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Applications of Google Earth Engine in fluvial geomorphology for detecting river channel change

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Abstract

Cloud-based computing, access to big geospatial data, and virtualization, whereby users are freed from computational hardware and data management logistics, could revolutionize remote sensing applications in fluvial geomorphology. Analysis of multitemporal, multispectral satellite imagery has provided fundamental geomorphic insight into the planimetric form and dynamics of large river systems, but information derived from these applications has largely been used to test existing concepts in fluvial geomorphology, rather than for generating new concepts or theories. Traditional approaches (i.e., desktop computing) have restricted the spatial scales and temporal resolutions of planimetric river channel change analyses. Google Earth Engine (GEE), a cloud-based computing platform for planetary-scale geospatial analyses, offers the opportunity to relieve these spatiotemporal restrictions. We summarize the big geospatial data flows available to fluvial geomorphologists within the GEE data catalog, focus on approaches to look beyond mapping wet channel extents and instead map the wider riverscape (i.e., water, sediment, vegetation) and its dynamics, and explore the unprecedented spatiotemporal scales over which GEE analyses can be applied. We share a demonstration workflow to extract active river channel masks from a section of the Cagayan River (Luzon, Philippines) then quantify centerline migration rates from multitemporal data. By enabling fluvial geomorphologists to take their algorithms to petabytes worth of data, GEE is transformative in enabling deterministic science at scales defined by the user and determined by the phenomena of interest. Equally as important, GEE offers a mechanism for promoting a cultural shift toward open science, through the democratization of access and sharing of reproducible code.

This article is categorized under:

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KEYWORDS

cloud-based computing, multitemporal, planform analysis, remote sensing, river science

1 | INTRODUCTION

Remote sensing is transforming what we map, measure, and analyze in fluvial geomorphology (Marcus & Fonstad, 2010), helping transform the field from a data poor to a data-rich science (Church, 2010). River channel mapping and the analysis of planimetric change have long been key foci of fluvial geomorphology research (Gilvear & Bryant, 2016). The acquisition of satellite imagery at predictable time intervals is a major advantage for this purpose (Carbonneau & Piégay, 2012) and, for very large river systems, aerial or satellite remote systems can be the only way to observe and quantify planimetric morphology (Gilvear & Bryant, 2016). Sensor advances have refined spatial and temporal resolutions, increasing the analytical space within which remote sensing geomorphic analysis can be undertaken (Smith & Pain, 2009). With increased availability of remotely sensed data, the methods used in fluvial geomorphology applications are changing (Piégay, Kondolf, Minear, & Vaudor, 2015), allowing us to see temporal change at wider spatial scales. Furthermore, multispectral satellite imagery is being used to reveal fluvial dynamics and support bio-geomorphological applications in large rivers (Henshaw, Gurnell, Bertoldi, & Drake, 2013). However, information derived from these remote sensing applications has largely been used to test existing concepts in fluvial geomorphology, rather than for generating new concepts or theories (Piégay et al., 2020).

Multitemporal analysis of multispectral satellite imagery has provided fundamental geomorphic insights into fluvial systems across a range of settings (Table 1). Satellite imagery analysis has often been complemented by analyses of other data sets, including historical mapping, aerial photography, topography, and field survey (e.g., Surian et al., 2016). Combined, these data have improved the understanding of river planform classification, planform evolution, bar morphodynamics, and planimetric form/process interactions over various spatiotemporal scales (e.g., Dixon et al., 2018; A. Gupta et al., 2002; Thorne et al., 1993). However, analyses have often been restricted in their spatial scale (i.e., analysis scales <500 km), focused on single "case study" river systems, and the temporal resolution between discrete analyses has been limited to interannual to decadal timescales. A spatiotemporal limit has therefore been imposed on fluvial geomorphology analyses through traditional approaches (i.e., desktop computing).

Traditional approaches whereby remotely sensed data are downloaded and stored on personal devices, before analysis tasks can be undertaken, are time-consuming and inefficient when dealing with large data sets (Sudmanns et al., 2020). Commercial software and/or licences are often required as part of processing workflows, alongside considerable computational resources, especially for multitemporal analyses over large spatial areas. Furthermore, suboptimal satellite imagery (e.g., obstructions from cloud or vegetation cover) may prevent observation and limit geomorphic interpretation (Kondolf & Piégay, 2016). The above factors combine to pose considerable challenges and limit the scale of inquiry for multitemporal analyses of large river reaches.

Technological advances in digital infrastructure, increased computing power, and data storage capabilities have given rise to cloud-based computing platforms, providing on-demand access to high-performance computing facilities without the need to own and maintain physical hardware (Sudmanns et al., 2020). This could potentially revolutionize remote sensing applications in geomorphology. The platforms can support massive data storage, helping to resolve data intensity problems associated with the large volumes of Earth observation data (C. Yang et al., 2011). An example of such a platform is Google Earth Engine (GEE), a cloud-based computing platform, accessible through a web-based interface, for planetary-scale geospatial analysis (Gorelick et al., 2017). GEE holds a data catalog of publicly available freely accessible remotely sensed imagery (including Landsat and Sentinel collections), geospatial and other environmental data sets. The cloud-based computing platform aligns with the concept of virtualization, freeing users from resource management and concerns around their physical implementation (Lee, Gasster, Plaza, Chang, & Huang, 2011), meaning that users can bring their own algorithms to the data (Wulder & Coops, 2014). Virtualization allows users to interact with Earth observation data without investing in computing and data management infrastructure (Giuliani, Chatenoux, Piller, Moser, & Lacroix, 2020), removing logistical and know-how constraints from resource-poor researchers (Mutanga & Kumar, 2019). As such, cloud-based computing platforms have been described as a democratizing force (Sultan, 2013), especially as more platforms become available in the future. A key distinction is made here between Google Earth, a virtual globe for viewing digital imagery of the Earth's surface (Tooth, 2013) and GEE, a planetary-scale platform for analyzing geospatial information (Google, 2020). GEE is not the only cloud-based computing platform available, Earth on Amazon Web Services also provides on-demand cloud-based computing resources, though the registry of Earth observation and geospatial data is currently (in 2020) smaller than that of GEE.

To date, there has been only a limited uptake of GEE in fluvial geomorphology compared with similar data-intensive environmental-facing disciplines. In meta-analysis of 300 peer-reviewed journal articles from 2011 to 2017 that contained the term "Google Earth Engine" or "GEE", Kumar and Mutanga (2018) reported that only 4% were

TABLE 1 Fundamental fluvial geomorphic insights gained from multitemporal, multispectral satellite imagery analyses of river channel change

Study area	Remotely sensed products used	Analysis scale	Temporal range	Temporal resolution	Fundamental insight	References
Manu, Ucayili, Marañón, and Amazon Rivers (Peru)	Aerial photographs and Landsat satellite imagery	~100 km	1979–1983	Interannual (1976, 1979, and 1983)	Quantification of average lateral channel erosion rates	Puhakka, Kalliola, Rajasilta, and Salo (1992) and Salo et al. (1986)
Brahmaputra River (Bangladesh)	Landsat and SPOT satellite imagery	220 km	1973–1991	Interannual to decadal (mainly 1988 and 1989)	Planform evolution and bar morphodynamics	Thorne, Russell, and Alam (1993)
Mekong River (Laos)	SPOT satellite imagery	Not specified (4 SPOT scenes)	1996–1999	Interannual (1996, 1997, and 1999)	Planform classification and evolution	A. Gupta, Hock, Xiaojing, and Ping (2002)
Araguaia River (Brazil)	Aerial photographs and Landsat satellite imagery	570 km	1965–1998	Decadal (1965, 1975, and 1998)	Detailed geomorphological mapping and sediment budgeting	Latrubesse, Amsler, de Morais, and Aquino (2009)
Taquari River (Brazil)	Landsat satellite imagery	250 km	1985–2009	Intraannual (99 images in 24 years)	Avulsion dynamics	Buehler, Weissmann, Scuderi, and Hartley (2011)
Ganges-Padma River (Bangladesh)	Landsat satellite imagery	314 km	1973–2011	Interannual (8 epochs in 38 years)	Planform evolution (correlated with annual average discharge)	Dewan et al. (2017)
Various large river confluences	Landsat satellite imagery	Not specified	1972–2014	Interannual to decadal (e.g., 7 epochs in ~40 years)	Large river confluence dynamics and conceptual classification	Dixon et al. (2018)
Po di Pila mouths, Po River delta (Italy)	Landsat and Sentinel satellite imagery	<10 km	1972–2017	Landsat = interannual to decadal Sentinel = intraannual	Delta progradation processes	Ninfo, Ciavola, and Billi (2018)
Sittang River Estuary (Myanmar)	Landsat satellite imagery	80 km	1987–2017	Annual	Cyclic channel migration in estuary evolution	Shimozono, Tajima, Akamatsu, Matsuba, and Kawasaki (2019)
Amazon Basin (South America)	Landsat satellite imagery	4,000 km	1987–2017	Various: > decadal for slowest migrating rivers, 30 years	Meander dynamics for 1,600 bends[a]	Sylvester, Durkin, and Covault (2019)
Xiaolangdi Dam, Yellow River (China)	Landsat satellite imagery	860 km	1987–2017	Interannual (8 epochs in 30 years)	Morphodynamics impacted by dam-induced changes	Kong, Latrubesse, Miao, and Zhou (2020)

Note: The examples listed use traditional, desktop computing-based approaches for remote sensing analysis, unless otherwise specified.

[a]Applied a quasi-automated Python workflow based on RivaMap (Isikdogan, Bovik, & Passalacqua, 2017).

categorized as geoscience contributions. In other disciplines, GEE has been leveraged for global analyses, including terrestrial and mangrove forest inventories and change detection (Hansen et al., 2013; Thomas et al., 2017); surface water occurrence mapping (Donchyts et al., 2016; Pekel, Cottam, Gorelick, & Belward, 2016); coastal erosion and accretion estimates (Mentaschi, Vousdoukas, Pekel, Voukouvalas, & Feyen, 2018); tidal flat distributions (Murray et al., 2019); and delta morphologies (Nienhuis et al., 2020). For smaller areas, multitemporal analyses of morphological change in river and tidal zones (Khoi et al., 2020), semiautomated landslide detection from time series (Deijns et al., 2020) and the mapping of sediment transport regimes in arid and semiarid landscapes (Olen & Bookhagen, 2020) have been successfully demonstrated. Drawing parallels with the perspective of Millington and Townshend (1987), who argued that early applications of satellite remote sensing in geomorphology lagged behind those of most other disciplines (including geology and ecologically based subjects), we suggest a similar situation has arisen for applications of GEE in fluvial geomorphology.

In this paper, we review applications of GEE in fluvial geomorphology, with a specific focus on multitemporal analyses that leverage data from medium resolution, multispectral satellite imagery, and apply pixel-based approaches to assess planimetric river channel change. We describe the flows of big geospatial data that are openly accessible to fluvial geomorphologists, explore the opportunities to look beyond the water toward the wider dynamics of fluvial systems and critically examine the implications for geomorphic theory. Aiming to raise awareness of the platform to a wider audience, we review recent fluvial geomorphology GEE applications and comment on common themes relevant to future planimetric river channel change studies. By taking a 20 km reach of the Cagayan River (Luzon, Philippines), we illustrate some strengths of GEE for spatiotemporal active river channel change analysis through a demonstration workflow. Finally, we offer our perspective on some of the potential applications of GEE for (a) river channel change analyses and (b) fluvial geomorphology more widely, before discussing opportunities and future challenges.

2 | BIG GEOSPATIAL DATA FLOWS

The GEE data catalog is an online repository of publicly available geospatial data. Included are analysis-ready observations from satellite and aerial imaging systems, environmental variables, climate, land cover, topographic and socioeconomic data sets (Gorelick et al., 2017). The repository contains more than 600 data sets equating to ∼29 petabytes of data (Ilyushchenko & O'Neill, 2019) and includes observations from over 30 satellites/instruments (Herwig, 2018). As an example, three available GEE data catalog products are shown for the Cagayan-Ilagan River confluence (Luzon, Philippines), all data were acquired within ±4 days in February 2019 (Figure 1). The properties of these remotely sensed products are reported in Table 2.

Multitemporal, multispectral satellite observations from the Landsat program and Sentinel constellation are particularly useful in fluvial geomorphology. With data available from the 1970s onward, Landsat imagery (Figure 1a) is a significant resource because of the archive length and repeat coverage for monitoring (Smith & Pain, 2009). An open data policy was adopted by the Landsat program in 2008, facilitating accelerated uptake and increased interdisciplinary breadth of applications (Wulder, Masek, Cohen, Loveland, & Woodcock, 2012). Sentinel-2 imagery offers finer temporal resolution and higher spatial resolution than Landsat imagery (Figure 1b), which can allow for almost continuous monitoring of geomorphological evolution (Ninfo et al., 2018). However, Sentinel-2 imagery is only available from 2015. In terms of data volume, the Landsat program provides ∼0.5 TB of data per day (Baumann et al., 2016), while Sentinel constellations provide ∼20 TB of data per day (Esch et al., 2018). These data are updated automatically within the GEE data catalog, with a typical latency of ∼24 hr from scene acquisition (Gorelick et al., 2017). With multiple Landsat and Sentinel-2 satellites currently in orbit, observations can be acquired every few days for most parts of the world (Li & Roy, 2017).

A key feature of both Landsat and Sentinel data is the availability of multispectral bands (e.g., near-infrared and short-wave infrared). Spectral bands can be combined to calculate multispectral indices, useful for indicating the relative abundance of features of interest (e.g., vegetation and water). Frequently used multispectral indices include the normalized difference vegetation index (NDVI; Rouse, Haas, Schell, & Deering, 1973), the enhanced vegetation index (EVI; Huete et al., 2002), the normalized difference water index (NDWI; McFeeters, 1996), and the modified normalized difference water index (MNDWI; Xu, 2006). Different multispectral indices can therefore support highly differentiated fluvial geomorphology applications (Spada, Molinari, Bertoldi, Vitti, & Zolezzi, 2018).

Further data sets available through the GEE data catalog include Sentinel-1 Synthetic Aperture Radar (SAR) and Shuttle Radar Topography Mission (SRTM) data. SAR data (Figure 1c) have been used as an alternative to optical
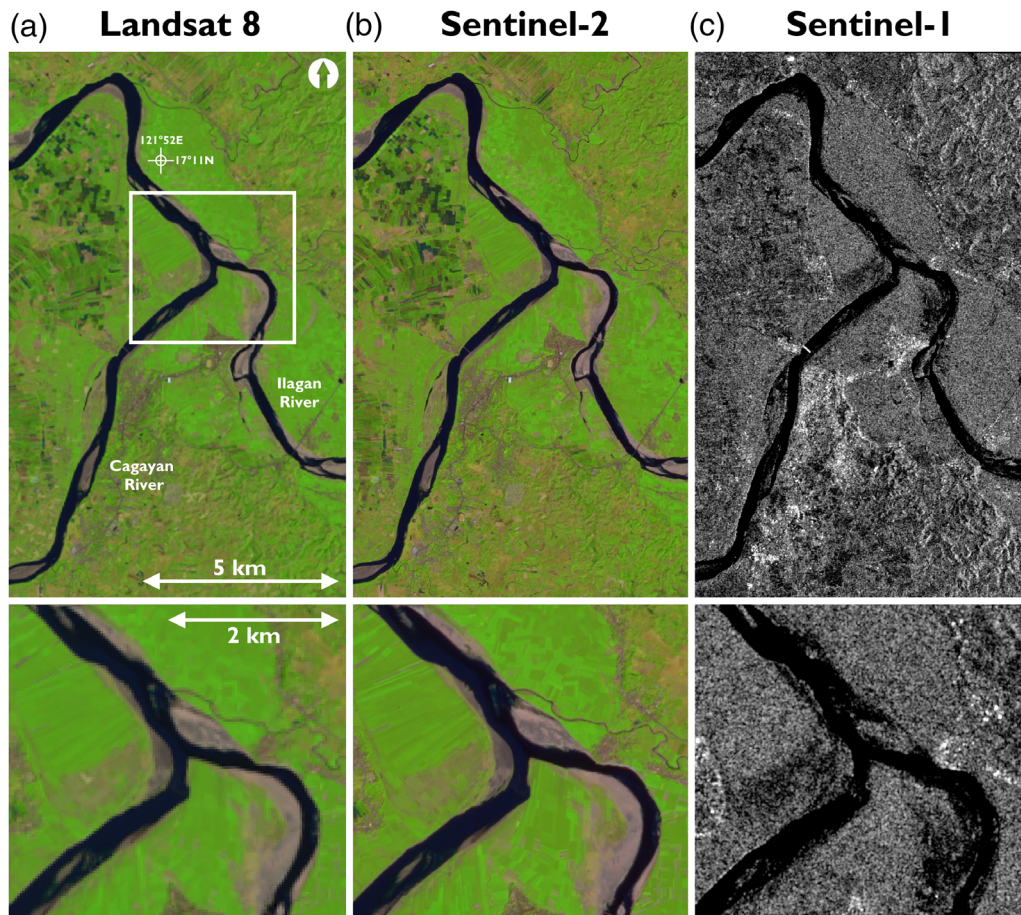
FIGURE 1 Example of three available Google Earth Engine (GEE) data catalog products for the Cagayan-Ilagan River confluence (Luzon, Philippines; 17°11′37.4″N, 121°52′32.2″E), all acquired within ±4 days in February 2019: (a) false-color Landsat 8 imagery (bands B6, B5, B4), (b) false-color Sentinel-2 imagery (bands B11, B8, B4), and (c) Sentinel-1 SAR ground range detected (GRD): C-band (VV polarization). Flow direction is from south to north

TABLE 2 Properties of some available data sets relevant to fluvial geomorphology applications in the Google Earth Engine data catalog (adapted from Gorelick et al. 2017)

Data set	Spatial resolution	Temporal revisit	Temporal archive	Spatial coverage
Landsat				
Landsat 1–5 MSS	60 m	16–18 days	1972–2012	Global
Landsat 5 TM	30 m	16 days	1984–2012	Global
Landsat 7 ETM +	30 m	16 days	1999–now	Global
Landsat 8 OLI/TIRS	30 m	16 days	2013–now	Global
Sentinel				
Sentinel-1 SAR GRD	10 m	12 days[a]	2014–now	Global
Sentinel-2 MSI	10/20 m	10 day[a]	2015–now	Global
Topography				
Shuttle Radar Topography Mission	30 m	Single	2000	60°N–54°S

Abbreviations: ETM, enhanced thematic mapper; GRD, ground range detected; MSI, multispectral instrument; MSS, multispectral scanner system; OLI, operational land imager; SAR, synthetic aperture radar; TIRS, thermal infrared sensor; TM, thematic mapper.

[a]Temporal revisit times shown are for a single satellite, taking both Sentinel constellations together, the temporal revisit time is reduced to 6 and 5 days for Sentinel-1 and Sentinel-2 (although this varies across the globe).

imagery for mapping flood extents over large areas (Bizzi, Demarchi, Grabowski, Weissteiner, & Van de Bund, 2016; Clement, Kilsby, & Moore, 2018) and for river network delineation in data-sparse regions (Obida, Blackburn, Whyatt, & Semple, 2019). The opportunity to bring algorithms to multiple data sets enables data integration in a common space, including merging optical satellite imagery with SAR data for improved surface water mapping (Coltin, McMichael, Smith, & Fong, 2016; Markert, Chishtie, Anderson, Saah, & Griffin, 2018), which has led to advances in the near real-time monitoring of floods (DeVries et al., 2020). In addition to merging data sets, users have the ability to upload their own georeferenced data sets to GEE. Wu et al. (2019) demonstrate this functionality by integrating multitemporal National Agriculture Imagery Program aerial imagery (available within the GEE data catalog) with 1-m resolution LiDAR data that were obtained externally, improving wetland inundation dynamics mapping. The opportunities for integrating, merging, and uploading data sets widen the applicability of GEE in fluvial geomorphology applications, especially as new data sets become available.
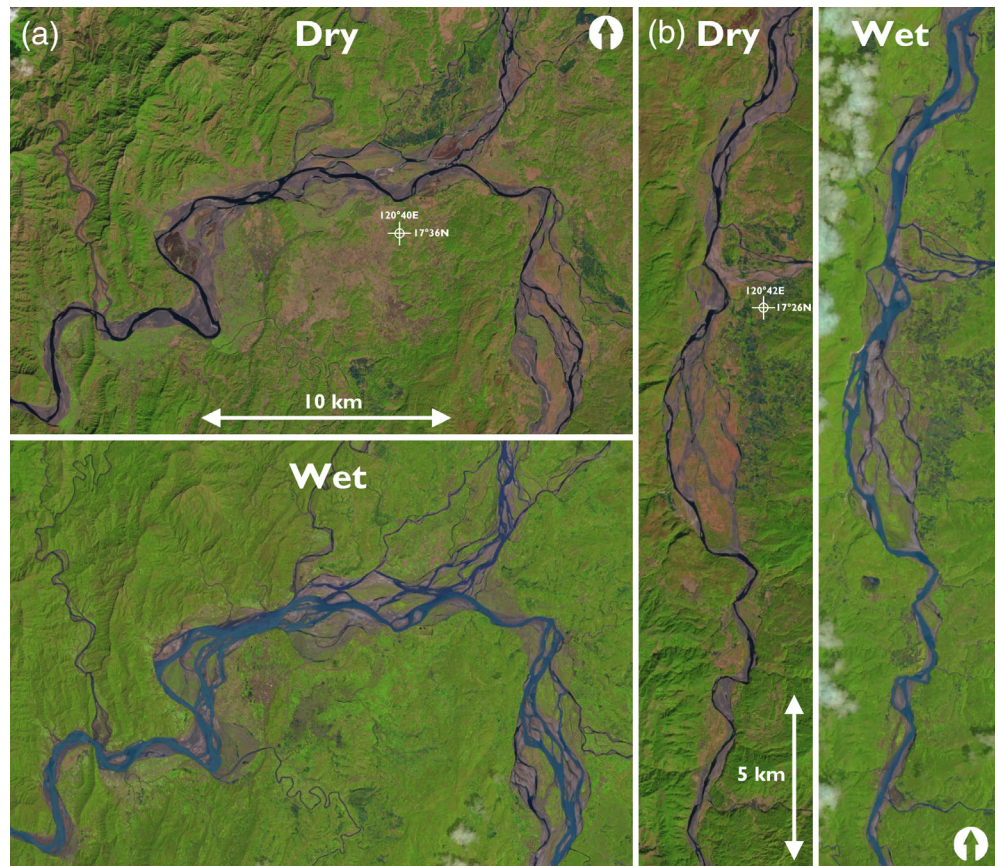
3 | LOOKING BEYOND THE WATER

It is important to acknowledge that river systems encompass more than just the surface water. The wider definition of a river system has been expressed in several ways, including the ecologically facing spatially continuous riverscape concept (Fausch, Torgersen, Baxter, & Li, 2002) which identifies patches, interfaces, mosaics, and regions (Carbonneau, Fonstad, Marcus, & Dugdale, 2012), through to the definition of the river corridor as an inseparable unit consisting of river channels, fluvial deposits, riparian zones, and floodplains (Harvey & Gooseff, 2015). Within the river corridor perspective, river channels are integrally connected to adjacent surfaces and subsurface areas (Wohl, 2014). Dynamic zones have been defined across the river corridor, each dominated by different hydrogeomorphological processes and characteristics (Gurnell, Corenblit, et al., 2016) and the spatial envelopes of these zones have fuzzy and temporally dynamic edges (Gurnell, Bertoldi, Tockner, Wharton, & Zolezzi, 2016).

Surface water extent mapping is a popular way to derive an understanding of morphological evolution in rivers. GEE has been used for the mapping, and derived change detection, of surface waters from the Landsat data archive using multispectral indices. This approach includes regional- to planetary-scale analyses of the changes in water and land occurrence (Donchyts et al., 2016) and the spatiotemporal variability of surface water dynamics over months, years, and decades (Pekel et al., 2016; Pickens et al., 2020; Zou et al., 2018). At the catchment scale, analyses have determined annual maximal and minimal surface water spatial extents (Wang, Jia, Chen, & Wang, 2018) and defined permanent and seasonal water bodies (Deng, Jiang, Tang, Ling, & Wu, 2019). Contemporary analyses have been benchmarked against the Global River Widths from Landsat (GRWL) database (Allen & Pavelsky, 2018). However, the wetted part of a channel is temporally variable and depends on stage, as shown for the Abra River (Luzon, Philippines), where the position, number, and width of active wetted channels vary between dry and wet season satellite imagery (Figure 2). Variation in river stage can be significant for determining planform configuration (Welber, Bertoldi, & Tubino, 2012) and consideration of only the wetted channel would influence the geomorphic interpretation (e.g., river channel pattern classification). Although long-term aggregations of Landsat data capture a wide range of flow conditions in the Earth's large rivers, minimum and maximum flow conditions are not recorded in most locations (Allen et al., 2020). Recognizing that river systems are more than just the wetted channel extent, and appreciating the temporal variation in river stage, consideration for how we analyze the relationships between variables that impact river morphology at river corridor scales is essential for remote sensing studies of planimetric change.

As an alternative to the stage-dependent surface water extent, bankfull channel extents can be used to identify the physical boundaries of the river channel (Rowland et al., 2016; Schumann, Bates, Horritt, Matgen, & Pappenberger, 2009). The bankfull channel extent captures more units of the riverscape, particularly important for systems with dynamic sediment bars and vegetated islands. However, there are various concepts and definitions for bankfull (Williams, 1978), with strategies for delineating the bankfull channel including the classification of open water and nonvegetated alluvial surfaces from optical and multispectral remotely sensed products (Gurnell, 1997; Winterbottom & Gilvear, 1997), or the extraction of bankfull and floodplain geometries from topographic data (Dodov & Foufoula-Georgiou, 2006). Given the broadening views of the river corridor beyond the channel margin (Harvey & Gooseff, 2015) and the capacity for GEE to provide unprecedented information on land-surface changes (Entwistle, Heritage, & Milan, 2018), the opportunity now exists to look beyond the water and capture the wider dynamics of fluvial systems. Given the computational strengths and availability of big geospatial data in GEE, practical and transferable definitions of the bankfull channel extent can be developed to investigate river channel change. By

FIGURE 2 Sensitivity of planimetric interpretations with changes in river stage for the Abra River (Luzon, Philippines). False-color Sentinel-2 imagery (bands B11, B8, B4) acquired January 06, 2018 (dry season) and September 18, 2018 (wet season) for the Abra River between (a) Bucay and Carsuan (17°36′22.9″N, 120°40′12.1″E) and (b) Luba and Bucay (17°26′35.0″N, 120°42′47.3″E). Flow direction is east to west in (a) and south to north in (b)

extending analyses beyond the surface water, this potentially allows for the investigation of river evolution over a more geodiverse range of morphologies, expanding analysis opportunities across different geomorphic settings and climatic regions.

4 | THINKING FAST AND SLOW

One of the key limitations of traditional remote sensing applications for planform channel change has been the temporal resolution of analyses. Using traditional approaches (Table 1), multitemporal analysis has often been limited to interannual or decadal epochs, with geomorphic characteristics compared over time intervals of several years. Here it is important to consider what could be absent from these "snapshots" or "endpoints," which can reveal gross change in river planform and time-averaged lateral erosion rates, but mask compensatory changes in the intervening period (Boruah, Gilvear, Hunter, & Sharma, 2008; Kondolf & Piégay, 2016). Information on the temporal continuity or discontinuity of the system is missing (Koohafkan & Gibson, 2018). The issue is further complicated where features of interest typically have amorphous boundaries in space and time (Karpatne, Ebert-Uphoff, Ravela, Babaie, & Kumar, 2019), with fluvial systems adjusting to reflect the complex interplay of nonstationary anthropogenic, sediment, and climatic influences (Slater, Khouakhi, & Wilby, 2019). For snapshot analyses, the temporal resolution should be appropriate to the geomorphic processes of interest (i.e., the amount of change being detected) and the overall trajectory of the system (Grabowski, Surian, & Gurnell, 2014). However, awareness of timescale dependence in process rate estimations is also needed. Short-term average process rates can substantially and systematically exceed longer-term average process rates for the same system (Brunsden, 1990; Sadler, 1981; Sadler & Jerolmack, 2015; Straub, Duller, Foreman, & Hajek, 2020). Short time intervals are necessary to capture the episodic nature of channel migration and response, whereas migration rates estimated over longer time intervals may include both periods without channel change (hiatuses) and periods of reversed direction of movement, meaning that migration rates systematically decrease when averaged over longer timescales (Donovan & Belmont, 2019). Often, however, the temporal resolution of multitemporal satellite imagery analyses is more practically defined, with satellite imagery selected where the obstruction effects are lowest (i.e., cloud cover).

This can potentially misrepresent landscape characteristics when prevailing conditions such as seasonal vegetation or hydrodynamic effects (Figure 2) influence the geomorphic identification and characterization (Koohafkan & Gibson, 2018), with implications for delineation of channel and flow boundaries (Güneralp, Filippi, & Hales, 2014). These issues raise concerns for the suitability of snapshot analyses of dynamic systems, particularly without explicit consideration for the geomorphic processes in operation, their functioning timescales and the time dependence effects associated with process rate estimation. A challenge is therefore posed to monitor rapid and abrupt planform changes in addition to those progressive and incremental changes that often interplay in fluvial systems (Coppin, Jonckheere, Nackaerts, Muys, & Lambin, 2004; Vogelmann, Gallant, Shi, & Zhu, 2016).

Alternative approaches that leverage cloud-based computing platforms and big geospatial data can partially satisfy this challenge. In the wider remote sensing community, a recent shift toward continuous monitoring is allowing for the more precise characterization of the timings of change and the determination of change drivers (Woodcock, Loveland, Herold, & Bauer, 2019). Millington and Townshend (1987) suggested that the most innovative future use of remotely sensed data in geomorphology would lie in monitoring geomorphological change and hazard prediction. Recently this potential has started to be realized, where near-real-time monitoring from satellite imagery is becoming possible (Woodcock et al., 2019), and observations from combinations of remotely sensed products are being used for analysis of continuous river network change (Piégay et al., 2020). Central to this is the ability to retain "good" data from all available satellite imagery. Algorithms have been developed to automatically mask obstructions in satellite imagery from cloud, cloud shadow, and snow (Foga et al., 2017; Zhu, Wang, & Woodcock, 2015), meaning that unobscured observations are retained, while obstructed observations are omitted from subsequent analysis. Composite images (aggregations of spatially overlapping images) have been built to overcome data shortcomings associated with the scan line corrector (SLC) failure aboard Landsat 7 (Pringle, Schmidt, & Muir, 2009), obstructions (Wulder & Coops, 2014), and for the representation of a particular period or season for analysis (Flood, 2013). For channel change analyses, image compositing can help to optimally resolve exposed in-channel sediment, provide consistent estimates of bankfull channel planform and integrate planform changes over consistent time intervals (Schwenk, Khandelwal, Fratkin, Kumar, & Foufoula-Georgiou, 2017). These advances are being facilitated through virtualization, cloud-based computing and the availability of big geospatial data, thereby allowing for both abrupt and progressive changes in fluvial systems to be monitored.

Burton (1963) argued that the data explosion associated with the quantitative revolution in geography produced a need for new ideas and theory. The development of GEE, and other platforms, is producing a significantly greater relative increase in data availability than occurred in the 1950s and 1960s, enabling spatiotemporal analyses over unprecedented scales. This data resource has important implications for advancing geomorphic theory, as the feasible modes of explanation change as instruments and analytical capabilities improve (Church, 1996). We consider the evolutionary trajectory of both the pixel and the typical analysis scales for remotely sensed data used in fluvial geomorphology applications (historical maps, aerial photography, Landsat, and Sentinel satellite imagery) and link these back to the characteristic spatiotemporal domains for the four modes of theory construction in fluvial geomorphology suggested by Church (1996). Here the evolutionary trajectory refers to changes in position along the spatial-temporal domain as sensor and computational processing capabilities improve. The pixel scale is defined as the nominal size of a single pixel, whereas the analysis scale refers to the typical scale at which analysis is undertaken. At the pixel scale, a shift from the contingent to the chaotic zone is shown, driven largely by finer temporal resolutions of analysis (Figure 3). A more complex evolutionary trajectory is shown for the analysis scale, first moving from the chaotic to the deterministic zone (driven by finer temporal resolutions) and then further toward the interior of the deterministic zone (as multitemporal analysis is facilitated over larger distances). The evolutionary trajectory within the GEE spatiotemporal domain (dashed box, Figure 3) implies that we can now seek deterministic explanations using entire satellite scenes or larger areas. Where analysis had previously been limited to interannual to decadal temporal epochs, now we are limited only by the repeat acquisition interval of satellites (either from individual or combined platforms). We suggest that this shift is transformative in enabling deterministic science at the analysis scale and that this will allow formal incorporation of spatial scale-dependent temporal change into analyses of river channel change and channel pattern classification. As such, multitemporal analysis should allow for theories of geomorphic change to be tested and developed, including the reexploration of some classic and forgotten concepts in fluvial geomorphology (e.g., river sensitivity; Fryirs, 2017). Working retrospectively through satellite imagery archives, multitemporal analysis will allow for planform adjustments and lag times to be assessed, providing new opportunities to disentangle natural and anthropogenic drivers of change (Piégay et al., 2020). Importantly, the analysis scale can be defined by the user and determined by the phenomena of interest.
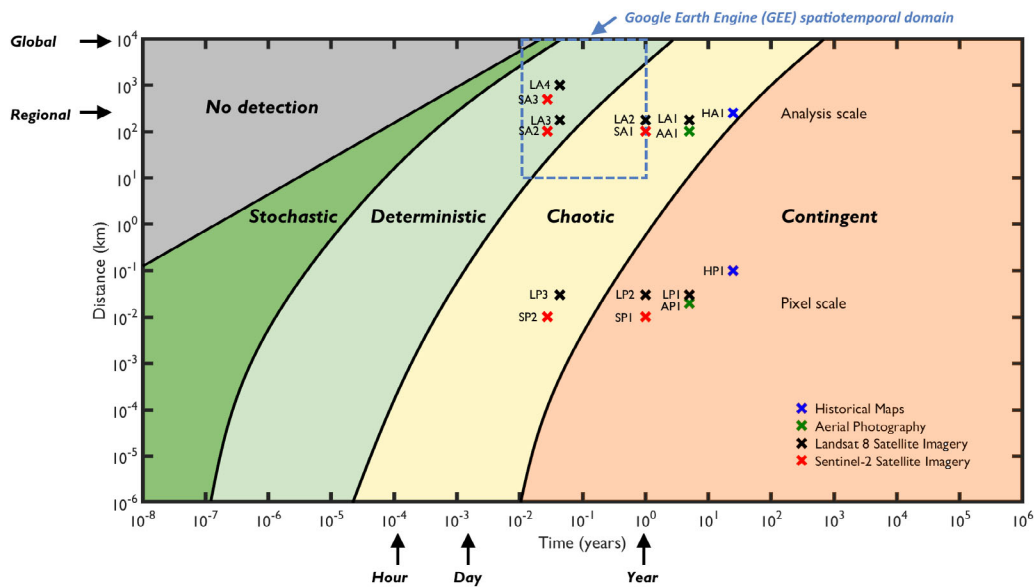
FIGURE 3 Spatial–temporal domain trajectories of remotely sensed data typically used in fluvial geomorphology applications. The trajectories are plotted along the conjectural division of characteristic spatiotemporal domains of four modes of theory construction suggested by Church (1996). Analysis scale refers to the typical scale of analysis achievable. Pixel scale refers to the nominal characteristics of a single pixel. Dashed blue box indicates the typical spatiotemporal domain for GEE analyses. Analysis scale abbreviations: AA1, aerial photography (5-year temporal resolution, 100 km coverage); HA1, historical maps (25-year temporal resolution, 250 km coverage); LA1, Landsat 8 (10-year temporal resolution, 175 km coverage); LA2, Landsat 8 (1-year temporal resolution, 175 km coverage); LA3, Landsat 8 (16-day temporal resolution, 175 km coverage); LA4, Landsat 8 (16-day temporal resolution, >1,500 km coverage); SA1, Sentinel-2 (1-year temporal resolution, 100 km coverage); SA2, Sentinel-2 (10-day temporal resolution, 100 km coverage); SA3, Sentinel-2 (10-day temporal resolution, >500 km coverage). Pixel scale abbreviations: AP1, aerial photography (20 m spatial resolution); HP1, historical maps (100 m spatial resolution); LP1–LP3, Landsat 8 (30 m spatial resolution), SP1–SP2, Sentinel-2 (10 m spatial resolution)

5 | APPLICATIONS OF GEE IN FLUVIAL GEOMORPHOLOGY

Given the potential benefits of using GEE for spatiotemporal analyses, relatively few published studies have to date utilized this application. In this section, we list examples of where GEE has been applied in a fluvial geomorphology context (Table 3) and synthesize common themes that could inform future river channel change analyses. The list is not supposed to be exhaustive, but indicative of the topics investigated and the ways in which GEE has already been used. The first common theme is that GEE has been used as a tool for mining the satellite imagery data archive (particularly Landsat collections), cloud-masking images and then generating multitemporal image composites (e.g., Aadland & Helland-Hansen, 2019). The examples also demonstrate the variety of temporal resolutions over which GEE has been applied, enabling the analysis of shorter-term (e.g., monthly median surface sediment concentrations; Markert, Schmidt, et al., 2018) and longer-term river responses (e.g., median suspended sediment concentrations between 1999 and 2013; Overeem et al., 2017). The utility of multispectral indices for classification purposes is demonstrated (e.g., X. Yang, Pavelsky, Allen, & Donchyts, 2020) and application of transformations to fingerprint specific geomorphic processes (e.g., Tasseled cap transformation; Valenza et al., 2020). Relevant to planimetric river channel change, the examples show how image compositing over timescales determined by the phenomena of interest can be useful for multitemporal analysis. The second common theme is that many applications have provided accessible methods (e.g., shareable links to the GEE or source code) and accessible results (e.g., data repositories), promoting transparent and open science. For river channel change analysis, the algorithms can be tested across geodiverse settings and shared between researcher and practitioner communities. The final common theme is that cartographic, graphical, and statistical analyses are almost always completed outside of the GEE environment. Although GEE has the functionality to complete some of these tasks, and additional packages are available to analyze and visualize data sets interactively within Jupyter-based environments (e.g., Wu, 2020), some users choose to export their data to environments or tools with which they have greater familiarity. Reporting this important methodological information would improve the future transparency, methods reproducibility, and completeness of analytic reporting (Goodman, Fanelli, & Ioannidis, 2016).

TABLE 3 Recent applications of Google Earth Engine in fluvial geomorphology

Application and study area	GEE data catalog products used	Analysis scale	Temporal range	Temporal resolution	Comment on how GEE was used	Accessible methods	Accessible results	Reference
Data mining and classification within GEE (analysis outside of GEE)								
River avulsions in Andean and Himalayan foreland basins	Landsat collection	55 avulsions over mountain fronts 7,000 and 2,000 km in length	1984–2014	Annual (composite)	Constructed annual Landsat composite images, reduced to the most recent, cloud-free value for each pixel. Multispectral indices used to visually differentiate between land and water to find avulsions. Geometric measurements and analysis outside of GEE	Code unavailable	Output data available	Edmonds, Hajek, Downton, and Bryk (2016)
Planform evolution and morphodynamics of Ucayali River, Peru	Landsat collection	>1,500 km	1985–2015	Annual (composite)	Constructed annual Landsat composite images within a 5-month search window (from 01 June to 31 October) to produce bankfull channel masks. Spatiotemporal quantification of planform evolution and morphodynamics outside of GEE using RivMAP toolbox	Code available	Output data available	Schwenk and Foufoula-Georgiou (2017), Schwenk et al. (2017)
Data mining, classification and (some) analysis within GEE								
Suspended sediment concentration in Greenland	Landsat 7	160 rivers throughout Greenland	1999–2013	Long term—averaged over temporal range	Related in situ suspended sediment concentration measurements to visible and near-infrared light reflectances. Restricted analysis to snow-free periods and active summer discharge season (days 160–240)	Code available	Output data available	Overeem et al. (2017)
Surface sediment concentrations in the Lower Mekong basin	Landsat collection	44 water quality stations in Lower Mekong basin	1985–2011	Intraannual—118 discrete instances	Related in-situ surface sediment concentration measurements (SSSC) to visible, near-infrared and short-wave infrared reflectances. Queried	Code available	Output data as GEE application	Markert, Schmidt, et al. (2018)

TABLE 3 (Continued)

Application and study area	GEE data catalog products used	Analysis scale	Temporal range	Temporal resolution	Comment on how GEE was used	Accessible methods	Accessible results	Reference
					Landsat collections that coincided with in situ measurements, extracted spectra to develop an empirical SSSC model and produced an online suspended sediment application			
Paleo-river networks and historical morphodynamics in Northwest India and Pakistan	Landsat 5, SRTM, and ALOS	80 km—80,000 km²	1984–2013	Bimensal— averaged over temporal range	Constructed bimensal Landsat 5 composites of multispectral indices (e.g., average EVI between January and February, in the temporal range 1984–2013) for identification of paleo-rivers. Calculated seasonal vegetation indices and performed spectral decomposition techniques. ALOS global digital surface model used to extract microtopographic information	Code available	Output data available	Garcia, Orengo, Conesa, Green, and Petrie (2019) and Orengo and Petrie (2017)
Progradation rates at river outlets (global coverage)	Landsat collection	331 deltas, reduced to 137 progradation rates	1984–2015	Interannual to > decadal (2–31 years)	Calibrated MNDWI, applied cloud masking procedure and averaged over the 20 least cloud covered Landsat images to produce a temporal composite. Change detection between temporal composites to quantify total land area gained and lost	Code unavailable	Output data available	Aadland and Helland-Hansen (2019)
River avulsions in Andean, Himalayan and New Guinean basins	Landsat collection	Avulsion behavior for 63 avulsions	1986–2017	Annual (composite)	Constructed annual Landsat composite imagery (from images <20% cloud cover), applied Tasseled cap	Code available	Output data available	Valenza, Edmonds, Hwang, and Roy (2020)

(Continues)

TABLE 3 (Continued)

Application and study area	GEE data catalog products used	Analysis scale	Temporal range	Temporal resolution	Comment on how GEE was used	Accessible methods	Accessible results	Reference
					transformation (TCT) and identified avulsion activity			
River widths across the United States and Canada	Landsat collection and GRWL	519 gauging stations across the United States and Canada	1984–2018	N/A	Extracted river mask from Landsat image using multispectral indices and GRWL data set, derived centerline along the river mask, measured river width along the centerline and assigned quality flags based on impact of cloud, cloud shadows, topographic shadows, and snow/ice	Code available	Validation data available	X. Yang, Pavelsky, Allen, and Donchyts (2020)
Global river ice	Landsat collection and GRWL	7.5 million river centreline locations	1984–2018	Various	Extracted snow/ice conditions from the quality band of Landsat images and aggregated pixel-level snow/ice conditions into a river ice extent	Code available	Output data available	Yang, Pavelsky, and Allen (2020)

Abbreviations: ALOS, Advanced Land Observing Satellite; GEE, Google Earth Engine; GRWL, Global River Widths from Landsat.

From a planimetric river channel change perspective, not all analyses need to be completed within the GEE environment, workflows can be designed for data to be exported at designated "exit points", ready for analysis within existing tools and software packages (Section 6.2).

It should also be noted that several semiautomated and automated applications and toolkits available within GEE can assist fluvial geomorphology users, although to the authors' knowledge no explicit applications or toolkits for planimetric river channel change analysis are currently available. Relevant fluvial geomorphology examples that use multispectral satellite imagery from the GEE data catalog include: Deltares Aqua Monitor for detection of land and water changes over 30 years (Donchyts et al., 2016); GEE Digitization Tools for rapid access to imagery time series and the generation of cloud free composites and Margin change Quantification Tools for margin change analysis (Lea, 2018); CoastSAT for shoreline change detection (Vos, Splinter, Harley, Simmons, & Turner, 2019); RivWidthCloud for extraction of river centreline and widths (X. Yang, Pavelsky, Allen, & Donchyts, 2020); and Spectral Point to extract quantitative, contrast-corrected brightness data (Brooke, D'Arcy, Mason, & Whittaker, 2020). Likewise, the multiscale relief model can be used for the visual interpretation of landforms from digital surface models (Orengo & Petrie, 2018) for bankfull channel definition. Some of the applications and toolkits can improve accessibility to data within GEE (e.g., Lea, 2018), whereas others have been developed for specific geomorphological purposes (e.g., Orengo & Petrie, 2018). Applications and toolkits could potentially be repackaged and repurposed for planimetric river channel change analyses, with new additions likely to be developed in the coming years.

6 | EXAMPLE APPLICATION: EXTRACTING AND QUANTIFYING SPATIOTEMPORAL ACTIVE RIVER CHANNEL CHANGE

In this section, we provide a demonstration application for extracting and quantifying active river channel change over a ~20 km reach of the Cagayan River (Luzon Island, Philippines). The Cagayan River is the main trunk channel of the Cagayan catchment (~27,000 km^2), the largest catchment in the Philippines, and is frequently impacted by flooding. Global climate models predict an increase in the return interval for maximum river flow rates in this region (Tolentino et al., 2016), transforming the frequency and magnitude of typhoons and tropical storms, so increasing flooding and geomorphic risks (Eccles, Zhang, & Hamilton, 2019). Records of active river channel change are limited in this region, so GEE provides an opportune platform for investigation using remotely sensed data. Further information on the Cagayan catchment can be found in Dingle et al. (2019). The example demonstrates a practical application of GEE for planimetric river channel change analysis and illustrates some of the strengths of GEE that were outlined earlier in the paper (e.g., virtualization, cloud-masking and temporal compositing). We first provide a workflow to show how GEE can be used to construct and extract active channel river masks from the GEE data catalog, before applying an external tool to quantify spatiotemporal planform change outside of the GEE environment.

6.1 | Extracting the active river channel within GEE

A visual workflow for extracting active river channel masks from the Landsat collection is shown in Figure 4, with a link to the GEE code provided in the notes section. We identify the physical boundaries of the active river channel as the bankfull channel extent (Rowland et al., 2016; Schumann et al., 2009). The workflow is designed to be modifiable, so that it can be applied over larger extents and for different temporal resolutions. The main workflow steps include:

- Time and region of interest (ROI) filtering: Define a time period for active channel mask extraction, for example, intraannual, annual, or interannual interval. Draw the ROI, the geometry over which the satellite imagery will be analyzed. Using all available Landsat surface reflectance imagery (including Landsat 5 thematic mapper [TM], Landsat 7 enhanced thematic mapper [ETM+], and Landsat 8 operational land imager [OLI]/thermal infrared sensor [TIRS]), image collections containing satellite images are automatically constructed for the specified time period and ROI. The surface reflectance product has been atmospherically corrected, facilitating a more reliable comparison of spectral reflectance measurements between acquisitions.
- Cloud masking procedure: For each satellite image in the image collection, a cloud masking algorithm is applied to mask obstructions from cloud and cloud shadow pixels (CFmask algorithm; Foga et al., 2017). Unobstructed pixels in the satellite images are retained.
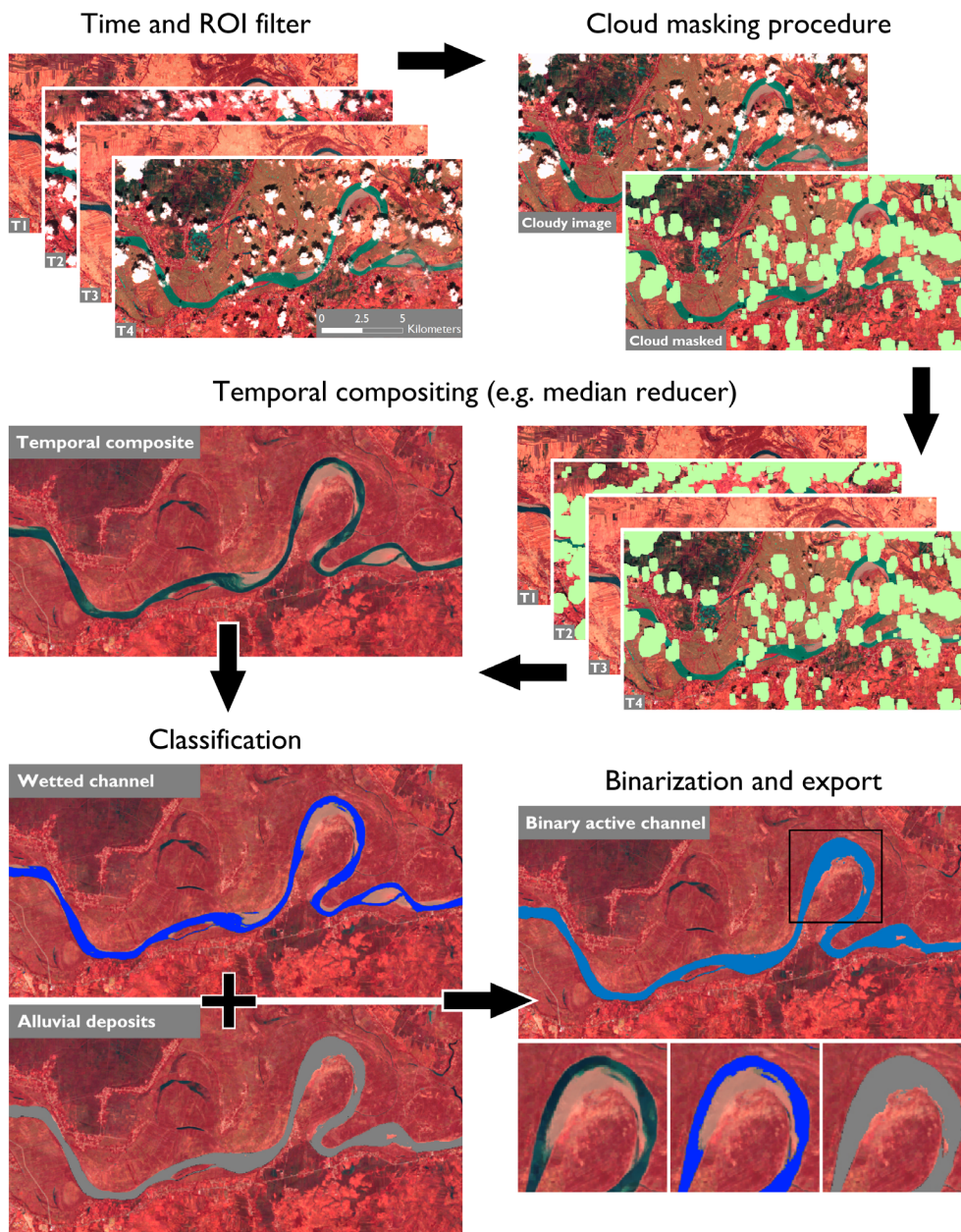
FIGURE 4 Visual workflow example for extracting the active channel from a series of Landsat satellite images in Google Earth Engine. Region of interest (ROI) refers to the region of interest. Time filter was set to January 01, 2019 to January 01, 2020. Wetted channel classification followed Zou et al. (2018), alluvial deposits were classified using a relational operator where modified normalized difference water index (MNDWI) ≥ -0.4 and normalized difference vegetation index (NDVI) ≤ 0.2

- Temporal composition: The retained pixels are aggregated using a median reducer. This generates a single composite image for all the spectral bands for the specified time period (e.g., intraannual, annual, or interannual). Alternative approaches could use different percentile (e.g., 10th/25th/75th/90th) or maximum/minimum reducers depending on the purpose of the composition (Diniz et al., 2019).
- Wetted channel classification: The classification method of Zou et al. (2018) is used to classify water pixels in the temporal composite image, producing a binary water mask. The water classification uses multispectral indices including the MNDWI, NDVI, and EVI. A review of surface water detection and classification methods is provided by Huang, Chen, Zhang, and Wu (2018).
- Alluvial deposits classification: The same multispectral indices used for wetted channel classification are used to classify alluvial deposits, with the active channel boundary enforced by excluding vegetated pixels. The approach is similar to Monegaglia, Zolezzi, Güneralp, Henshaw, and Tubino (2018), although no additional benefit was observed by including the SWIR 2 band (used for emerging sediment bar detection). Active channel pixels were classified using relational operators where MNDWI ≥ -0.4 and NDVI ≤ 0.2. An NDVI threshold of 0.2 is established in the literature for dense riparian vegetation (Bertoldi, Drake, & Gurnell, 2011).

- Binarization and export: Binary wetted channel and alluvial deposit masks are combined (i.e., geometric union) to give an active channel river mask. An optional step for cleaning/noise removal could be implemented here. Final binary masks are exported to Google Drive as a GeoTIFF file for subsequent analysis outside of the GEE environment.

We applied this workflow to extract annual active channel masks at 5-year intervals between 1989 and 2019 ($n = 7$ masks; 1989, 1994, 1999, 2004, 2009, 2014, and 2019). Five-year intervals were selected to ensure that geomorphic change was detected, an appropriate timescale for the river channel change processes of interest (i.e., given the multiple drivers of geomorphic change in this setting).

6.2 | Quantifying spatiotemporal active channel change outside of GEE

Numerous automated and semiautomated tools for planform analysis exist, with the outputs from GEE ready to be used to derive planform statistics and quantify change. Established examples include tools for extracting centerline position and channel width from single binary masks, for example, RivWidth (Pavelsky & Smith, 2008), ChanGeom (Fisher, Bookhagen, & Amos, 2013), and RivaMAP (Isikdogan et al., 2017), in addition to those intended for the quantification of multitemporal planform change, for example, SCREAM (Rowland et al., 2016), RivMAP (Schwenk et al., 2017), and PyRIS (Monegaglia et al., 2018). Here we quantify the reach averaged migration rate using the RivMAP toolbox for centerline analysis in MATLAB (Schwenk et al., 2017). RivMAP was selected because of the single-thread nature of the active channel, whereas SCREAM would be more suitable for multithreaded channels.

Spatially heterogenous shifts in the active channel centerline indicate the complex and active morphodynamics over the demonstration reach (Figure 5). This includes lateral migration of the active channel in addition to meander expansion (erosion and accretion) and cutoff processes. The migration rate is calculated from the migrated area divided by the centerline length (divided by the time interval, 5 years). Over the 30-year time period, the average active river channel migration rate was 11.1 m.a-1 (range 8.6–16.3 m.a-1). However, the local migration rate will be spatially variable given the heterogenous shifts in centerline position. Note that although a 5-year interval was selected for demonstration purposes, analysis can readily be undertaken at intraannual or annual intervals for improved temporal understanding. No assessment of uncertainty of these rates was carried out for the purposes of this demonstration. Such spatiotemporal analyses have useful river management implications, providing the areal extents necessary for erodible corridor and
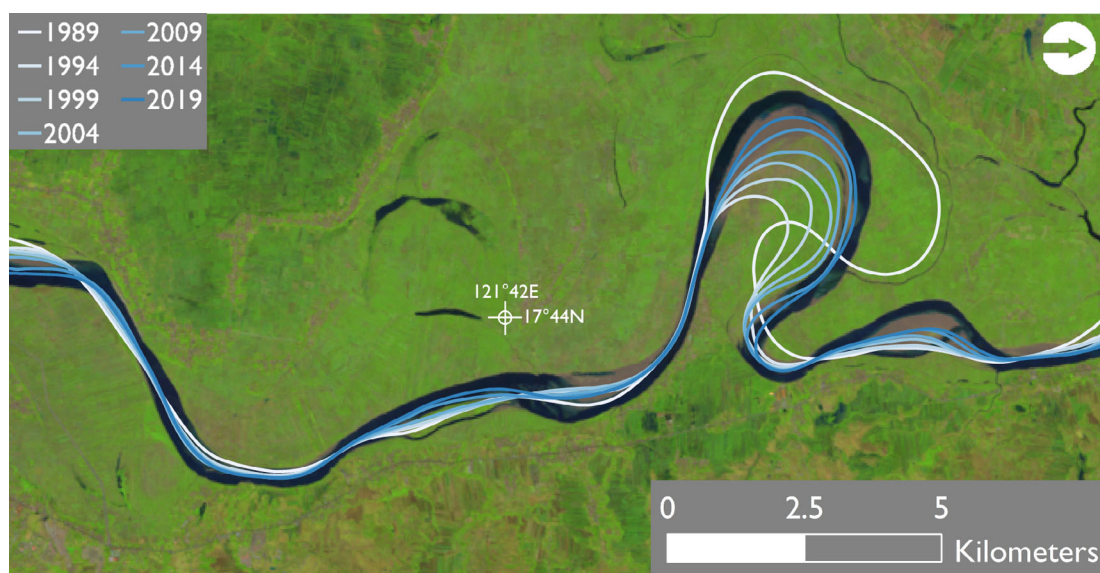

FIGURE 5 Active channel centerline change for the Cagayan River near Iguig (Luzon, Philippines—17°44′17.3″N, 121°42′51.2″E). Spatially heterogenous shifts in the active channel centerline are shown, with meander expansion (erosion and accretion) and cutoff processes recorded. Base map is an annual temporal composite (2019–2020) using Sentinel-2 imagery (bands B11, B8, B4)

freedom space for rivers applications (Biron et al., 2014; Piégay, Darby, Mosselman, & Surian, 2005). The example application demonstrates the utility of GEE in extracting active channel masks for the specific purpose of multitemporal planform analysis. Coupled with information from additional variables such as discharge (see Section 7.2), planform analyses such as those demonstrated in this example can be used to test theoretical models such as the geomorphological effectiveness of floods (Costa & O'Connor, 1995).

7 | POTENTIAL APPLICATIONS, OPPORTUNITIES, AND FUTURE CHALLENGES

7.1 | Potential applications of GEE for river channel change analysis

A temporal analysis of past river processes and natural inheritance is necessary to understand present river conditions (Grabowski et al., 2014). In a systematic literature review on channel morphology responses to drivers of river channel change, Downs and Piégay (2019) note that reach-scale changes in mainstem channels are the focus of many studies (rather than tributary channels), and expert judgment is commonly used to interpret channel changes based on temporal synchronicity and spatial proximity of causal features. Most fluvial systems are cumulatively impacted by multiple drivers of river channel change, but geomorphologists are better at observing and stating these changes than ascribing the cause and effect for impacts and drivers (Downs & Piégay, 2019). GEE offers the capacity to work across scales, making catchment-scale analyses of river systems a more tractable task (Fryirs, Wheaton, Bizzi, Williams, & Brierley, 2019). In providing a platform for spatially and temporally comprehensive and consistent analyses, GEE facilitates a shift toward detailed (i.e., reach differentiated) catchment and intercatchment comparisons of planform river channel change. Multitemporal analyses can be undertaken across a larger portion of the stream network (i.e., beyond the mainstem channel) using a comparative framework for analysis (e.g., paired analysis between catchments, rather than for a single case study). By integrating the analysis of remotely sensed data across spatial and temporal scales, the diachronous-synchronous approach to working should improve the rigor of cause and effect interpretations of river channel change (Downs & Piégay, 2019; Piégay, 2016).

7.2 | Potential applications of GEE across fluvial geomorphology

To date, applications of GEE in fluvial geomorphology have mainly focused on wetted river channel planform, morphodynamics and suspended sediment concentrations (Section 5). Here we suggest further possible applications, providing specific examples of where GEE could be used, and the end-users (additional to fluvial geomorphologists) who may benefit (Table 4). We suggest that GEE could provide data for the analysis of river evolutionary trajectories and their sensitivities, supporting efforts to embed geomorphologically informed applications within practice and policy (Brierley et al., 2013; Brierley & Fryirs, 2016). Remote sensing has been viewed as a technical and methodological framework to monitor the processes and estimate the trajectories of rivers in the Anthropocene (Piégay et al., 2020) and we suggest that GEE analyses could support this for a subset of the Earth's rivers. For this potential application to be realized, the integration of data sets will be necessary (e.g., discharge time series, landcover maps, historical records). While these data may not be available everywhere and accessible to everyone, global data sets of variables such as discharge are emerging that have record lengths that are similar to those of optical satellite remote sensing (e.g., the GloFAS-ERA5 global river discharge analysis 1979-present; Harrigan et al., 2020). Here we suggest a critical evaluation of available discharge record data (including spatial and temporal resolutions) relative to the functional timescales of the geomorphic processes and the specific purposes of the application. Moreover, we note overlap between the identified applications and suggest this could facilitate cross-disciplinary collaboration, particularly at the interface of process systems (e.g., fluvial-coastal interactions; Kuenzer, Heimhuber, Huth, & Dech, 2019). GEE analysis will broaden the range of river morphological types for which we have significant data sets enabling improved identification of morphological style from the sedimentary record, of interest to source-to-sink sedimentologists, and potentially extending inferred river analogues to other planets (Santos et al., 2019).

7.3 | Opportunities

The primary opportunity for GEE in fluvial geomorphology is enabling deterministic science embedded in an open science culture. We have discussed the transformative potential of GEE at the analysis scale, allowing for the formal incorporation of temporal change in geomorphic theory (Brunsden, 1990). For theories of geomorphic change to be reexplored, tested and developed, this will rely on collaborative, transparent and community-driven science. The potential for GEE to widen the participation through virtualization and democratization of access should help to achieve this. An open-source approach to community-driven code development and documentation has been vital across climate, glaciological, and hydrological sciences in advancing numerical analyses, computational simulations, and associated statistical analysis (Beven & Freer, 2001; Blackmon et al., 2001; Hurrell et al., 2013; Larour, Seroussi, Morlighem, & Rignot, 2012). Similar practices in fluvial geomorphology are encouraged, as they would promote the evaluation of code and data before and during peer review, contribute toward realizing the value of these data (especially in applied contexts), and have beneficial pedagogic roles throughout the community (Lane, 2019).

Another opportunity exists in the novel combination of technologies, techniques, and approaches. Technological advances in remote sensing have improved our ability to analyze, quantify, and view landscapes in dimensions and detail like never before (Fryirs et al., 2019). By integrating remotely sensed data from multiple sources (e.g., optical satellite imagery with high-resolution digital elevation models), we can build a more complete understanding of river morphology trajectories and behaviors, and the conditions that promote planform mobility. Potential opportunities include topographic analyses in upper catchments (i.e., sediment producing source zones) coupled with multitemporal satellite imagery analysis of channel mobility in sediment transfer/accumulation zones; through to the quantification of bank angles and degrees of channel confinement that influence planimetric river channel change. At the same time, rapid developments in open-source machine leaning, deep learning, and artificial intelligence have crossed disciplines (Piégay et al., 2020). Here we have only discussed pixel-based analysis approaches, but object-based approaches (e.g., Bizzi et al., 2019; Demarchi, Bizzi, & Piégay, 2016) and the fusion of pixel- and object-based approaches offer the potential to assess riverscape unit and planform changes at scale. In the remote sensing community, a shift from change detection to continuous monitoring is increasingly accepted (Woodcock et al., 2019). Furthermore, the emergent area of environmental data science sits in a cross-disciplinary space that requires new means of organization and a fundamentally different culture of working (Blair et al., 2019). The opportunity therefore exists to exploit these multiple data sets, techniques, and approaches within cloud-based computing platforms such as GEE, offering possibilities of transformation and breakthrough in the discipline. As such, GEE can be viewed as a tool for realizing the promise of environmental data science (Blair et al., 2019).

A final opportunity exists for improved scientific communication, particularly for those end users identified in Table 4. A promising example of this is demonstrated by the "Dancing Rivers" tool to support river management in Myanmar, developed as part of the SERVIR-Mekong project (SERVIR-Mekong, 2020). Landsat and Sentinel satellite imagery is processed within GEE to map premonsoon and postmonsoon river morphologies and measure widths along a 2,000-km section of the Ayeyarwady River. The tool is designed to enable government agencies to assess erosion and deposition areas, inform riverbank protection planning, and prioritize investment. However, the workflow is yet to be fully documented and openly shared. Tools are often developed using Earth Engine Apps, allowing users to interactively explore and download data sets. Successful examples include the Global Forest Change time series analysis from Landsat imagery (Hansen et al., 2013), MapBiomas initiative for annual land cover and land use changes in Brazil (MapBiomas, 2017), and Mekong-SSC for suspended sediment monitoring (Markert, Schmidt, et al., 2018). Such applications are useful tools for the visualization and communication of scientific information, and for actively engaging the wider community.

7.4 | Future challenges

Although potential applications have been outlined, GEE is unlikely to be a panacea for all studies involving remote sensing in fluvial geomorphology. Here we identify three future challenges—scaling, transferability, and data uncertainties—and provide some additional cautionary notes.

In fluvial geomorphology applications, a critical relationship exists between the width of the river and the spatial resolution of the satellite imagery suitable for analysis. For medium-resolution satellite imagery (i.e., Landsat and Sentinel collections), analysis of small- to medium-sized rivers (<100 m wide) is generally limited in application (Gilvear &

TABLE 4 Potential applications of Google Earth Engine (GEE) in fluvial geomorphology

Applications	Specific examples	Potential end users
Understand fluvial processes and the range of existing fluvial patterns on Earth	Planimetric river and geomorphic unit classification, planform mobility dynamics (e.g., meander migration, channel reorganization, confluence dynamics), sediment dynamics (e.g., bar migration), hillslope/channel couplings (e.g., sediment cascades from mass movements and alluvial fans)	River management practitioners River scientists
"Anthropogenic" fluvial geomorphology	Planimetric responses to river and flow management practices (e.g., dams, artificial channel alignment, erosion control measures and tailings dams). Interactions with critical infrastructure (e.g., lateral erosion around bridges). Planimetric response to sand mining/gravel extraction activities (e.g., detection of illegal mining)	Engineers Regulators Governments River management practitioners
Evolutionary trajectory analysis	Assessment of river histories, appraisal of system responses (including to natural and anthropogenic fluxes), their sensitivities and determination of potential future states	River management practitioners
Rivers in the sedimentary record	Assessment of the range and dimensions of morphological forms in different settings, with application to rivers from the Archean to the Holocene, and to inferred rivers on other planets	Quaternary and geological scientists
Biogeomorphic interactions	Multitemporal vegetation dynamics (composition, abundance and health), morphodynamic stability, boundary conditions for biogeomorphic and hydraulic models (e.g., roughness treatment for riparian vegetation)	Biologists Ecologists
Fluvial-coastal interactions	Planimetric delta classification (including hydraulic geometry), sensitivity to natural and anthropogenic forcing	Coastal scientists
Geohazards	Rapid flood inundation and geomorphic change mapping, morphological response to glacial lake outburst flood, landslide, tailings dam failures, and volcanic hazards (e.g., lahars)	Disaster managers Governments

Note: There is likely overlap between the applications.

Bryant, 2016; Legleiter & Fonstad, 2012). This is exemplified where river widths <90 m (three Landsat pixels) were found to be less accurate and more incomplete in the GRWL database (Allen & Pavelsky, 2018). Data sources must therefore be appropriate for the purposes to which they are to be used (Fuller, Reid, & Brierley, 2013) and an awareness of limitations to applicability in certain river settings is needed (e.g., awareness of the limited application of optical satellite imagery approaches in high energy and small headwater streams; Righini & Surian, 2018). Recent and future improvements in the spatial resolution of satellite imagery will likely increase the applicability of approaches to smaller systems (Khorram, Van der Wiele, Koch, Nelson, & Potts, 2016). However, most high-quality, high spatial resolution imagery remains unavailable to the public at zero cost (Chi et al., 2016). At present, therefore, the risk exists that larger river systems that are readily detectable in the satellite imagery data archive could bias geomorphic theory development. Further data sets, at the subpixel scale, are still needed.

Secondly, the transferability of analyses should be considered. Here transferability is used as a term to describe how information or analysis from one river or region can be applied elsewhere (i.e., the universality). In river planform analysis, some of the commonly used tools have only limited transferability across the full diversity of global river systems (e.g., unsuitable for complex multithreaded systems), and this can restrict the size and extents of analysis (Rowland et al., 2016). In remote sensing applications of submerged aquatic vegetation, Marcus, Fonstad, and Legleiter (2012) warn against the direct transfer of analyses from large water bodies to smaller streams without further study and validation. Caution is therefore needed to avoid inappropriately transferring GEE analyses between unsuitable fluvial settings. One practical suggestion to minimize this risk is to test and validate GEE analyses across discrete river types, for example, across multiple regions and geodiverse river morphologies characteristic of the existing conditions on Earth.

Furthermore, it is suggested that authors uphold good practice when sharing code by documenting and explicitly stating the transferability of the analysis (i.e., a statement describing the geomorphic and hydrologic setting over which the analysis was developed).

A further challenge exists around data uncertainties, a common issue in many remote sensing applications. In the first instance, this can refer to the positional accuracy of the satellite imagery, with the potential error becoming greater as sensors increase in spatial resolution (Congalton & Green, 2008). This is pertinent when newer satellites tend to have higher spatial resolutions and more bands, and it should be ensured that the satellite imagery used for analysis is fit for purpose (Priestnall & Aplin, 2006). Further data uncertainties arise as a function of sensor resolution relative to the size of the object of interest. Where satellite imagery pixel edges do not coincide with the edges of objects on the ground, pixels will contain a number of objects (mixed pixels), for example, bed material, water, and vegetation (Gilvear & Bryant, 2016). Even for the largest rivers, mixed pixels are found at the boundaries between bank links and channel bar boundaries (N. Gupta, Atkinson, & Carling, 2013). Such issues raise questions about the extent to which true geomorphic change can be detected, given the multitude of factors that affect uncertainty (e.g., Table 1 in Donovan et al., 2019), and difficulties in distinguishing morphodynamic change from other sources of change (Koohafkan & Gibson, 2018). To address these problems, a comprehensive framework for evaluating uncertainty in estimates of river migration and channel width changes has been developed by Donovan et al. (2019). The framework encourages the use of level of detection (LoD) thresholds to determine statistically significant changes. Here we suggest that a similar LoD approach to uncertainty estimation would be valuable to support spatiotemporal analyses of geomorphic change in GEE.

Finally, we provide some additional cautionary notes on applications of GEE in fluvial geomorphology. Selection of suitable tools or approaches for the geomorphic analysis of rivers can be challenging (Fryirs et al., 2019) and the GEE platform is not designed to direct or guide users toward a "correct" approach. Regardless of the workflow designed for analysis, technical and interpretative demands are placed on the user, akin to choosing the most appropriate software and analysis routines in traditional remote sensing approaches. Technical challenges are partly resolved through access to an increasing number of sharable and reproducible GEE code examples and are assisted by having a community of GEE users active through geospatial analysis question and answer forums. However, the interpretative challenge remains as the geomorphic analysis of rivers will never be fully automated (Fryirs et al., 2019). Pitfalls exist around producing visually appealing imagery without advancing the geomorphological understanding. Here we return to the old adage that just because something looks good, does not mean that it is good (Marcus et al., 2012). Danger exists for superficial interpretation based on two-dimensional planforms alone (Tooth, 2013), as rivers also adjust in the vertical dimension which is neglected in planimetric analysis, so critical human interpretation is always required as part of geomorphic analysis (Fryirs et al., 2019). By incorporating formal uncertainty assessments within GEE analysis, we suggest that some of these risks could begin to be minimized.

Next, an acknowledgement for what might be missing from the satellite imagery data archive is needed. At best, these archives may allow for multitemporal analysis back to the 1970s, which is a timespan of ∼50 years at present. This time period may be shorter than the full lifecycle of geomorphic processes of interest, for example, the inception-to-cutoff timescale of most meandering rivers is longer than the available data archive (Schwenk et al., 2017). Likewise, the natural relaxation time after disturbance for large systems is likely longer than that of the data available (Church, 1996). Location-for-time substitution, to develop sequences of adjustment and change from multiple sites, has been used in the assessment of river evolution (Fryirs, Brierley, & Erskine, 2012). However, location-for-time substitution implicitly assumes no change in boundary conditions over the time period; this assumption may not be held when different process controls are imposed by events (e.g., sediment input from landslides), human influence (e.g., dams, embankments, bank protection), and climate change. Problems also arise in the definition of the "characteristic form condition" for landscapes not in equilibrium (Paine, 1985). Contextualization of observations in relation to larger scale system processes (e.g., climate/tectonics) are therefore essential as geomorphic systems evolve over timescales that can be longer than the timescales of adjustment of the controlling variables.

A trade-off exists in geomorphic analyses between complexity and generalization. GEE offers the potential (and temptation) to reduce petabytes worth of data to simple indices. Across fluvial geomorphology, there has been a tendency to emphasize and create similarity between rivers, using static descriptors of morphology (Richards, 1996). However, the linking of particular descriptors (e.g., channel width) with surrogate process variables (e.g., discharge) provides little information on formative geomorphic mechanisms, and generalizations based on these relationships risk being the product of sampling and experimental design (Lane & Richards, 1997). New statistical tools may therefore be required to link these data sets. Moreover, to overcome the limitation of two-dimensional analyses of three-dimensional river systems to investigate planimetric change at network scales, it may be necessary to adopt spatially nested

approaches that combine high-resolution topographic monitoring at representative sites with network-scale two-dimensional analysis (cf. Wheaton et al., 2018). Rivers are diverse and spatially variable (Richards, 1996), we suggest that GEE analyses should appreciate river complexity and be used as a tool to complement field, flume, geochronology and computer modeling studies.

8 | CONCLUSIONS

GEE offers transformative potential for the spatiotemporal quantification of planimetric river channel form in large-scale fluvial geomorphology applications. Virtualization, cloud-based computing, and access to big geospatial data allow for analyses at higher spatial resolutions, over greater spatial extents and at finer temporal resolutions than ever before. By enabling fluvial geomorphologists to take algorithms to petabytes worth of data, GEE is transformative in enabling deterministic science at scales defined by the user and determined by the phenomena of interest. GEE allows for the formal incorporation of temporal change in analyses of river channel change and channel pattern classification, meaning that theories of geomorphic change can be tested and developed, and classic concepts in fluvial geomorphology can be reexplored. This will require users to look beyond the surface water toward the wider river corridor, so utilizing all of the available information on the diversity and complexity of river systems. Multitemporal analyses can be completed at temporal resolutions relevant to the functional timescales of geomorphic processes of interest. In doing so, this should allow for the monitoring of both gradual and abrupt changes within these systems. Previously, this had not been possible due to the spatiotemporal limits imposed by traditional analysis approaches (i.e., spatial or temporal resolution restrictions), whereas GEE offers analysis within a different spatiotemporal domain. Through spatially and temporally comprehensive and consistent analyses, GEE facilitates a shift toward detailed (i.e., reach differentiated) catchment and intercatchment comparisons of planimetric river channel change. Analyses are not without limitations, currently only a subset of the Earth's large rivers can be investigated, and two-dimensional analyses do not always map onto three-dimensional systems. However, the potential for GEE analyses will only continue to increase as further data sets become available, particularly when looking to the near future, where Earth observation data from newer satellites will allow almost continuous characterization of mid- to large-sized river features, and their changes in space and time (Piégay et al., 2020).

Equally important, GEE offers a mechanism to promote a cultural shift toward open science in fluvial geomorphology and can contribute toward the realization of environmental data science. Transparent, open science is promoted through the ability to share algorithms and reproduce analyses, while participation is widened through virtualization and the democratization of access. This should have pedagogic benefits for the fluvial geomorphology community and encourage collaborative and multidisciplinary working practices. The broadening of users, opportunities for merging and integrating data sets within a common space and innovative combinations of data science techniques (e.g., machine learning) can help make sense of the ever increasing complexity and variety of data available (Blair et al., 2019).

We are not suggesting that GEE will be a panacea for all river channel change studies involving remote sensing in fluvial geomorphology. Challenges remain around issues of scaling, transferability and data uncertainties; particularly for small- to mid-sized rivers where medium-resolution, multispectral satellite imagery is rarely suitable for geomorphic analyses. Rather, we advocate for GEE to be used as another tool for fluvial geomorphologists, complementing field, flume, geochronology, and computer modeling.

CONFLICT OF INTEREST
The authors have declared no conflicts of interest for this article.

AUTHOR CONTRIBUTIONS

DATA AVAILABILITY STATEMENT

Code for the Google Earth Engine workflow (Figure 4) is available here: https://code.earthengine.google.com/f6551e76d148bbf837035feb7a9f7c8a. Data used in this manuscript can be obtained by contacting the lead author.

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