nationally consistent LiDAR dataset and 1 m DEMs within the USGS 3D Elevation Program (3DEP; Figure 6a; NOAA 2021; USGS 2022). 3DEP products will be used to improve the detail and positional accuracy of nationwide stream mapping through the USGS 3D Hydrography Program (3DHP; Archuleta and Terziotti 2020; Terziotti and Archuleta 2020). The current Iowa stream layer (Table 3) was developed using LiDAR and demonstrates the promising approaches used to create more consistent and repeatable maps of aquatic systems (Figure 6b).

LiDAR is also helpful to define detailed linear flow paths for stream extent estimates in steep (Sofia et al. 2011; Russell et al. 2015) and low-gradient landscapes (Bailly et al. 2008; Lang et al. 2012; Roelens et al. 2018). One challenge is determining where along a headwater flowpath the stream begins (channel head) because stream initiation often results from a complex combination of geology, landcover, climate, and topography (Jaeger et al. 2007; Garrett and Wohl 2017; Wohl 2018). The simplest methods for estimating channel initiation involve catchment area thresholds and catchment-slope relationships (Montgomery and Dietrich 1989; Montgomery and Dietrich 1992; Montgomery and Foufoula-Georgiou 1993; Clarke et al. 2008; Matsunaga et al. 2009; James and Hunt. 2010; Henkle et al. 2011; Avcioglu et al. 2017; Wohl 2018; Pena et al. 2018). However, this approach sometimes performs poorly (Wohl 2018).

Given the complexities of headwater initiation, several studies rely on the morphology of the initiation area. Curvature (rapid changes in slope or aspect) and other linear features can help identify channel heads using moderate resolution DEM (James and Hunt 2010; Gonzalez-Ferreras and Barquin 2017; Gonga-Saholiariliva et al. 2011; Julian et al. 2012) and LiDAR (e.g., Pirotti and Tarolli 2010; Sofia et al. 2011; Cazorzi et al. 2013; Hooshyar et al. 2016; Roelens et al. 2018; Shavers and Stanislawski 2020). As an example, Shavers and Stanislawski (2020) used LiDAR and measured variation in curvature at cross-sections to determine where the stream profile becomes less visible and thus where channel head initiation was likely to occur.

To aid in channel delineation and initiation, several tools have been developed to prepare LiDAR-derived DEMs. Artifacts generated during LiDAR data collection or processing (e.g., false "pits") and apparent barriers to flow (e.g., bridges, culverts, dams) often need to be corrected before realistic drainage and flow paths can be created. While challenging to apply at broader scales, several approaches, including filling and breaching techniques (Poppenga et al. 2013; Lindsay 2016; Sangireddy et al. 2016; Xu et al. 2021), have been used to automatically pre-process LiDAR DEMs. Once corrected, tools can then identify and connect physical flowpaths and estimate channel heads by either curvature, variation in that curvature, or other filters (Lashermes et al. 2007; Clubb et al. 2014; Passalacqua et al. 2010; Pelletier 2013; Sangireddy et al. 2016; Xu et al. 2021). Xu et al. (2021), for example, used multiple LiDAR derivatives with neural networks to extract streamlines and associated waterbodies for a small catchment in North Carolina. Aerial imagery can also aid in identification of channel initiation when used together with the LiDAR (Lang et al. 2012).

LiDAR evaluations have mostly been tested on small areas of interest, yet statistical and machine learning approaches may help expand LiDAR estimates to larger areas. Russell et al. (2015) used a multiple logistic regression on field-verified channel initiation sites in Western North Carolina that included LiDAR-derived slope, drainage area, area-slope and curvature measures combined with land cover and soil factors. Similarly, Villines et al. (2015) used 10 m-derived DEM metrics to identify channel heads via field surveys and to develop Random Forest models that included DEM, geologic, and soil metrics to predict channel initiation locations across the entire catchment.

LiDAR-based mapping of wetlands has primarily focused on identifying and characterizing depressions and other areas of water accumulation within the landscape. LiDAR-derived digital elevation models (DEMs) and other associated derivatives (e.g., maximum vegetation height, topographic wetness indices, landform indices) have expanded rapidly in the last decade and have been used to help map depressional wetlands (Lang et al. 2013; Rampi et al. 2014a; Millard and Richardson 2015; Wu and Lane 2016; Jones et al. 2018; Wu et al. 2019a; O'Neil et al. 2019; O'Neil et al. 2020). However, elevation data only indicates the relative likelihood of wetlands in depressional areas (Lang et al. 2013; O'Neil et al. 2019) or the maximum extent of pooled water (Lane and D'Amico 2010; Serran and Creed 2015; Wu and Lane 2017; Jones et al. 2018; Wu et al. 2019a). Therefore, elevation data are often used in conjunction with other imagery to determine wetland extents (Figure 7; Maxa and Bolstad 2009; Wu et al. 2014; Kloiber et al. 2015; Millard and Richardson 2015; Hird et al. 2017; Vanderhoof et al. 2017a; Vanderhoof et al. 2018; Wu et al. 2019b). LiDAR elevation can also help mask upland areas or identify where shadows might cause spectral confusion during landscape classification (Irwin et al. 2017).

In addition to the LiDAR elevation data that provide high horizontal resolution for DEMs, the intensity (relative strength) of LiDAR return signals provides information about the materials reflecting LiDAR pulses and thus can also inform stream and wetland mapping. High absorption of LiDAR near-infrared by surface water results in weak (low intensity) returns compared to dry land. Thus, several researchers have used LiDAR intensity datasets to help map riparian vegetation and stream edges (Liu et al. 2018), wet stream segments in California (Hooshyar et al. 2015), streamlines in North Carolina (Xu et al. 2019), drainage ditches in Belgium (Roelens et al. 2018), forested depressions in Delmarva bays (Lang and McCarty 2009; Huang et al. 2014; Lang et al. 2020), and open surface waters (Höfle et al. 2009; Rampi et al. 2014b; Rapinel et al. 2015; Hird et al. 2017; Wu and Lane 2017). Huang et al. (2014) used intensity data from two dates to identify areas of inundation in Delmarva bays, then related inundation to Landsat imagery to develop sub-pixel inundations estimates. While LiDAR intensities are helpful in mapping detailed waters, they are often limited to only one or two time periods making it difficult to use in any temporal analyses.

5.1.2 Multi-Spectral Remote Sensing—High-resolution (< 10 m pixel) remote sensing platforms are available for mapping headwaters (Table 5), but their use is limited. Numerous examples illustrate the use of medium resolution, or > 10 m, multispectral imagery (e.g., 30 m resolution Landsat) to help map river systems at regional (Das et al. 2007; Jiang et al. 2014), national (Allen et al. 2020; Gardner et al. 2021) and global (Yamazaki et al. 2015; Pekel et al. 2016; Allen and Pavelsky 2018) extents (Table 5). However, at medium spatial resolutions, streams and rivers with widths less than 30–90 m are not reliably captured (Allen and Pavelsky 2018; Vanderhoof and Lane 2019) – and this would include most headwaters (Allen et al. 2018). While relatively few headwater studies have used multispectral data, higher resolution imagery (<3 m) can be used in arid, glacial, and agricultural areas where lack of trees or unique riparian vegetation allow for identification. However, these analyses have been limited to small areas (Table 6; Akasheh et al. 2008; Dunn et al. 2011; Yang and Smith 2012; Hamada et al. 2016; Spence and Mengistu 2016; Macfarlane et al. 2017; Manning et al. 2020). For example, Vanderhoof and Burt (2018) used panchromatic brightness on Worldview imagery and object-based analysis to measure change in four stream segments in the Missouri River headwaters with a high degree of accuracy.

High-resolution multispectral sensors are more common in wetland systems. They have been successfully deployed throughout multiple settings and can support more accurate and frequent mapping of wetland extent and spatiotemporal dynamics (examples within Table 7). Several reviews have detailed these approaches for mapping headwater extents and dynamics (Klemas 2013; Tiner et al. 2015 and numerous chapters therein; Guo and Li 2017, Wu 2018, Mahdianpari et al. 2020a).

Historically, researchers relied on aerial imagery for high-resolution wetland mapping, and these approaches have been maintained by the NWI through the present. Thus, aerial imagery has been used in multiple studies at high resolutions with both sub-meter imagery (e.g., Neale et al. 2007) and publicly available 1–2 m imagery to identify wetlands (Bowen et al. 2010; Halabisky et al. 2011; Wu et al. 2019b). The publicly available aerial imagery (Table 5) is typically leaf-on imagery, which limits the detection of underlying water in forested or riparian wetlands (Vanderhoof et al 2017a). There are additional examples of leaf-off imagery used to help identify geographically isolated wetlands in South Carolina forests (Pitt et al. 2011), Minnesota wetlands (Rampi et al. 2014b), and vernal pools in Massachusetts (Burne and Lathrop 2008). Classification of high-resolution aerial imagery has often relied on some manual interpretation (e.g., Bowen et al. 2010), which raises the time, costs, and repeatability of the project. The use of Unmanned Aerial Vehicles (UAVs) has aided wetland mapping (Abeysinghe et al. 2019; Briggs et al. 2019). While limited to smaller areas, the use of UAVs in wetland and stream mapping is likely to increase in the future for two primary reasons: (1) the cost savings over aircraft and (2) the use of UAVs in other related commercial industries like field mapping for precision agriculture.

With the increasing availability of high-resolution satellite imagery (Table 5) and the computational power to store and process that imagery, continued surface water mapping will rely more on satellite sources. Several studies have used high resolution satellite imagery to map wetlands (Table 7) including IKONOS imagery (3 m; Wei and Chow-Fraser 2007; Maxa and Bolstad 2009), Quickbird (2.4 m; Kumar and Sinha 2014) and WorldView (2 m; Irwin et al. 2017; McCarthy et al. 2018; Vanderhoof and Lane 2019). The advent of high-resolution satellites with expansive coverage and rapid revisit times (e.g., Worldview 3 or the Planet constellation) creates powerful potential to advance the mapping of wetland dynamics. Yet these advancements in surface water mapping using commercial imagery may be slowed in the near term by limited data years, computational and storage constraints, and the costs of acquiring commercial data. Furthermore, as new high-resolution imagery is acquired, additional challenges include the limited number of bands (e.g., a lack of Short Wave Infrared, SWIR, which is helpful in identifying surface water) and variability with georeferencing – both of which add to the complexity of using high-resolution imagery in time-series analyses.

High-resolution imagery typically forces limitations on the size of the area and the temporal record of analysis because of the previously discussed challenges. Therefore, many researchers still employ moderate resolution imagery like the publicly available Landsat (30 m), which has a long-term library that can be used to consider wetland change mapping over multiple decades (Berhane et al. 2020; Vanderhoof et al. 2020) and dynamic wetland hydrology (Baker et al. 2006; Frohn et al. 2011; Rover et al. 2010; Mwita et al. 2013; Xie et al. 2015; Dvorett et al. 2016; Pekel et al. 2016). The 30 m resolution for Landsat inherently means that derived wetland maps will omit small wetlands (<1 ha; Reif et al. 2009). Thus, mixed-pixel approaches (percent water fraction or water-vegetation mixtures) are used to partially reduce such omissions (Huang et al. 2014; Halabisky et al. 2016; DeVries et al. 2017; Jones 2019; Vanderhoof et al. 2020). Though actual wetland classification is not assigned, sub-pixel products can help differentiate vegetated wetlands from other land covers (Jones 2019). As Sentinel 2 imagery (10 m) becomes more available, more research will likely use the increased resolution to aid in mapping smaller wetlands as exemplified by Hird et al. (2017) in Alberta, Canada (Table 7) or Mahdianpari et al. (2019) in Newfoundland, Canada. Likewise, the increasing computation power through cloud-based tools such as Google Earth Engine and the inclusion of more processing tools and data on these public platforms will further enhance wetland mapping (Wu et al. 2019b; Mahdianpari et al. 2019; Vanderhoof et al. 2020; Amani et al. 2020; Mahdianpari et al. 2021).

5.1.3 Synthetic Aperture Radar (SAR)—SAR can be used to map stream systems and has two main benefits: it has less obstruction by clouds and vegetation, and it can be collected at night (Martinis and Rieke 2015; Hess et al. 2015). Yet these platforms currently have minimum spatial resolutions of 10–20 m and are therefore currently too coarse to map many headwaters and wetlands. While future satellites like the NASA-ISRO SAR (NISAR) mission scheduled for 2024 may introduce some SAR capabilities for headwaters, with potential imagery captures up to 3 m resolution every 6–12 days (https://nisar.jpl.nasa.gov/- accessed 11/23/2021), the only active sensors currently well suited for mapping headwaters are interferometric synthetic aperture radar (IfSAR) flown for coastal areas and Alaska (Stanislawski et al. 2021) and LiDAR (discussed in 5.1.1).

The use of microwave sensors such as SAR to map wetlands is much more prevalent than for streams (Table 8). Surface waters have been clearly identified using C-band (Brisco et al. 2009; White et al. 2015) and X-band SAR (Irwin et al. 2017). C-Band SAR platforms (RADARSAT and Sentinel-1) have been useful to map marshes in the US and Canadian Great Lakes (Bourgeau-Chavez et al. 2009, Battaglia et al. 2021), France (Muro et al. 2016) and forested wetlands in Maryland using data with smaller incidence angles (Lang and Kasischke 2008; Lang et al. 2008). The longer wavelengths (L-band) can penetrate farther into tree canopies, and L-band sensors have been successfully used to map inundation patterns in vegetated wetlands in Minnesota (Kloiber et al. 2015), California (Torbick and Salas 2015), Alaska (Whitcomb et al. 2009; Clewley et al. 2015), and the Amazon (Hess et al. 2015). The combination of the various SAR bands is likely to provide greater accuracy than any single band alone (Fu et al. 2017; Mahdianpari et al. 2017; Mahdianpari et al. 2021). The planned NISAR mission may also further the availability and utility of L-band imagery for smaller wetlands.

SAR products have unique advantages that help detect wetlands, but SAR data also can be challenging because several factors, including season, soil moisture, the angle and direction of the satellite and distortions from topography, affect the wave signal. Additional information about techniques and challenges using SAR to map wetlands can be found in Brisco et al. (2015) and White et al. (2015).

5.1.4 Fusion of Multi-Sensor, Multi-temporal Platforms—While single platforms (e.g., Landsat imagery) with pixel-based classifications (e.g., Maximum Likelihood) are still used to classify pixels individually (e.g., Jollineau and Howarth 2008; Kumar and Sinha 2014; Pistolesi et al. 2015; Dvorett et al. 2016), researchers are increasingly moving towards employing combinations of platforms and classification schemes (Table 7 and 8; Figures 5 and 6). The use of image segmentation and object-oriented analyses moves away from pixel-based classifiers and towards pattern recognition approaches for identifying features (objects) and typically outperforms traditional classifiers (Frohn et al. 2009; Frohn et al. 2011; Serran and Creed 2015; Knight et al. 2015, Mahdianpari et al. 2020a). The fusion of temporal stacks of imagery and multiple platforms for wetland classification has often used decision trees (Baker et al. 2006; Corcorcan et al. 2011; Panigrahy et al., 2012; Rapinel et al. 2015; Irwin et al. 2017; McCarthy et al. 2018; Mahdianpari et al. 2020b, 2021) and machine-learning based Random Forest algorithms (Whitcomb et al. 2005; Corcoran et al. 2011; Torbick and Salas 2015; Kloiber et al. 2015; Clewley et al. 2015; Bourgeau-Chavez et al. 2015; Vanderhoof et al. 2017a; Chignell et al. 2018; Berhane et al. 2018). For example, Clewley et al. (2015) incorporated L-band data from multiple platforms, topographic data (e.g., slope, elevation) and locational information (latitude, longitude) and trained the model using Random Forest to derive a map of vegetated wetlands in Alaska. Vanderhoof et al. (2017a) used RADARSAT at multiple dates, worldview imagery and LiDAR-derived depression and wetness indices within Random Forest to determine forested depressions in Maryland (Figure 8).

High-power computing capability, increasing availability of multi-source imagery, and advances in multisource data fusion techniques are relying on other machine learning techniques, including support vector machine learning (Xie et al. 2015), and shallow and deep neural networks (Morris et al. 2005; Rezaee et al. 2018; Mahdianpari et al. 2018; Pouliot et al. 2019; Du et al. 2020; O'Neil et al. 2020; Hosseiny et al. 2021; Stanislawski et al. 2021; Xu et al. 2021). In particular, deep convolutional neural network (CNN) models have been applied to map Alaska streams (Stanislawski et al. 2021) and forested Maryland wetlands (Du et al. 2020), landscapes that pose unique challenges to remote sensing of hydrographic features. One factor typically limiting the automation of remotely sensed images is the lack of large-scale reliable training data (Huang et al. 2017). Transfer learning could provide a potential solution to the paucity of labeled training data in remote sensing (Yosinksi et al. 2014; Pires de Lima and Marfurt 2020; Brewer et al. 2021). Transfer learning, in part, involves training a model (e.g., wetland type in a particular data-rich location) and applying those results/weights later on or in a differ neural network to help solve a related classification (e.g, similar wetland type in a different location; Brewer et al. 2021).

5.2 Field-based Data to Inform LiDAR and RS Applications

While remotely sensed products of DEMs and imagery are essential to expanding headwater and wetland mapping, results must rely on field-based training and validation data to create and verify classifications or to calibrate statistical relationships. Headwaters are often small and narrow; therefore, mapping often involves physically walking watershed stream networks to discern channel heads and dynamics flows. Some groups have conducted single field visits to map channel heads (e.g., Brooks and Colburn 2011; Henkle et al. 2011; Julian et al. 2012; Russell et al. 2015) and others have looked at either entire stream networks or specified stream segments during wet and dry seasons to map stream dynamics (Wigington et al. 2005; Roy et al. 2009; Fritz et al. 2013; Godsey and Kirchner 2014; Shaw 2016; Whiting and Godsey 2016; Jensen et al. 2017; Lovill et al. 2018). Water level data loggers have also been used to map stream extents and dynamics (see section 7.2; Jaeger and Olden 2012; Goulsbra et al. 2014; Jensen et al. 2019).

Most stream mapping efforts to date use a static representation of the stream extent. Yet some statistical methods also consider overall measures of stream length, density and the dynamics of extent and flow (see section 7), which are difficult to convey in static maps. Furthermore, field observations of stream length and density have been quantitatively related to discharge (Godsey and Kirchner 2014; Whiting and Godsey 2016), topographic properties like slope and curvature (Prancevic and Kirchner 2019), and local geology (Jensen et al. 2017).

Few fully field-based wetland mapping efforts exist in recent literature. The lack of field-based wetland methods may be due to the evolution of digital imagery: fine-scale imagery and topographic maps can estimate standing water in pools to sufficient detail and can identify wetland vegetation and depressions. Indeed, most research with a field-based wetland mapping component is either to support the development or validation of remote sensing methods (Neale et al. 2007; Burne and Lathrop 2008; Lang et al. 2008; Rebelo et al. 2009; Bowen et al. 2010; Panigrahy et al. 2012; Kumar and Sinha 2014; Vanderhoof et al. 2018), the mapping of specific wetland vegetation (e.g., Underwood et al. 2006, Jollineau and Howarth 2008; Zomer et al. 2009) or identification of hydrologic functions of small wetland complexes (e.g., Brooks and Colburn 2011). A few notable examples of mapping wetlands in the field are at long-term study sites that seek to understand the dynamics of wetland complexes (Winter 2003; LaBaugh et al. 2016; Leibowitz et al. 2016) or their interactions with the stream network (Spence 2007; Shaw et al. 2012).

Wetland field work does significantly contribute to the specific mapping of individual wetlands for the express purposes of wetland delineations for US federal or state permits. Regulatory definitions for wetlands considered for US Clean Water Act protection require precise boundary determinations and confirmation of hydrology, wetland soils, and wetland plant characteristics which are difficult to determine solely from remote sensing. The US Army Corps of Engineers (USACE) has developed both national delineation manuals (Environmental Laboratory 1987) and regional supplements (USACE 2012) to measure specific indicators of hydric soils, provide lists of approved hydrophytic vegetation, and provide guidelines for identifying the presence of hydrology. Handbooks and guides have been written and updated to supplement the training of wetland field specialists for government and private consultants (Tiner 2016; Lyon and Lyon 2019). Publicly available spatial datasets that house confirmed field-based delineations are lacking or incomplete but could be used to inform models and wetland analyses (Vanderhoof et al. 2020).

6. Emerging Approaches in Streamflow Permanence

6.1 Remote Sensing in Arid or Low-Vegetation Regions

Advances in remote sensing techniques for estimating headwater streamflow permanence are currently limited and focus primarily on large river or low-vegetation systems. However, some promising results are emerging. Multi-temporal remote sensing platforms like Landsat, Sentinel-1, and Sentinel-2 provide insights into streamflow dynamics but are necessarily focused on efforts in large rivers (Tulbure et al. 2016; Miller et al. 2014; Isikdogan et al. 2017; Allen and Pavelsky 2018; DeVries et al. 2020; Yang et al. 2020), particularly in intermittent rivers in arid regions (Hou et al. 2019; Pereira et al. 2019; Kostianoy et al. 2020). For example, Hou et al. (2019) used Landsat imagery over 27 years to track river dynamics within rivers with a width >25 m in Australia.

Remote sensing as a tool for headwater streamflow duration is currently limited by the resolution of existing imagery, the temporal frequency of the imagery, and the presence of vegetative cover, and cloud cover for optical sensors. However, pixel-fraction approaches developed with Sentinel data (10 m resolution) and used for wetlands (Mahdianpari et al. 2019) may find similar utility in intermittent streams and rivers and may help determine streamflow permanence. As high-resolution, high-frequency imagery, such as the Planet constellation (3–4 m resolution with 1–3 day intervals), become more available and develop a more robust temporal record, work in arid and semi-arid areas with reduced vegetative cover may yield useful analyses of temporal dynamics and streamflow duration in headwaters. Proof of concept approaches have begun and are promising (Garcia et al. 2020).

6.2 Field-based Methods to Support Emerging Models

Streamflow duration literature often rely on field-based techniques to understand hydrological processes, dynamics, and duration classifications. These techniques include long-term repeat observations via stream gauges, recording the stream extent on multiple field visits, and logger or time-lapse photography data that indicate the presence of streamflow at specific points through time.

Long-term streamflow gauges often provide continuous data about hydrology and have been used extensively to produce hydrologic metrics that inform classification schemes (Olden and Poff 2003; Henriksen et al. 2006; Olden et al. 2012; Eng et al. 2017). Specific hydrologic metrics have been used to classify streamflow duration including: days or percent of the year with flow or with zero flows (Granato et al. 2017; Yu et al. 2018; Reynolds et al. 2015), thresholds or minimums of daily discharge (e.g., Beaufort et al. 2018; Rea and Skinner 2009), drying regimes (Price et al. 2021), or creating flow duration curves thresholds that define periods of low flow or minimum flows (Booker and Snelder 2012; Huxter and van Meerveld 2012; Pruski et al. 2013). As an example, Reynolds et al. (2015) analyzed 115 gauging stations in the Upper Colorado River Basin and determined a third of the gauges were on strongly or weakly intermittent reaches based on the number of zero flow days and zero flow months. A more detailed list of hydrologic metrics relevant to duration classifications can be found in Fritz et al. (2020).

Once classification via the gauge data has occurred, statistical techniques (e.g., multiple regression and Random Forest) have been used to predict classifications in neighboring catchments and basins based on relationships to climate, landscape, and topological variables. Prediction of gauge-related stream duration classifications have been primarily done at regional (Bent and Steeves 2006; McManamay et al. 2012; Pruski et al. 2013; Snelder et al. 2013; Reynolds et al. 2015), national (Kennard et al. 2010; Dhungel et al. 2016), and global levels (Messager et al. 2021). The approaches have helped identify the ubiquity of non-permanent systems (Messager et al. 2021) and their sensitivity to shifts in climate (Dhungel et al. 2016). Headwater gauges, however, are limited (Poff et al. 2006), though some conclusions can be reached if small, gauged catchments are exclusively selected. For example, Prancevic and Kirchner (2019) studied gauges from 17 small, mountain stream networks from across the US and found that stream length, expansion, and contraction and drainage density were primarily functions of catchment area, slope, and curvature. Expansion of gauge networks across headwater streams are needed if gauge data is expected to contribute fully to future headwater classifications.

In the absence of stream gauge data, walking streams lengths to determine the presence or absence of streamflow is a primary method of studying headwater dynamics. Due to the inherent difficulty of multiple visits, often in rough or vegetated terrain, the area studied and the number of repeat visits are often small but still informative. The time period used in past studies varied from single low-flow season visits (Olson and Brouillette 2006), to

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multiple season visits within one year (Shaw 2016; Robinson et al. 2016; Whiting and Godsey 2016; Jensen et al. 2017) to limited seasonal visits each year for multiple years (Fritz et al. 2008; Johnson et al. 2009; Roy et al. 2009 Fritz et al. 2013; Godsey and Kirchner 2014; Gonzalez-Ferreras and Barquin 2017; Jensen et al. 2017; Lovill et al. 2018). For example, Lovill et al. (2018) walked and mapped wetted area across four small catchments during wet and dry seasons for three years, hiking over 1,000 km through rugged terrain in Northern California. Targeting specific reaches in proximity to roads allows for greater spatial coverage and potential prediction (Olson and Brouillette 2006; Roy et al. 2009; Fritz et al. 2013; Gonzalez-Ferreras and Barquin 2017). Field-validated segments can then be used to inform or validate statistical and mechanistic modeling of wetting and drying (Jensen et al. 2017; Ward et al. 2018; Jensen et al. 2019). Methodologies for determining reach-specific streamflow duration classifications via rapid assessment methods (Streamflow Duration Assessment Methods) have also been developed using field visits and are an important tool in supporting and managing headwaters (Nadeau et al. 2015; Fritz et al. 2020; Mazor et al. 2021).

An emerging approach to minimize the time and efforts required for field visits is the development of citizen science and data mining of historical records to inform streamflow duration classifications and predictions. Citizen-organized surveys of wet and dry stream segments along select rivers is helping to better understand stream and river dynamics along Arizona intermittent rivers (Turner and Richter 2011; Allen et al. 2019) and in streams in France (Datry et al. 2016). Several mobile applications are being developed to assist in collecting and recording citizen-science stream data (www.streamtracker.org; www.crowdhydrology.com; www.crowdwater.ch). Furthermore, data mining of historical data has helped inform the development streamflow duration classifications in Montana (Sando and Blasch 2015) and the Pacific Northwest (Jaeger et al. 2019), highlighting the usefulness and importance of data collection and data availability as well as the need for collaborative integration of existing and future data collection (Jaeger et al. 2021).

Various types of automated field data collection can assist streamflow duration studies. Automated loggers have been used with more frequency in recent years to inform streamflow duration classifications. Inexpensive data loggers that use relative electrical conductivity (EC) can signal a shift from dry to wet conditions and record the state change (Blasch et al. 2002; Chapin et al. 2014). Since their development, EC loggers have been used to determine wet/dry conditions in the arid southwest (Jaeger and Olden 2012; Arismedni et al. 2017; Levick et al. 2018; Gallo et al. 2020), deciduous forests in the Indiana, Kentucky, Ohio, and Virginia (Johnson et al. 2009, Williamson et al. 2015, Jensen et al. 2019), peatlands in the United Kingdom (Goulsbra et al. 2014), and in a mixed catchment in Luxembourg (Kaplan et al. 2019). Multiple EC loggers have measured longitudinal network connectivity and disconnectivity along reaches (e.g., Jaeger and Olden 2012; Jensen et al. 2019) while other studies have deployed EC loggers across watersheds to validate seasonal field measurements (Fritz et al. 2020) or modeling results (Williamson et al. 2015).

In addition to loggers, time-lapse photography has also shown promise for measuring stage and flow in headwaters in New York and Connecticut (Royem et al. 2012; Bellucci et al. 2020), arid urban headwaters in New Mexico (Schoener 2018), and headwaters in

Luxembourg (Kaplan et al. 2019). The benefit of photography over data loggers is that the image may be more representative of the larger reach and multiple metrics including flow magnitude can be considered in addition to a wet/dry status in the classification (Bellucci et al. 2020). However, image processing can be time-consuming and the thresholds of wet versus dry may be challenging to discern (Royem et al. 2012; Bellucci et al. 2020). In addition, remote or trail cameras may experience issues with image quality (Royem et al. 2012; Kaplan et al. 2019) or vandalism (Kaplan et al. 2019).

6.3 Modeling for Streamflow Permanence for Probabilities of Flow

With adequate field data, statistical models are well positioned to estimate probabilities of streamflow intermittency (Olson and Brouillette 2006) or permanence (Bent and Steeves 2006; Jaeger et al. 2019; Sando et al. in review). Likewise, statistical water balance models with appropriate zero-flow thresholds may provide estimates of intermittency (Yu et al. 2018; Yu et al. 2020; Hafen et al. 2022). Probabilities describe the continuum of permanence, and such continuous measures may be useful in determining the cumulative influence of stream reaches. Yet continuous measures of streamflow permanence are likely regional and complex. While measurements could potentially be taken in multiple regions, large amounts of training data – resulting in high resource expenditures – would be required for accurate predictions. Thus, a combination of continued and new strategically identified field data collection, data mining, and collaboration is needed. In addition, many current policies and management strategies continue to rely on discrete streamflow permanence classifications, so the complex relationship between probability measures and classifications requires further study.

Process-based watershed modeling can also aid in determining streamflow duration and provide probabilities of flow based on simulated model output. Process-based models employ the first principles of physics and time-step simulations of water balances using ordinary or partial differential equations. While the discipline of process-based hydrologic modeling for streamflow in river systems is extensive, many models are too coarse in their depiction of stream networks to include headwaters (Figure 4a). Moreover, low flows are difficult to predict (Belmar et al. 2011; Querner et al. 2016; Hafen et al. 2022). In semi-arid regions where intermittent rivers are prevalent, rainfall-runoff models have approximated months with relative zero flows (Belmar et al. 2011).

The few examples of process-based watershed models explicitly including headwaters have been developed at the small catchment scale, focusing on modeling streamflow duration and spatial dynamics. Ward et al. (2018; 2020) developed a simplified mechanistic model of the stream channel and its hyporheic zone to estimate current and future streamflow and reach connectivity in small mountain catchments in Oregon. Validation of the model was provided by headwater gauges and field observations of wet and dry sections. Williamson et al. (2015) used a regional rainfall-saturation excess model (TOPMODEL), which focused on the upland contributions to the stream network for a forested catchment in Kentucky. The model was more successful with differentiating the duration of upland contributions between perennial and intermittent reaches while contributions to intermittent and ephemeral reaches had greater overlap.

7. Emerging Approaches for Better Wetland-Stream Integration

Only a limited number of studies have considered wetlands with their connection to stream systems, even though wetland-headwater stream interactions are important to understanding how wetland, stream, and watershed systems function (Calhoun et al. 2017; Golden et al. 2017; Leibowitz et al. 2018; Evenson et al. 2021; Lane et al. 2022). Studies focused in areas with high densities of wetlands and streams in the US are limited, with most relevant research occurring in the Delmarva Peninsula (Delaware, Maryland, and Virginia) or in the Prairie Pothole Region (PPR, mainly North Dakota, South Dakota, Iowa, Minnesota, and Montana in the US, though the PPR reaches far into Canada).

Several studies of wetland-stream interactions via remote sensing have been published in the Delmarva Peninsula, Maryland, where depressional wetlands are surrounded by both natural and altered streams (Lang et al. 2012; Vanderhoof et al. 2018; Yeo et al. 2019a). Yeo et al. (2019a) developed inundation maps derived from sub-pixel water extent with Landsat and combined them with weather and hydrological records as well as the NWI and found that inundation was highly correlated to local stream discharge (r=0.81). Within the PPR, the connections between wetlands and streams were studied using 20 years of Landsat imagery (Vanderhoof et al. 2016; 2017b), LiDAR-derived flowpaths and aerial imagery (Wu and Lane 2017), aerial imagery and field observations (Phillips et al. 2011), and Landsat imagery combined with isotopic evaporative signals (Brooks et al. 2018). As high-resolution imagery continues to advance, inclusion of both streams and wetlands in surface water designations will further the ability to consider both surface waters in models and management.

Several models also link the spatial and temporal connection of wetland with streams (e.g., Golden et al. 2014; Jones et al. 2019). In the Delmarva peninsula, wetland depressions were incorporated into process-based watershed hydrology models to link wetlands and streams to determine the effects of depressional storage on watershed discharge (Evenson et al. 2018; Yeo et al. 2019b). Evenson et al. (2018) used remote sensing to help validate water storage estimates but also noted that their model stream network was limited in extent. Likewise, the PPR of the US and Canada contains significant surface water storage in wetlands and has thus been the subject of hydrology models where individual wetlands and a stream network were included (Shook and Pomeroy 2011; Chu et al. 2013; Shook et al. 2013; Evenson et al. 2016; Ahmed et al. 2020). For example, Ameli and Creed (2017) delineated over 130,000 depressions in a PPR watershed located in Alberta, Canada and modeled surface and subsurface flows with a new computationally efficient model that combined a 3-D groundwater-surface hydrology model with a 2-D overland flow model. Ahmed et al. (2020) developed an efficient cellular automata model of simulating fill-spill-merge dynamics with depression complexes and connected them to streams via overland flow in two Canadian PPR watersheds of 11 km^2 and 22 km^2. High-resolution images confirmed the modeled surface water extents within the basins with 85% accuracy.

8. Future directions for mapping headwater streams and wetlands

Headwater stream and wetland mapping has come a long way in the US over the past several decades. However, it is evident that clear gaps in the data remain, and emerging methods can help us move toward closing these gaps. Therefore, based on our literature review findings, we call for the following to facilitate improved future mapping of headwater streams and inland wetlands:

A. Support the NHD enhancement via LiDAR for stream networks.

This action is needed to improve consistency and the inclusion of headwaters in national datasets. The NHD is the most comprehensive stream dataset that we have for the United States. Policy makers, managers, and researchers rely on the NHD for information about stream extent and streamflow classes. With such heavy reliance, there are numerous efforts between the USGS and collaborators to improve and enhance those datasets, notably through the USGS 3DEP, which is acquiring nationwide LiDAR (IfSAR in Alaska) to establish a national baseline of consistent high-resolution topographic elevation data (see section 3.1.1). As high-quality LiDAR is acquired, USGS is in the initial stages of implementing the 3DHP and continued research is needed to efficiently process the LiDAR-derived layers and extract accurate representations of complete stream networks nationwide. Work must be done to understand how methods for automating those extractions might differ across regions and land uses, and how to effectively work with and process such large data volumes. Machine learning approaches will assist greatly in this effort and tools that can automate the multiple processes will be needed.

B. Support the production of contemporary, interoperable NWI data using multiplatform inputs and techniques.

States, tribal communities, federal agencies, non-profits, and the commercial sector rely on NWI data to support strategic, science-based decision-making across multiple high-priority areas, including infrastructure development, natural disaster mitigation, conservation planning, and climate change response. Although it is not currently possible to create FGDC standard compliant wetlands data solely using an automated workflow, recent advancements in the availability of fine resolution input data (e.g., LiDAR and multispectral imagery) as well as new processing techniques (e.g., artificial intelligence and cloud computing) hold promise for improving the efficiency of NWI data production. Additional research is needed to refine workflows that leverage these approaches and integrate them within NWI's established framework.

C. Strengthen existing partnerships and promote access to high-resolution data for NWI and NHD enhancement, including more accurate representation of stream and wetland dynamics.

Both the NWI and NHD continue to develop and update their respective products with new high-resolution imagery, since they are the primary foundations for nationally mapped surface water data. However, the programs receive limited funding and lack automated processes and tools for data extraction. While the volume of high-resolution imagery has increased dramatically in the past 5–10 years, public-private partnerships are needed to make the imagery more publicly available. This public availability will, in turn, expedite classification technique innovations, automated processing workflows, and usable tools. For stream dynamics, high spatial and temporal-resolution optical imagery (e.g., new Planet Lab constellations) may be used in streams without extensive tree cover though temporal analyses may require efforts to improve imagery geolocation. New high-resolution platforms of L-band SAR (e.g., NISAR (10 m resolution with a planned launch in 2024) can aid mapping stream and wetland dynamics in more vegetated systems in the future. As those datasets and surrounding tools mature, methods and workflows to handle such large data analysis need continued development and will likely occur in cloud-based server platforms.

D. Encourage the use of multiplatform, multitemporal combinations to improve surface water mapping and allow for analysis of temporal dynamics.

Tremendous opportunities are available to improve the spatial and temporal resolution of wetland and headwater mapping as multiple platforms and stacks of temporal images are combined, analyzed, and enhanced via advanced machine learning approaches and cloud computing technologies. These approaches have already shown promise in wetland classifications. Therefore, it is anticipated that developing temporal stacks of high resolution imagery used within machine learning will aid in the development of remote sensing techniques in stream networks as well.

E. Develop probabilistic streamflow models and metrics for more regions and over the entire water year.

Additional ways to estimate, visualize, and “bin” streamflow permanence are needed. Probabilistic methods and machine learning have already shown their value for stream permanence classification in efforts like the PROSPER model developed for the Pacific Northwest for wet or dry classifications during summer. Continued research in probabilistic streamflow estimation and related data collection to develop metrics for other regions are encouraged. To support the implementation and management of policies related to stream permanence, more research is needed to describe relationships between probabilistic continuums and discrete classifications. Along with the statistical models, process-based watershed models that include headwaters can simulate streamflow dynamics, highlight dominant processes and drivers in various regions, and derive streamflow metrics. Dominant processes of those more spatially focused process-based models should also be connected to larger scale models so that regional differences in streamflow permanence in headwaters can be examined.

F. Encourage continued stream field data collection, citizen science and collaborative datasets to provide training and validation data.

While advanced LiDAR, imagery, machine learning, and modeling approaches will be essential to building more accurate and detailed headwater and wetland datasets, these approaches cannot succeed without observations on the ground to support them. Accurate model results will continue to depend on training data of wetland, stream, and channel head location. Sustaining field operations (e.g., Stream Duration Assessment Methods) and field observations via headwater gauges, emerging logger technologies, UAV technologies, and the development of citizen scientist programs and apps need to be prioritized and encouraged. Much of current stream mapping efforts are limited to mountain streams. Therefore, continued efforts of field mapping in diverse locations are needed and might benefit from citizen science efforts. Collaborative datasets will also be key in providing training data, whether from data mining and collaborative science or additional public data from federal entities (e.g., delineated wetland permits).

G. Increase the integration of wetland and stream systems in datasets and process-based models with remotely sensed inputs.

A striking result of this review of headwater streams and inland wetlands is the limited number of studies that consider both headwater and wetland systems together (see section 7), despite the fact that wetland-headwater stream interactions are critical to understanding whole-watershed functions. First, efforts to enhance NWI-NHD interoperability through various governance structures (e.g., National Geospatial Data Asset Water-Inland Theme; https://ngda-water-inland-geoplatform.hub.arcgis.com/), should greatly improve the synergistic use of these datasets and foster the development of models that holistically address the interaction between wetlands and streams. Second, efforts to explore combined dynamics of headwaters and wetlands in the US via modeling and remote sensing have been focused in the Mid-Atlantic Coastal Plain and Northern Plains. More work is needed in developing process-based watershed models to simulate stream-wetland interactions in other regions. Remote sensing techniques with increased observations could help in calibrating and validating statistical and process-based models as well.

H. Develop tools using integrated models to address short- and long-term management needs arising from changing climate and land use.

As integrated models are developed to account for both wetlands and headwaters, such tools can be used to better understand how changing conditions and future scenarios will affect these freshwater resources.

9. Conclusion

Mapping and understanding of the dynamics of headwaters and wetlands has advanced remarkedly over the past two decades. Existing national datasets and related efforts continually support and inform important policies and management related to protecting and maintaining aquatic resources. These should be prioritized for continued support and development. To aid in that development and refinement, emerging remote sensing platforms that provide finer and more frequent imagery, classification techniques and fusion approaches that highlight and identify the unique strengths of each data layer, and additional software technologies that allow the incorporation and analysis of large amounts of data, will continue to advance the science. Modeling advancements will build upon and integrate with these remotely sensed products. The continued collection of field data through gauges, loggers, and citizen science will support and validate the emerging work from remotely sensed and modeling products. To fully take advantage of these advancements, research must focus on the wetland landscape and watershed system in its entirety when mapping, modeling, and understanding our aquatic resources. Using this holistic systems approach will better inform policy and management and minimize uncertainties into the future.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Box 1.

Remote Sensing Primer

Remote Sensing Primer: Broadly defined, remote sensing is the process of detecting and monitoring physical characteristics of the earth by measuring reflected and emitted radiation at a distance, typically from aircraft or satellites. The types of sensors used in mapping streams and wetlands include:

(1) *Active optical* sensors (e.g., use of laser emissions in light detection and ranging, LiDAR) that transmit pulses of visible or near-infrared (NIR) energy at ground targets to obtain information about their shapes and material properties. By precisely measuring the timing and intensity of those returns, detailed bare-earth elevation maps, vegetation heights, and numerous other LiDAR-derived products are created.

(2) *Passive optical* sensors that depend on natural solar radiation, which is absorbed and reflected differently by different surface features. Multispectral imagery typically includes sensors that capture a small number of bands (often 3–6) of electromagnetic waves reflecting from the earth's surface. These bands are usually within the visible spectrum of blue, green and red wavelengths but may also include infrared bands such as near-infrared (NIR) and shortwave infrared (SWIR) wavelengths. The inclusion of the NIR and SWIR wavelengths is extremely helpful in providing a strong contrast between water (IR absorbed) and vegetation (IR strongly reflected) and is used in helpful indices like the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI) (Lang et al. 2015). Hyperspectral imagery refers to numerous, narrow bands (100+) that encompass the electromagnetic spectrum from UV to infrared and provide a continuous spectral signature for each pixel. Few satellite hyperspectral platforms exist at moderate or fine resolution, limiting their applicability for mapping small aquatic features.

(3) *Active radar* sensors such as Synthetic Aperture Radar (SAR) that illuminate the ground with radio frequency waves (typically in the microwave bands: C, L, and X) and can function at night and penetrate clouds and some vegetative cover. SAR sensors measure the intensity and polarization of the microwave returns to detect physical properties of water, soil, and vegetation. Open, smooth water reflects the waves away from the sensor (diffuse reflection or "specular scatter") creating weak to no returns over open water. Vegetation with water below creates a "double-bounce" return making the signal distinct from those vegetated areas with no water below which produces backscatter in multiple directions or "volume scatter". Most current sensors have both horizontal (H) and vertical (V) polarizations and the intensity return of horizonal (HH) or vertical (VV) or a switch in polarization (HV or VH) can be diagnostic in determining structure (Bourgeau-Chavez et al. 2009).

Sources of remotely sensed imagery are characterized by their spatial resolution, temporal resolution (revisit period), and receiving bands which in the case of optical sensors, influence spectral resolution (Table 5). While single platform approaches rely on only one sensor to identify surface waters, current research demonstrates that *multi-source remote sensing* approaches that use imagery from multiple sensors, often in combination with ancillary data, can improve the detection and classification of small or variable surface water features (e.g., Kloiber et al. 2015; Judah and Hu 2019; Amani et al. 2020; Mahdianpari et al. 2020a; Battaglia et al. 2021).

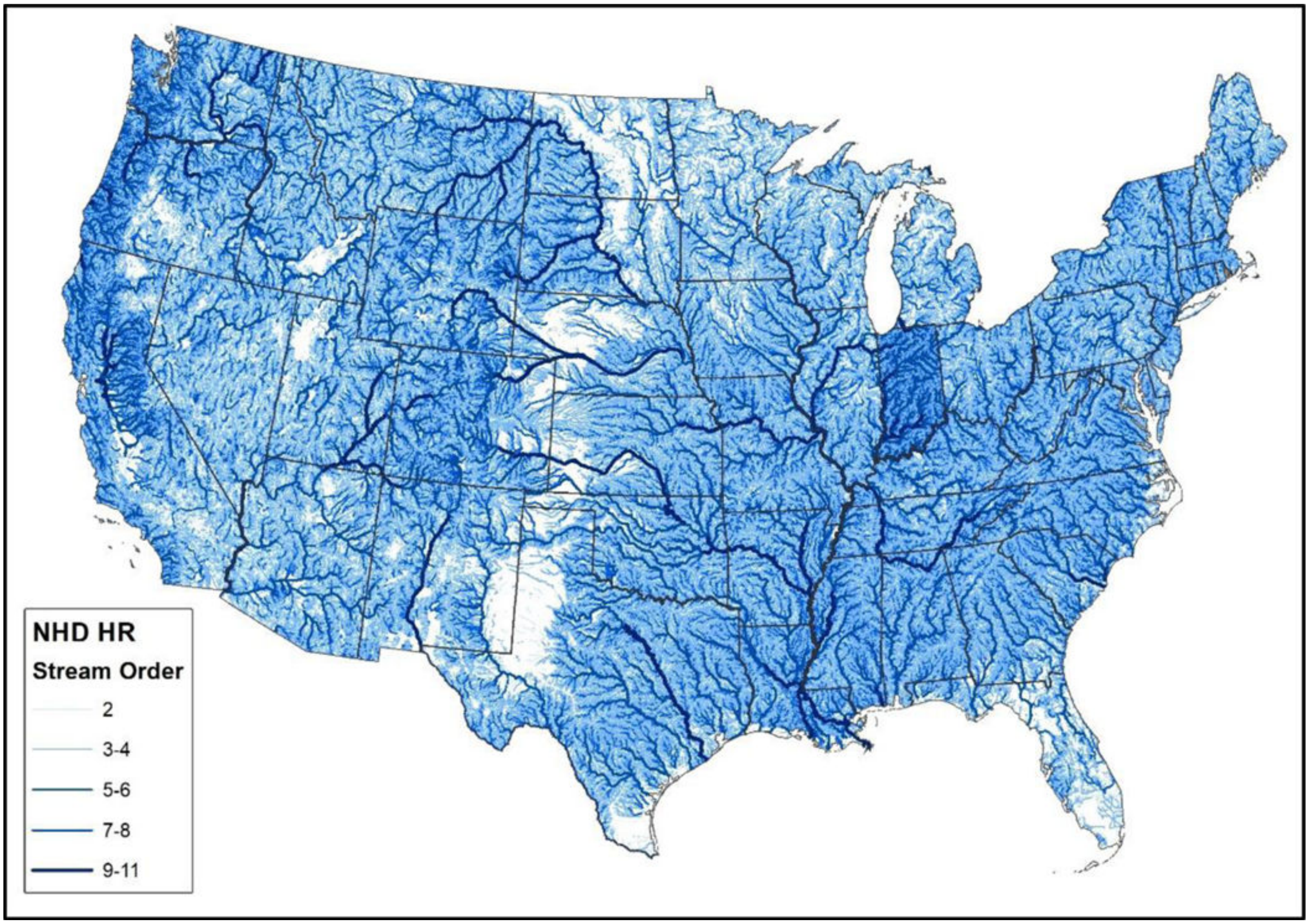

Figure 1.
Depiction of National Hydrography Dataset (NHD) High Resolution (HR) for the CONUS by stream order. Note that stream order 1 has been removed from the image to allow for the visualization of the remaining orders. Darker shades of blue indicate high stream orders (i.e., larger streams/rivers). The variability of stream densities due to geophysical properties (e.g., West Texas) or cartographic decisions (e.g,. Indiana) is visible. Due to scale, streams appear to cover much of the CONUS, please refer to figure 4 for local scale depictions of the NHD HR.

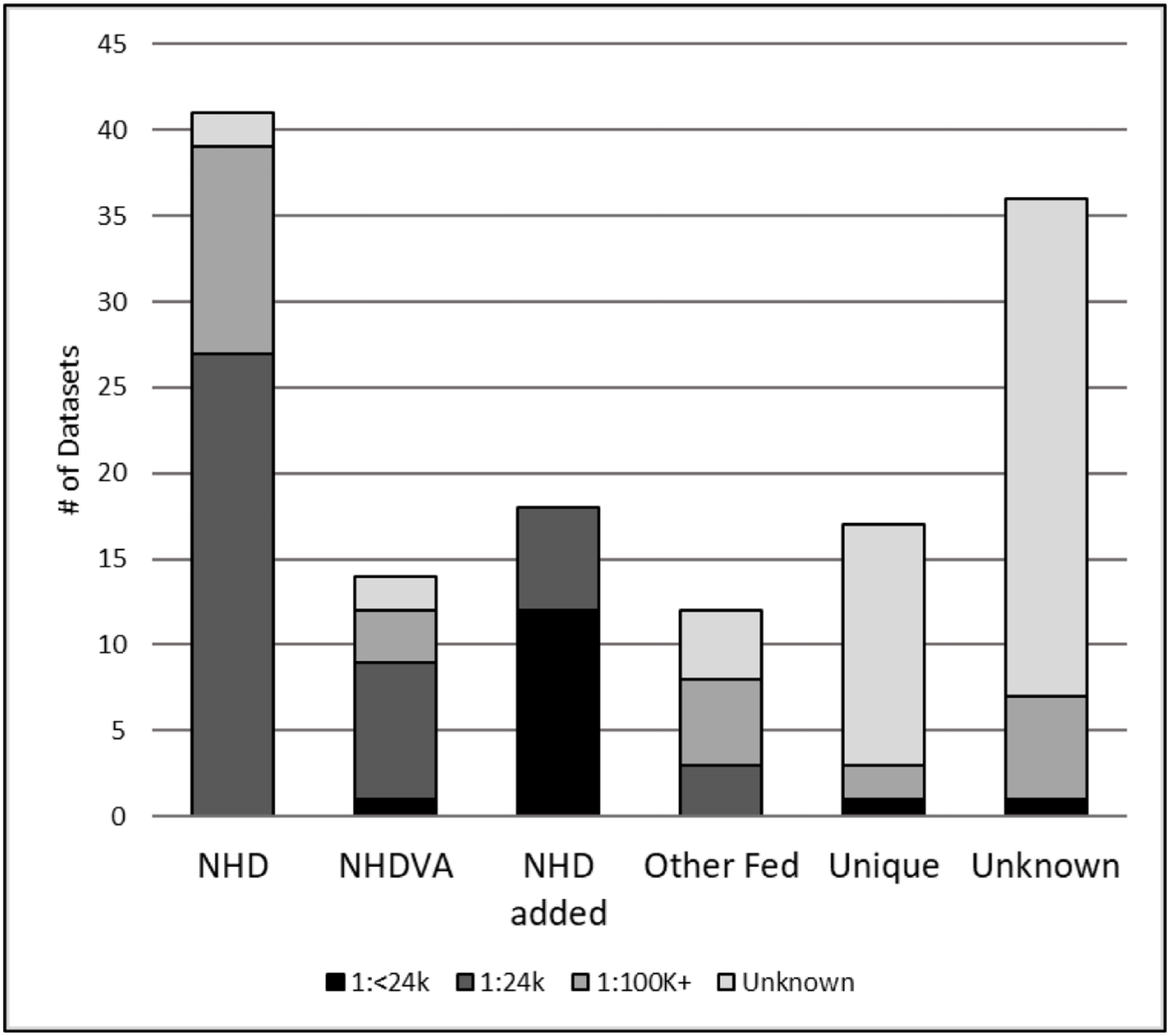

Figure 2.

Number of US state-level datasets found according to their source data and stated resolution. NHD – National Hydrography Dataset; NHDVA – National Hydrography Dataset with value added attributes; NHD added – National Hydrography Dataset with state-derived stream additions; Other Fed – includes EPA reach files, US Census TIGER (Topologically Integrated Geographic Encoding and Referencing), and National Scenic Rivers data. See SI Table 1 for the underlying datasets.

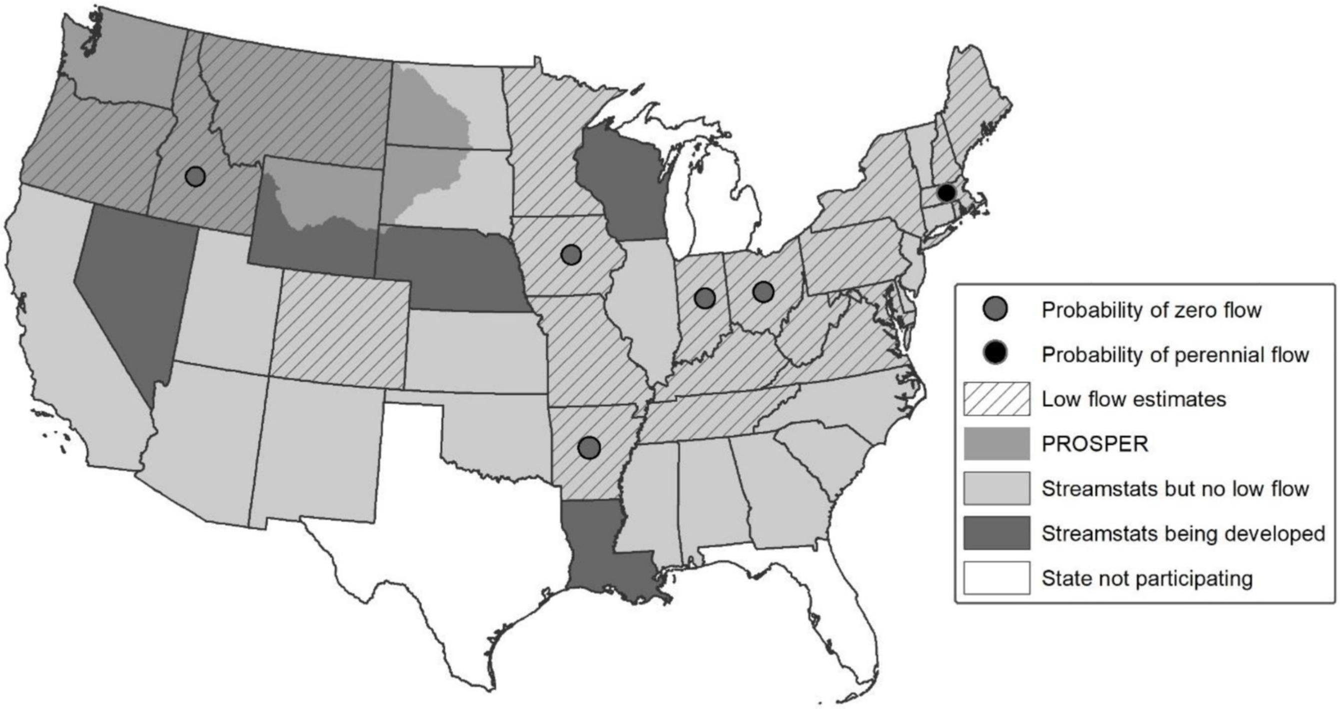

Figure 3.
State participation in USGS StreamStats identifying those states that have low flow estimations, probabilities of zero flow or perennial flow, estimates from the PROSPER model, or other StreamStats information (e.g., peak streamflow). See SI Table 2 for state specific flow metrics. Current as of March 2022.

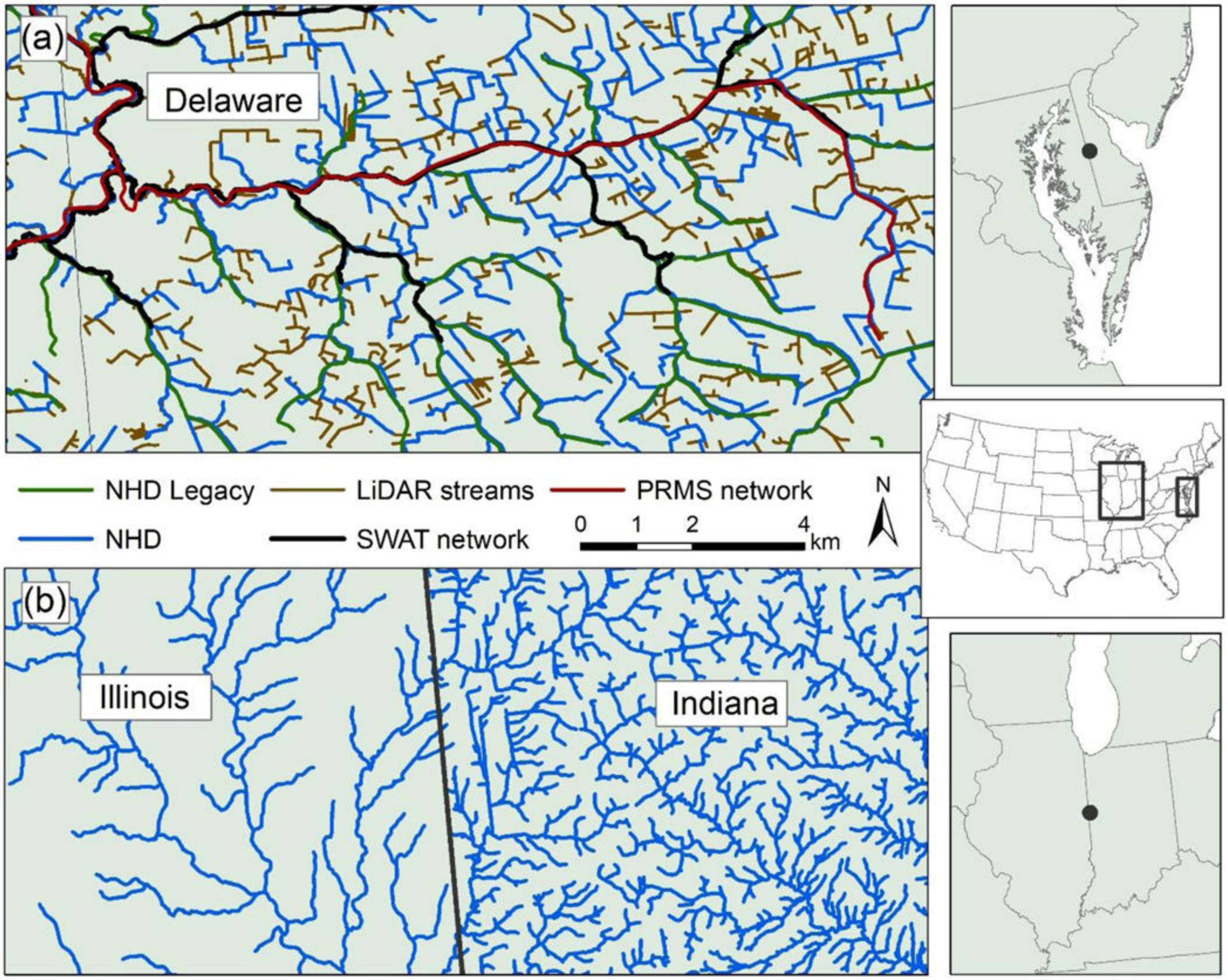

Figure 4.

A) Comparison of a LiDAR-derived stream network, NHD (1:24,000 or better resolution), NHD legacy (1:100,000), and stream segments for a local (SWAT; Evenson et al. 2018) and a national scale hydrology model (PRMS; Regan et al. 2018) in the Choptank catchment of Maryland and Delaware. B) Comparison of NHD 1:24,000 or better resolution along the Illinois-Indiana border to demonstrate the shift of stream density between the two states.

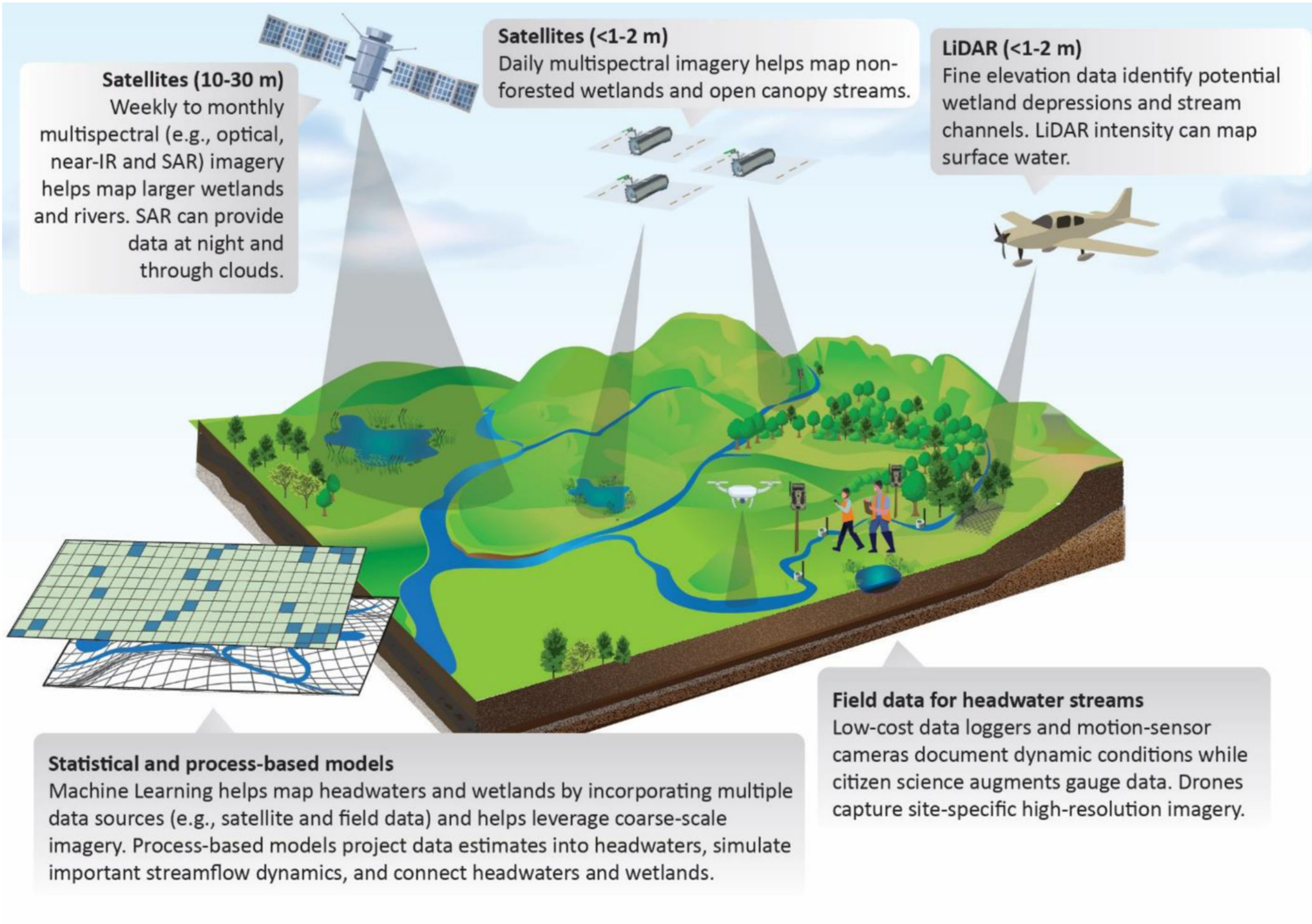

Figure 5.

Conceptual diagram of various emerging approaches to aid in the mapping of headwaters and wetlands.

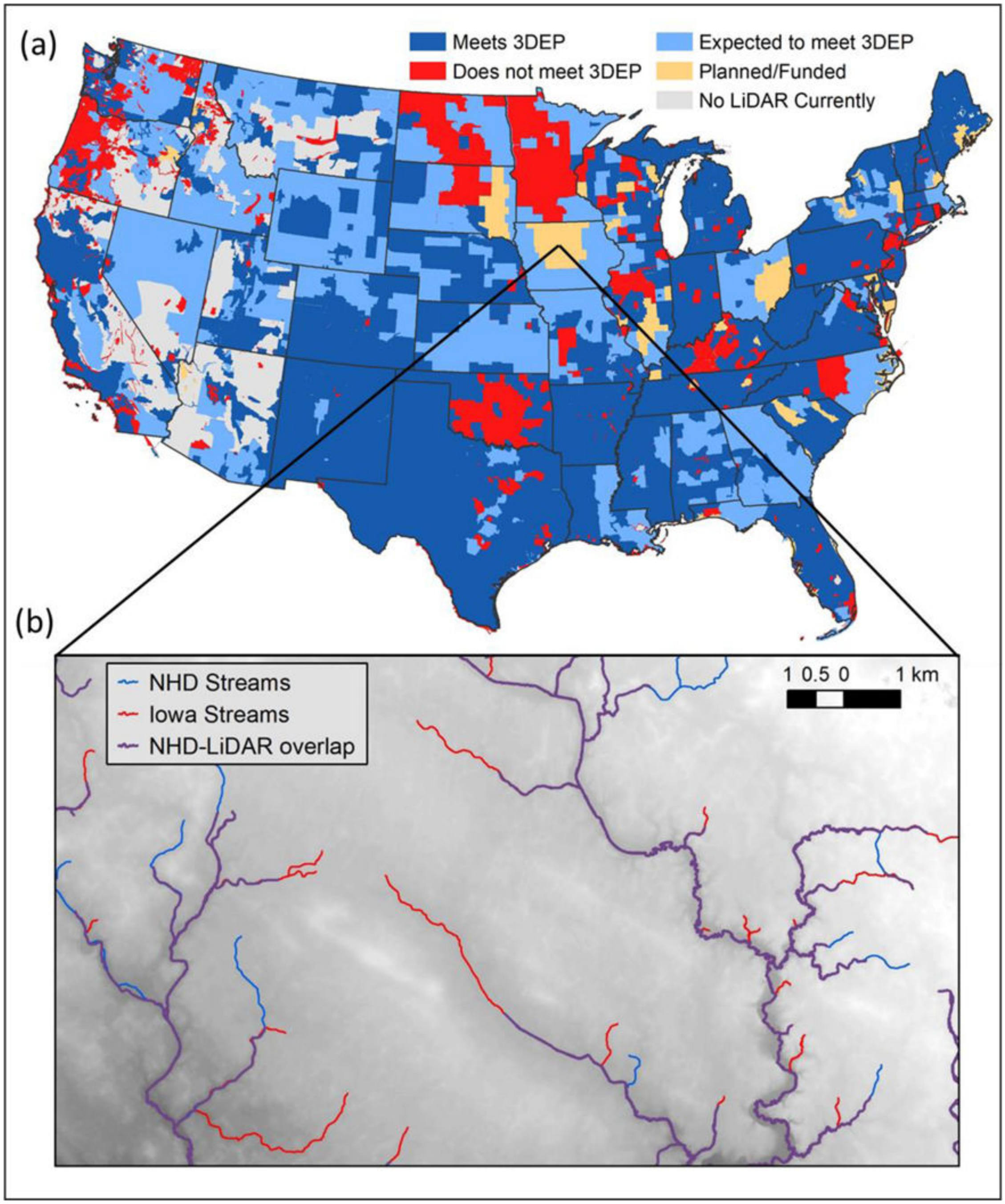

Figure 6.

a) Current LiDAR coverage within the US Interagency Elevation Inventory as of February 2022 showing datasets that meet, are expected to meet, or are planned for the USGS 3D Elevation Program (3DEP), and LiDAR of unknown quality or at lower resolutions that will not be included in 3DEP. b) Example of the Iowa stream layer in Story County, Iowa showing the overlap of the Iowa stream layer and the NHD. The layer is derived from previous 3 m LiDAR DEMs (in grey), a 9.7 ha flow accumulation threshold and 1 m imagery, which allows for the creation of a more consistent and repeatable workflow when mapping stream networks. The NHD streams are at 1:24,000 resolution.

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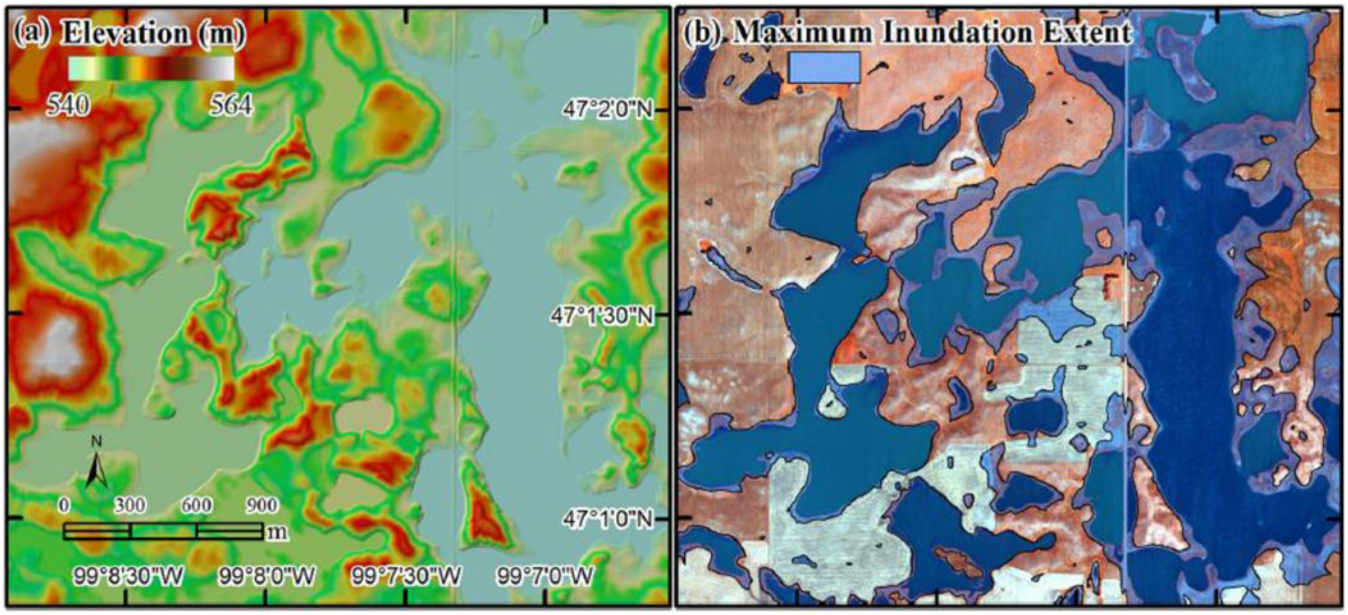

Figure 7.
An example of LiDAR-derived surface depressions for an area of the Prairie Pothole Region in North Dakota. The image shows an elevation relief map from 1 m LiDAR data (a) and the maximum inundation extent for potholes derived from the 1 m LiDAR data. The maximum extent is overlaid on a 1 m National Agricultural Imagery Program (NAIP) imagery from September 2015 to show the extent of surface waters to compare actual and maximum extents. Reprinted from Remote Sensing of Environment, vol 228, Wu et al. *Integrating LiDAR data and multi-temporal aerial imagery to map wetland inundation dynamics using Google Earth Engine*. July 2019, p1–13. with permission from Elsevier.

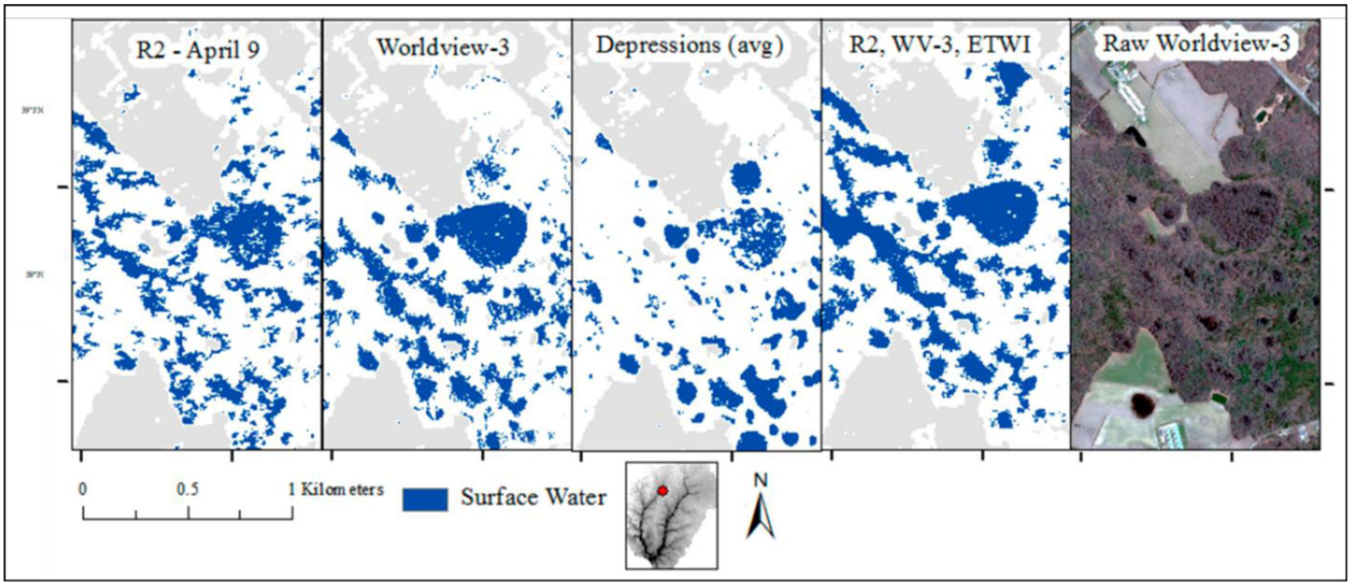

Figure 8.

Derived from Figure 6 of Vanderhoof et al. (2017a). An example of mapping forested surface waters in the Delmarva Peninsula, Maryland/Delaware USA, using a Radarsat-2 (R2) image, a Worldview-3 (WV3) image, and the combination of R2, WV3 and a relief-enhanced topographic wetness index (ETWI) based on LiDAR (3m) to highlight depressions on the landscape. All three inputs were placed within a Random Forest model for surface water classification and filtered by a LiDAR-derived depression layer to achieve overall accuracy of 94%. Copyright 2017 Digital Globe. Next View License. Used with permission.

Table 1.

Search terms used to look in federal and state websites for relevant stream and wetland datasets.

Level:	Search Terms used:
Federal	stream, wetland, river, GIS, channel head, channel origin, tributary, ditch, drainage ditch extent
State	remote sensing, river, waterway, stream, wetland, hydrology, GIS, Geographic Information System, geodatabase, database, channel head, channel origin, tributary, ditch, drainage ditch extent

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Table 2.

US National stream datasets identified during review. USGS National Hydrography current and legacy datasets found at https://www.usgs.gov/national-hydrography/nhdplus-high-resolution. NHDPlus dataset found at https://www.epa.gov/waterdata/nhdplus-national-hydrography-dataset-plus. National Waterway Network dataset found at https://geospatial-usace.opendata.arcgis.com/. Wild and Scenic Rivers dataset found at https://www.rivers.gov/mapping-gis.php.

National Stream Datasets	Resolution	Extent	Source
National Hydrography Dataset - Legacy (Medium Resolution)	1:100,000	CONUS, HI, partial AK	USGS National Hydrography
National Hydrography Dataset - Current (High Resolution)	1:24,000 min, 1:63,360 min Alaska	CONUS, HI, partial AK	USGS National Hydrography
National Hydrography Dataset Plus (NHDPlus)	1:100,000	CONUS, HI, partial AK	USEPA Water Data
National Hydrography Dataset Plus High Resolution (NDHPlus HR)	1:24,000 min, 1:63,360 min Alaska	CONUS, HI, partial AK	USGS National Hydrography
National Waterway Network	1:100,000	CONUS	USACE Digital Library
NLCS Wild and Scenic Rivers	1:24,000	Select rivers in 39 states	US Forest Service Geospatial Data Discovery

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Table 3.

US state-level datasets that modify stream network or duration class information beyond the National Hydrography Dataset (NHD). DEMs – Digital Elevation Models. USGS PROSPER – Probability of Streamflow Permanence model (Jaeger et al. 2019). See SI Table 1 for more details on NHD headwater extents and source links. See SI Table 3 for more details and available source links on state-level streamflow duration classes.

State Datasets that modify NHD headwater extent

State	Method	Resolution	Statewide?
California	Modified with aerial imagery	1:24000	No - ad-hoc additions
Massachusetts	Modified with aerial imagery	1:12000	Yes
Minnesota	Modified with aerial imagery	1:24000	No - ad-hoc additions
Rhode Island	Modified with aerial imagery	1:5000	Yes
Vermont	Modified with aerial imagery	1:5000	Yes
Washington	Modified with aerial imagery	1:24000	No - ad-hoc additions
West Virginia	Modified with aerial imagery	1:4800	Yes
Idaho	Modified with DEMs	1:24,000	Yes
Indiana	Modified with DEMs	2.4 Ha threshold	Yes
Iowa	Modified with DEMs	9.7 Ha threshold	Yes
North Carolina	Modified with DEMs	2.4 Ha threshold	No -western North Carolina
State Datasets that modify existing streamflow duration classes			
Vermont	Intermittent streams via landscape and soils regression	1:5000	No - 2 counties with no soils data excluded
Idaho	Perennial Streams via modeled flow threshold	1:24,000	Yes
Michigan	Non-perennial via base flow separation regression	1:24,000	Yes
Idaho	Probability classes of perennial flow (PROSPER)	1:100,000	Yes
Oregon	Probability classes of perennial flow (PROSPER)	1:100,000	Yes
Washington	Probability classes of perennial flow (PROSPER)	1:100,000	Yes
Montana	Probability classes of perennial flow (PROSPER)	1:100,000–1:24,000	Western Montana Eastern Montana
North Dakota	Probability classes of perennial flow (PROSPER)	1:24,000	No – Upper Missouri only
South Dakota	Probability classes of perennial flow (PROSPER)	1:24,000	No – Upper Missouri only
Wyoming	Probability classes of perennial flow (PROSPER)	1:24,000	No – Upper Missouri only

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Table 4.

Summary of US federal wetland datasets and state datasets that include additional information not found solely in the National Wetlands Inventory (NWI). NHD- National Hydrography Dataset, NLCD – National Land Cover Dataset, C-CAP – Coastal Change Analysis Program.

Federal Datasets	**resolution**	**Extent**	**Method**
NWI	1:12,000 to 1:80,000	CONUS, HI, partial AK	Aerial Imagery interpretation with limited field verification
NHD waterbodies	1:24,000	CONUS, HI, partial AK	Aerial Imagery interpretation with limited field verification
NLCD	30 m grid	All of US	Landsat imagery
C-CAP	30 m grid	Coastal CONUS, HI	Landsat imagery
C-CAP High Res	1-5 m grid	Limited projects	Aerial Imagery
GAP	30 m grid	CONUS	Landsat imagery
Dynamic Surface Water Extent	30 m grid	All of US	Landsat imagery – no wetland classification
State Datasets – modified NWI			
Delaware – wetlands	1:10,000	state-wide	updated imagery, enhanced with landform, water flow path, and other information.
Idaho – wetlands	1:24,000	specific projects	Includes NWI plus other landcover inputs for wetland prioritization, condition, and potential occurrence.
Idaho – Wetland Assessment Area	1:24,000	specific projects	Includes NWI in rapid assessment model assessing potential functions, values, and condition
Maine – Wetlands Characterization	1:24,000	state-wide	NWI wetlands characterized for six different wetland functions and values (floodflow alteration, sediment retention, finfish habitat, shellfish habitat, plant and animal habitat, and cultural value)
New Hampshire – Wetlands Base Map	Unknown	state-wide	NWI polygons dissolved to create unique wetland complexes to assess water quality
New Hampshire – NWI Plus	Unknown	state-wide	Adds a set of hydrogeomorphic-type descriptors to NWI for the prediction of wetland functions
North Carolina – NC CREWS	Unknown	Eastern Counties	Combines NWI, soils, and Landsat to determine probable wetland locations
South Carolina – NWI	1:24,000	state-wide	NWI with uplands added
Vermont – Significant Wetlands Inventory	1:24,000	state-wide	Adds class or protection information to NWI wetlands with some added wetlands
Vermont – Wetlands Advisory Layer	1:24,000	state-wide	Repurposed NWI with additions of class for state purposes
Washington – Forest Practices Wetlands	1:4,800+	state-wide	Reclassified NWI to classes to include hydric soils in forested regions
Unique State Datasets			
Alaska – Anchorage Watershed Management Wetland Mapping	1:100,000	Municipality of Anchorage	Methodology unknown
Boulder, Colorado Wetlands	Unknown	Boulder, Colorado	Wetland locations and boundaries within the City of Boulder based on field visits to each site.
Kansas – Playa wetlands	1:12,000	state-wide	Set criteria for playas of disconnection from streams and playa soils together with 1 m imagery
Arkansas – Potential	Unknown	Southeastern	Compilation of wetland coverages from 5 major
Natural Vegetations and Wetlands		Arkansas	projects

Federal Datasets	resolution	Extent	Method
Kansas – Potential Wetland Areas	1:24,000		Potential wetland identified using topographic tools
Wisconsin – Wetland Monitoring Layer Gallery	Unknown	state-wide	Aerial Imagery interpretation with limited field verification
Wisconsin Wetland Inventory	Unknown	state-wide	Aerial Imagery interpretation with limited field verification and reconfigured to be incorporated into the NWI

Table 5.

Common medium resolution (>10m) and high resolution (<10m) imagery used to identify stream and wetland systems and dynamics used across CONUS. Current as of March 2022, although new commercial satellite ventures are rapidly being added. NAIP - National Agricultural Imagery Program, NAPP- National Aerial Photography Program, Pan – panchromatic, CIR – color and infrared, B&W – black and white, NIR – near-infrared, SWIR – short-wave infrared.

Imagery Type	Platform	resolution (m)	Revisit period	Bands	data years	Availability
Aerial imagery	NAIP	0.5–2 m	1–3 years	3–4 True Color, CIR	2002-present	Public
	NAPP	1:40,000	var	B&W, CIR	1987–2007	Public
Multispectral satellite imagery						
Medium Res.	Landsat ETM†	15–30 m	16 days	8-Pan, Blue-SWIR	1999-present	Public
	Landsat 8 OLI	15–30 m	16 days	9-Pan, Coastal-SWIR	2013-present	Public
	Sentinel 2	10–20 m	5–10 days	12 - Coastal to SWIR	2015-present	Public
High Res	Rapid Eye	5 m	1–5 days	5-Blue-NIR	2008–2020	commercial*
	SPOT 6–7	1.5–6 m	task,	5-Pan, Blue-NIR	2012-present	commercial
	PlanetScope	3–5 m	<1 day	4-Blue-NIR	2015-present	commercial*
	Pleiades system	1–3 m	1 day	5-Pan, Blue-NIR	2012-present	commercial
	BlackSky	0.9–1.1 m	<1 day	4- Pan, Blue-Red	2018-present	commercial*
	IKONOS	0.8–3.2 m	3 days	5-Pan, Blue-NIR	1999–2015	commercial*
	Quickbird	0.7–2.4 m	1–4 days	5-Pan, Blue-NIR	2001–2014	commercial*
	Worldview 2	0.5–1.8 m	1–2 days	9-Pan, Blue-NIR	2009-present	commercial*
	GeoEye-1	0.5–1.7 m	2–8 days	5-Blue-NIR	2009-present	commercial*
	Worldview 3	0.3–1.3 m	1 day	17-Pan, Blue-NIR, SWIR	2014-present	commercial*
	Worldview 4	0.3–1.3 m	<1 day	5-Pan, Blue-NIR	2016–2019	commercial*
	Planet SkySat	0.5m	<1 day	5-Pan, Blue-NIR	2013-present	commercial*
Synthetic Aperture Radar (SAR)						
	Sentinel 1	5–40 m	6–12 days	C (VV-VH)	2014-present	Public
	RADARSAT-1	8–100 m	24 days	C (HH)	1995–2013	Public
	RADARSAT-2	3–300 m	24 days	C (Quad-Pol)†	2007-present	Public
	RADARSAT constellation	3–300 m	4 days	C (Quad-Pol)†	2019-present	Public
	PALSAR	10–100 m	46 days	L (HH-HV globally)^	2006–2011	Public
	TerraSAR-X	1–40 m	3–11 days	X (Quad-Pol)	2007-present	public-commercial‡

*Some government – commercial partnerships exist with access limited to one or more participating science agencies. Such licensing agreements and the imagery included in those agreements changes frequently.

†Resolution for Quad-Pol (HH+VV+HV+VH) is 9 m, all other combinations have 3–100 m depending on the swath mode

^Globally PALSAR collected various polarizations depending on the time of year and the region. See earth.esa.int for more info

‡Public-commercial designation for TerraSAR-X refers to the joint partnership of the platform. Scientific uses of the data require a submitted proposal by government agencies, in this case the German government.

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Table 6.

Highlighted examples of stream extent mapping at local spatial scales. NAIP - National Agricultural Imagery Program, UAV – Unmanned Aerial Vehicle.

Sensor/Platform	Application	Spatial scale	Methods	Citation
Worldview-2	Mapping glacial meltwater stream networks	Greenland, six test sites ranging from 1.7 to 9.3 km^2.	Use normalized difference index thresholds and shape analysis	Yang and Smith 2012
Worldview-2	Mapping surface water extent of headwater streams	Montana (US), four stream segments ranging from 0.8 to 3.8 km.	Use panchromatic brightness and object-based analysis	Vanderhoof and Burt 2018
NAIP – 1 m imagery	Mapping riparian vegetation in an arid watershed	Arizona (US), ~1.1 km of stream length	Normalized difference indices with thresholds	Manning et al. 2020
UAV – 0.02 m	Mapping intermittent streams within a wetland complex	Saskatchewan (Canada), streams and wetlands in a 0.09 km^2 area	Supervised classification of the UAV imagery	Spence and Mengistu 2016
Airborne 0.15 m imagery	Mapping ephemeral stream networks in an arid watershed	California (US), calibrated 600 m of stream, applied to 150 km^2 area	Vegetation and surface brightness and object-based analysis	Hamada et al. 2016

Table 7.

Highlighted examples of wetland extent mapping at local to regional spatial scales. NAIP - National Agricultural Imagery Program, DEM-Digital Elevation Model, UAV – Unmanned Aerial Vehicle, AOI- area of interest.

Sensor/Platform	Application	Spatial extent and scale	Methods	Citation
NAIP – 1 m imagery	Mapping depressional wetlands	Western Kansas (US), 46 counties minimal mapping unit of 0.03 ha	Manual delineation combined with DEM and soils data	Bowen et al. 2010
Airborne 0.5 m imagery – leaf off	Mapping depressional and forested wetlands	Minnesota (US), three watersheds ranging from 53 to 717 km^2. Minimum mapping unit of 0.2 ha	Automated delineation combined with LiDAR-derivatives and object-based analysis	Rampi et al. 2014b
UAV - 0.14 m	Mapping coastal wetland vegetation	Lake Erie, Ohio (US) 1.8 mk^2 AOI	Mid and later season imagery products within neural network model	Abeysinghe et al. 2019
Worldview-2	Mapping forested wetlands	Florida (US), 6500 km^2 watershed. 4 m resolution	Semi-automated processing of seasonal images using decision tree analysis	McCarthy et al. 2018
Sentinel-2	Mapping forested wetlands, bogs, and peatlands	Alberta (Canada), 13,700 km^2 AOI. 10 m resolution	Random Forest model combining Sentinel 1 and 2 and LiDAR indices	Hird et al. 2017
Landsat TM, ETM+, OLI	Mapping surface water fractions in wetlands	Saskatchewan (Canada), Delmarva Peninsula, MD (US) and Everglades, FL (US). 30 m resolution	Automated sub-pixel water fraction approach using Random Forest model	DeVries et al. 2017

Table 8.

Highlighted examples of wetland extent mapping at local to regional spatial scales using Synthetic Aperture Radar (SAR). AOI – Area of Interest, TSX – TerraSAR-X

Active radar sensors: Synthetic Aperture Radar				
Sensor/Platform	**Application**	**Spatial scale**	**Methods**	
Sentinel-1 C-band	Mapping a range of wetland types and complexes	Newfoundland (Canada) 3,500 km^2 AOI, 10 m resolution	Multi-temporal stack of SAR and Sentinel-2 imagery in deep learning models	Hosseiny et al. 2021
Radarsat-2 C-band	Mapping surface water and flooded vegetation	Lake Ontario (Canada), 1,872 km^2 AOI, 14 m resolution	Multi-temporal stack of SAR and fine DEMs in Random Forest models	Battaglia et al. 2021
PALSAR L-band	Mapping northern vegetated wetlands	Alaska (US), 590,000 km^2, 50 m resolution	SAR, slope, elevation and location within a Random Forest model	Clewley et al. 2015
TSX X-band	Mapping of surface waters	Ontario (Canada), 4 km^2 AOI	SAR, LiDAR derivatives, Worldview 2 classifications fused into decision tree	Irwin et al. 2017
Multi-SAR	Mapping forested wetlands	Newfoundland (Canada), 700 km^2 AOI; Canadian Wetland Inventory Map, 9.9 million km^2 AOI	RadarSat-2, PALSAR, TSX, and Rapid-Eye within an object based Random Forest model; Sentinel-1 and PALSAR-2 imagery with fine DEMs in Random Forest model	Mahdianpari et al. 2017; 2021