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Editorial

# A summary of the special issue on remote sensing of land change science with Google earth engine

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ABSTRACT

To embrace the burgeoning land change science studies that exploit public-domain cloud-computing platforms such as Google Earth Engine (GEE), for the first time, we organized a special issue entitled "Remote Sensing of Land Change Science with Google Earth Engine" in the journal "Remote Sensing of Environment". This paper serves as a summary to a collection of 19 papers that have been published since the inception of the special issue in November 2017. In particular, we summarized their contributions with regard to two perspectives: what new themes of questions are articulated, what contributions have been made. Taking account of the disciplinary difference, we carried out the summary separately in two major science domains: Remote Sensing of Environment (RSE), i.e., naturally-induced land change, and Remote Sensing of Society (RSS), i.e., human-induced land change. Furthermore, we presented a historical review of the developments of GEE-relevant studies published before our special issue. Finally, we provided a future prospect on how GEE will continue to evolve to further the study of land change science.

## 1. Introduction

A plethora of multi-temporal remote sensing data ranging from local, regional to global coverage have been made freely available to scientific communities via many public-domain platforms. Google Earth Engine (GEE), a cloud computing platform, has revolutionized the analyses of remote sensing data with its massive preloaded geospatial datasets and parallel processing capacity (Gorelick et al., 2017; Hansen et al., 2013). As such, it presents us an unprecedented opportunity to advance our scientific understanding of various dynamic processes associated with the earth system, specifically those in the land change science (Turner et al., 2007).

The first significant work of GEE was published in 2013 (Hansen et al., 2013). Since then, a steadily increasing number of publications have witnessed the early-stage developments of GEE-relevant applications between 2013 and 2016. In 2017, Gorelick et al. (2017) provided the first comprehensive introduction of GEE. The paper stirred immense interests in the remote sensing community by introducing the concept and applications of GEE in great depth. However, no special issue on GEE was made available prior to November 2017. In order to capture this pivotal point in the evolution of GEE, we started to organize a special issue entitled "Remote Sensing of Land Change Science with Google Earth Engine" in the journal "Remote Sensing of Environment" between November 2017 and March 2020 (Fig. 1). This issue aims to publish research papers that focus on both the methodology and applications of GEE in two main remote sensing domains dedicated to land change science: Remote Sensing of Environment (RSE), i.e., naturally-induced land change, and Remote Sensing of Society (RSS), i.e., human-induced land change. The overarching goal of this special issue is to uncover how GEE will transform the study of land change science.

Now that two and a half years have lapsed, our special issue has published 19 research articles. This paper serves as an overall summary of the published papers in this issue. Specifically, our objectives are in three folds:

1) To summarize the contributions achieved in all the papers published in our special issue;
2) To understand the historical contributions made prior to our special issue (before April 2018);
3) To envision the future prospect of GEE developments beyond the special issue.

Since the inception of our special issue in 2017, GEE has developed rapidly. This can be testified by the surging publication numbers in both 2018 and 2019 (Fig. 1). To this end, it should be noted that our intension for this paper is not to report the up-to-date progress of GEE, particularly the vast papers published in the last two years. Audience who are interested in such review can be directed to a paper published recently (Tamiminia et al., 2020).

Our organization of the paper is as follows. In Section 2, we first separate the 19 papers into two major science domains, i.e., RSE and RSS, then present a holistic summary of two aspects for each paper: what science questions are addressed in each paper? what contributions have been made utilizing GEE? In Section 3, we review the GEE publications before our special issue (between 2013 and April 2018) with regards to the two major science domains. In Section 4, we discuss the overall trend of how GEE has evolved to advance studies in RSE and RSS, and provide a future prospect detailed in four aspects after our special issue. Lastly in Section 5, conclusions are provided.

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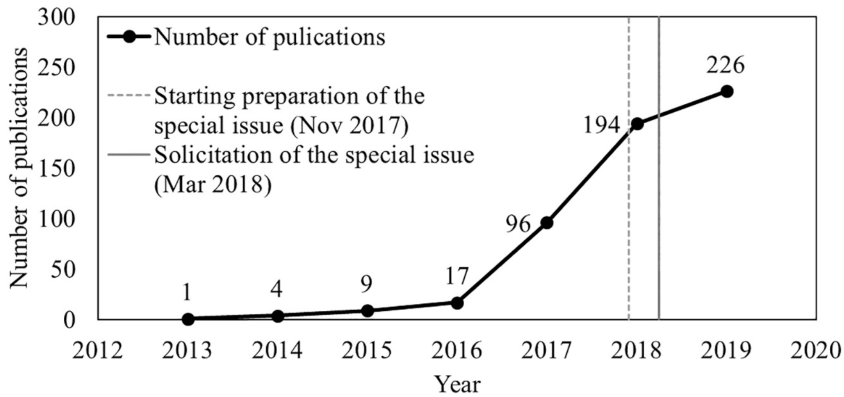


**Fig. 1.** Yearly number of GEE publications between 2013 and 2019. Numbers obtained by searching "Earth Engine" as the topic in Web of Science all databases.

## 2. GEE studies in the special issue

This section summarizes the 19 papers published in this special issue, presented in two major science domains and seven specific domains (Fig. 2). Subsequently, the domains are respectively described in descending order of the number of publications.

### 2.1. Remote sensing of environment (RSE)

Three publications in this special issue focused on forests and rangelands. One of the publications focused on detecting the change of forests: Bunting et al. (2019) assessed the response of plant production to seasonal climate variability across five deserts in the southwestern U.S. from 1988 to 2015. The other two were related to rangeland monitoring: Xie et al. (2019) presented a new approach to map the change of surface vegetation properties across large-scale rangelands in Queensland Australia, while Zhou et al. (2020) explored how the temporal relevance of training data influences the performance of surface conditions prediction in rangeland monitoring.

Three papers have been published about wetland in this special issue (Cao et al., 2020; Tian et al., 2020; Wu et al., 2019). They focused on three different topics: wetland inundation extends, land cover change and invasive species. Wu et al. (2019) mapped wetland inundation dynamics in the Prairie Pothole Region of North America at watershed scales. Alternatively, Cao et al. (2020) mapped the continuous coastal dynamics in Zhoushan Archipelago, China. In addition, Tian et al. (2020) mapped the long-term change of an invasive wetland species (*Spartina alterniflora*) and presented the first regional invasion outbreak in Beibu Gulf, South China Sea. The main data sources of Cao et al. (2020) and Tian et al. (2020) were time-series Landsat multispectral images, while Wu et al. (2019) integrated fine spatial resolution Light Detection and Ranging data and multi-temporal aerial images.

### 2.2. Remote sensing of society (RSS)

There are six publications in the special issue focusing on agriculture-relevant applications (Bey et al., 2020; Deines et al., 2019; Jin et al., 2019; Johnson, 2019; Parente et al., 2019; Thieme et al., 2020). Upon comparison with previous literatures, most of the studies target for more frequent (e.g., annual) and higher resolution cropland (or pastureland) and crop type mapping over wider geographical regions by leveraging unprecedented computational capabilities of GEE.

Three publications are pertinent to natural hazards, particularly to fire and flooding (Crowley et al., 2019; DeVries et al., 2020; Liu et al., 2020). A diverse suite of satellite imagery, including Moderate

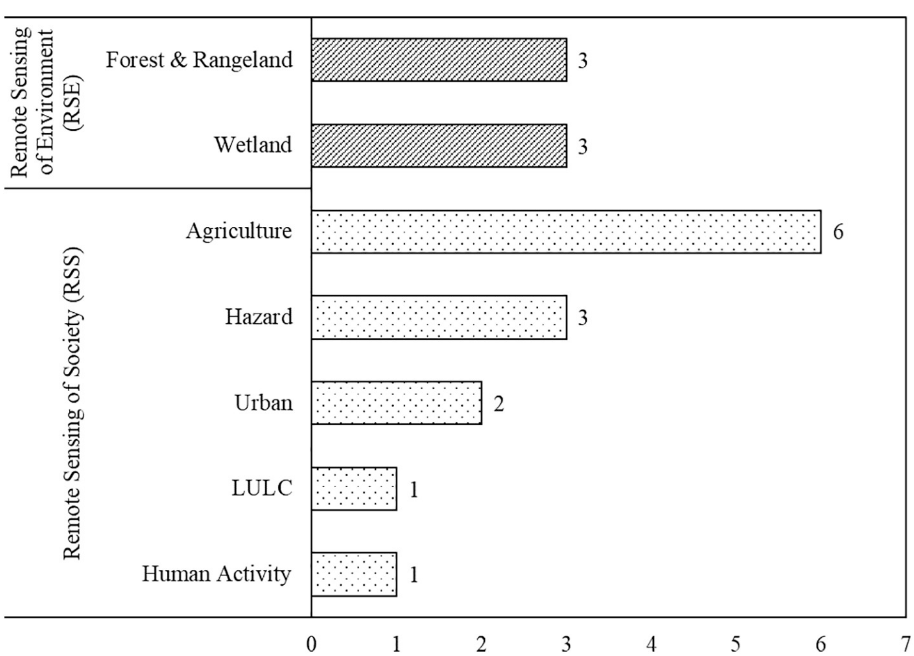


**Fig. 2.** Numbers of GEE publications in the special issue.

Resolution Imaging Spectroradiometer (MODIS), Visible Infrared Imaging Radiometer Suite, Landsat, Sentinel-1, and Sentinel-2 have been employed in GEE to monitor the extent and magnitude of natural hazards and to quantify the uncertainties of derived estimates.

Two papers focused on urban, particularly on the impervious surface distribution. Gong et al. (2020) mapped the global distribution of impervious areas, while Shao et al. (2019) evaluated local-scale hydrological environment conditions with impervious area distribution information.

One publication is dedicated to Land Use and Land Cover (LULC) change (Ge et al., 2019). The major contribution of this work is that they analyzed the spatial-temporal pattern of inter-annual land use changes in China's poverty-stricken areas.

This GEE special issue includes one paper about human activity (Wong et al., 2019). They automatically detect oil platforms in the Gulf of Mexico using Sentinel-1 Synthetic Aperture Radar (SAR) on GEE.

## 3. GEE studies before the special issue

By April 2018 when this special issue was officially announced, 239 GEE-related studies had been published, covering a wide spectrum of science domains (Fig. 3). This section provides a comprehensive review of these publications in terms of two major science domains, i.e., RSE (section 3.1) and RSS (Section 3.2). Subsequently, the topics are respectively described in descending order of the number of publications in each science domain.

### 3.1. Remote sensing of environment (RSE)

#### 3.1.1. Forest & rangeland

Researchers studying forests took the lead in utilizing GEE. Until April 2018, 41 publications focused on forest & rangeland problems, with forest being the major concentration (Table 1). Most works (27 publications) studied the change of forest cover or vegetation cover (Hansen et al., 2013; Joshi et al., 2016; Pratihast et al., 2014). Starting from 2016, a few more recent works studied the response of forests to climate change and hazards (Battles et al., 2017; Luo et al., 2016). In 2017 and 2018, eight GEE-based studies on estimating forest biophysical parameters got published, which concerned photosynthesis, phenology, aboveground biomass, carbon stock, etc. (Asner et al., 2018; Badgley et al., 2017; Wright et al., 2017; Yu et al., 2017). As the emphasis on accuracy and ecological analysis increases, the geographic extent of those forest & rangeland studies has a tendency to shrink from global and continental (Hansen et al., 2013; Tracewski et al., 2016) to regional and national coverage (Parente and Ferreira, 2018; Soulard et al., 2017; Wright et al., 2017).

**Table 1**
Number of GEE publications concerning forest- or rangeland- related problems.

| | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Total |
|---|---|---|---|---|---|---|---|
| Forest cover (change) | 2 | 1 | | 9 | 6 | 9 | 27 |
| Response to stress | | | | 2 | 3 | 1 | 6 |
| Biophysical parameter | | | | | 3 | 5 | 8 |
| Total | 2 | 1 | | 11 | 12 | 15 | 41 |

**Table 2**
Number of GEE publications concerning water-related problems.

| | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | Total |
|---|---|---|---|---|---|---|---|---|
| Extent change analysis | | | | 3 | 6 | 2 | | 11 |
| Extent mapping | | | | 1 | 3 | 2 | | 6 |
| Water level and storage | | | | 1 | 1 | 3 | 1 | 6 |
| Water quality | | | | 1 | | 1 | | 2 |
| Water temperature | | | | | 1 | 1 | | 2 |
| Hydrologic modeling | | | | 2 | | | | 2 |
| Total | 0 | 0 | 0 | 8 | 11 | 9 | 1 | 29 |

#### 3.1.2. Water

There are 29 GEE publications about water, in which water mapping and change analysis are the earliest (since 2016) and most popular topics (Table 2). More recently, water characteristics, such as water level, volume, water quality, temperature, flow and runoff, have been studied. Global long-term studies are still popular, while regional and local studies are more prevalent, with many investigations in the Tibetan area. Landsat imagery is the most used dataset, while other data sources such as MODIS, Sentinel, and even unmanned aerial vehicle data are also individually used or combined. A representative group was the group of Noel Gorelick and Gennadii Donchyts, who published three influential papers about water change monitoring.

#### 3.1.3. Ecosystem & Biodiversity

There are 27 publications centered on ecosystem- or biodiversity-related problems (Table 3). Among these studies, 14 studies are pertinent to ecosystem monitoring and assessment. The other 13 studies focus on modeling the distribution dynamics of species (or

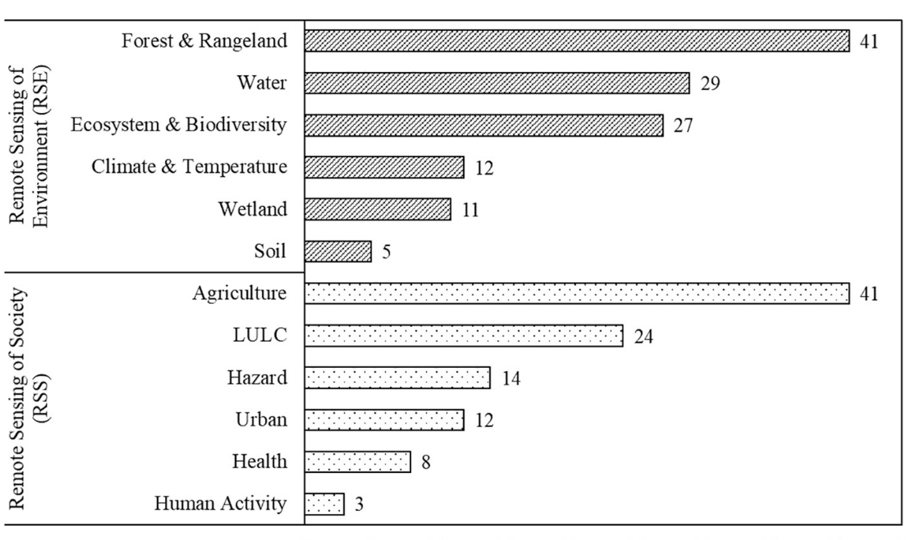


**Fig. 3.** Number of GEE publications before April 2018.

**Table 3**
Number of GEE publications concerning ecosystem- or biodiversity- related problems.

| | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Total |
|---|---|---|---|---|---|---|---|
| Ecosystem monitoring and assessment | | | 1 | 5 | 3 | 5 | 14 |
| Species/community dynamics | | | | 3 | 5 | 5 | 13 |
| Total | 0 | 0 | 1 | 8 | 8 | 10 | 27 |

communities), including seven animal species and five aquatic species (or communities). The research lying in ecosystem monitoring involves the evaluation of ecosystem services and functions via measures of satellite-based net primary production, vegetation cover, vegetation phenology, biodiversity, etc. The studies in species or community dynamics typically leverage satellite-derived variables as environmental factors to predict its potential distributions or movement dynamics. The geographical extent of this research topic varies from regional to global scales, with most studies conducted in North America and Africa. Landsat and MODIS are the primary satellite imagery used in GEE, particularly as environmental proxies in assessing ecosystem properties and species distributions.

#### 3.1.4. Climate & temperature

There are 12 publications focusing on climate change or temperature-related problems (Table 4). Five of them directly quantified climate change, four of the publications worked on the effects of climate change, and three focused on land surface temperature (LST). For the five climate change studies, the climate variables they studied were various, which included carbon turnover, greenhouse gas emissions, temperature, albedo, precipitation, solar radiation, vapor pressure, wind speed and so on. The research lying in the effects of climate change discussed the effects of climate on land surface phenology, the ratio of snowfall to total precipitation and tropical plumes.

#### 3.1.5. Wetland

There were 11 publications of wetland related studies (Table 5). They can be classified into three topics: wetland mapping or change monitoring, wetland hydrology, and carbon fixation. Wetland mapping or monitoring was conducted regionally in North America and South Asia utilizing machine learning algorithms (Farda, 2017; Hird et al., 2017). In the two wetland hydrology studies, wetness was evaluated to trace the status of water in wetlands (Alonso et al., 2017; Tang et al., 2016). In wetland carbon fixation studies, gross primary production or aboveground biomass and carbon were evaluated according to their relationship with multi-spectral or SAR images (Byrd et al., 2018; Knox et al., 2017). Data source for most studies was Landsat imagery with 30-m spatial resolution and full coverage of the earth starting from 1972.

#### 3.1.6. Soil

Until April 2018, there are five published studies in soil using GEE (Table 6). Three topics were studied including soil class mapping, soil organic carbon mapping, and soil mercury mapping. Among these five papers, two mapped both soil classes and organic carbon (Diek et al., 2017; Padarian et al., 2015), two focused on mapping soil organic carbon (Padarian et al., 2017; Sanderman et al., 2018), and one mapped

**Table 4**
Number of GEE publications concerning climate-related problems.

| | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Total |
|---|---|---|---|---|---|---|---|
| Climate change | | | | 3 | 2 | | 5 |
| Climate change effects | | | | | 3 | 1 | 4 |
| LST | | | | | 2 | 1 | 3 |
| Total | 0 | 0 | 0 | 3 | 7 | 2 | 12 |

**Table 5**
Number of GEE publications concerning wetland-related problems.

| | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Total |
|---|---|---|---|---|---|---|---|
| Mapping or change monitoring | | | 1 | 2 | 4 | | 7 |
| Wetland hydrology | | | | 1 | 1 | | 2 |
| Carbon fixation | | | | | 1 | 1 | 2 |
| Total | 0 | 0 | 1 | 3 | 6 | 1 | 11 |

**Table 6**
Number of GEE publications concerning soil-related problems.

| | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Total |
|---|---|---|---|---|---|---|---|
| Soil class/property and organic carbon mapping | | | 1 | | 1 | | 2 |
| Soil organic carbon mapping only | | | | | 1 | 1 | 2 |
| Soil mercury mapping | | | | 1 | | | 1 |
| Total | 0 | 0 | 1 | 1 | 2 | 1 | 5 |

soil mercury (Obrist et al., 2016). Early soil studies using GEE are countrywide mainly located on North and South American continents, and later studies are extended to the global scale.

### 3.2. Remote sensing of society (RSS)

#### 3.2.1. Agriculture

There are about 41 publications focusing on agriculture-related problems (Table 7), most of which are on crop mapping (17 publications), crop yield estimation (10 publications) and crop water management (10publications). Those agricultural studies are conducted at multiple geographical scales, ranging from regional to continental. Specifically, the geographical regions of crop mapping are mainly in Africa (6 publications) and Asia (4 publications), also with a few in North America, Europe and South America (Brazil). The mapping studies in Asia have mainly focused on paddy rice, while efforts in Africa are more general in estimating the extent and changes of croplands. The studies of crop yield estimation are mainly conducted for maize in the Midwestern region of the US, wheat in the northern India, and maize in the western Kenya. Of ten studies regarding crop irrigation or water management, four of which have been done in the US. The dataset in GEE used in agricultural-related applications are mainly Landsat, MODIS, Sentinel-2 and gridded weather data.

#### 3.2.2. LULC

There are 24 publications on LULC using GEE, which cover two categories: seven works focused on LULC mapping, i.e., mapping or classifying the LULC at a specific time with a set of remote sensing images, and 17 works focused on LULC change monitoring, i.e., monitoring the change of LULC over a long time period or rapid updating of LULC maps (Table 8).

LULC mapping has been studied since 2015 (Simonetti et al., 2015). Later studies focused more on LULC change monitoring. The LULC classes mainly include bare ground, water, urbanized areas, and subcategories of vegetation (e.g., deciduous forest), although the actual

**Table 7**
Number of GEE publications regarding agriculture-related problems.

| | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Total |
|---|---|---|---|---|---|---|---|
| Crop mapping | | | | 4 | 10 | 3 | 17 |
| Crop yield estimation | | | 1 | 2 | 6 | 1 | 10 |
| Crop water management | | | | 5 | 4 | 1 | 10 |
| Other | | | | 2 | 2 | | 4 |
| Total | 0 | 0 | 1 | 13 | 22 | 5 | 41 |

**Table 8**
Number of GEE publications concerning LULC-related problems.

| | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Total |
|---|---|---|---|---|---|---|---|
| Change monitoring | | | | 10 | 4 | 3 | 17 |
| Mapping | | | 1 | 2 | 4 | | 7 |
| Total | 0 | 0 | 1 | 12 | 8 | 3 | 24 |

classes included differ in each paper. Study sites ranged from small areas (e.g., within one Landsat scene) to global scales, while the time span ranged from as short as one time point all the way to 30 years. The largest project monitored LULC change at the global scale for 12 consecutive years. (Ying et al., 2017). Most studies used Landsat time-series data thanks to their relatively high spatial, temporal, and spectral resolutions, while other datasets were sometimes employed to provide additional information (e.g., MODIS providing land/atmospheric/ocean products (Eberle et al., 2016), Phased Array type L-band Synthetic Aperture Radar data penetrating cloud cover and characterizing vegetation structure (Johnson and Iizuka, 2016)). Besides various automatic mapping approaches being proposed or tested (e.g., (Azzari and Lobell, 2017; Simonetti et al., 2015)), visual interpretation is also greatly facilitated by GEE (e.g., (Miettinen et al., 2016)).

### 3.2.3. Hazard

About 14 publications in GEE focus on the natural hazard-related applications (Table 9). A multitude of types of hazards have been investigated in those studies, including fire, flooding, disaster, windstorm, and drought. Satellite imagery has been mostly utilized to monitor geographical areas affected by natural hazards and assess their influences on surrounding environment (e.g., land cover changes). For instance, the fire-related studies mainly employ satellite imagery to analyze the burnt and deforested areas caused by fire, burnt severity and its influence on vegetation (Petrakis et al., 2018; Reddington et al., 2015; Soulard et al., 2016; Verhegghen et al., 2016). The geographical extent of those natural hazard applications varies from regional to national scales, with representative studies conducted in the US, Brazil, and Congo. A range of satellite imagery, including Landsat, MODIS (e.g., aerosol optical depth and active fire products), Sentinel-1, Sentinel-2, have been explored to characterize the properties of natural hazards to facilitate the subsequent monitoring.

### 3.2.4. Urban

Characterization of urban land was one of the most popular domains in GEE applications (Table 10). Twelve articles related to urban land using GEE have been published since 2015 until April 2018. Seven of the 12 papers focused on urban extent mapping (Goldblatt et al., 2018; Goldblatt et al., 2016; Liu et al., 2018; Patel et al., 2015; Savory et al., 2017; Trianni et al., 2015; Zhang et al., 2015), which is the most popular urban topic. Following urban extent, urban ecosystems (Li et al., 2017; Meerow et al., 2017), socio-economic trends (Proville et al., 2017), population distribution (Li and Lu, 2016), and accessibility to city (Weiss et al., 2018) have also been investigated and mapped in GEE.

**Table 9**
Number of GEE publications concerning natural hazard-related problems.

| | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Total |
|---|---|---|---|---|---|---|---|
| Fire | | | 1 | 2 | | 1 | 4 |
| Flooding | | | | 1 | 1 | 2 | 4 |
| Disaster | | | 1 | 1 | 1 | | 3 |
| Windstorm | | | | | 1 | 1 | 2 |
| Drought | | | | | | 1 | 1 |
| Total | 0 | 0 | 2 | 4 | 3 | 5 | 14 |

**Table 10**
Number of GEE publications concerning urban-related problems.

| | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Total |
|---|---|---|---|---|---|---|---|
| Urban extent mapping | | | 3 | 1 | 1 | 2 | 7 |
| Urban ecosystem | | | | | 2 | | 2 |
| Socio-economic trends | | | | | 1 | | 1 |
| Population mapping | | | | 1 | | | 1 |
| Accessibility mapping | | | | | | 1 | 1 |
| Total | 0 | 0 | 3 | 2 | 4 | 3 | 12 |

### 3.2.5. Health

There are about eight studies centered on health-related applications (Table 11), which can roughly be categorized into three topics (i.e., disease risk mapping, influential factors for disease distribution, and urban health assessment). Disease risk mapping was conducted mainly for malaria and tick bite (Garcia-Martí et al., 2017; Larsen et al., 2017; Smith et al., 2017; Sturrock et al., 2014; Tatem et al., 2014). A variety of factors influencing the generation and distribution of diseases were investigated in GEE, including forest fire (Reddington et al., 2015), environmental and human factors (Garcia-Martí et al., 2017), location (Larsen et al., 2017), age and gender (Smith et al., 2017), and urban heat island (Méndez-Lázaro et al., 2018). Urban health was assessed according to the availability and accessibility of green space in urban areas (Huang et al., 2017). The geographical extent of those health-related applications varies from regional to national scales, with representative studies conducted in Africa, North America, and Europe. Several datasets in GEE, including Landsat, MODIS, topography, land cover, and weather data, have been explored as environmental covariates in assessing the disease risk and transmission dynamics.

### 3.2.6. Human activity

Three papers focused on human activities and their environmental impacts using GEE until April 2018 (Table 12). It was a field waiting to be further explored. Two topics were explored: one paper attempted to detect human activities on the ocean and the other two papers estimated temperature-related environmental impacts caused by human activities. SAR data in GEE were utilized to extract mining activity at a local scale (Chaussard and Kerosky, 2016), and MODIS LST data were used to link the intensity of human activities to the temperature change (Benz et al., 2017; Elhacham and Alpert, 2016). Although these three studies were at local or country scales, the use of GEE would make the proposed methods applicable in further global studies.

**Table 11**
Number of GEE publications concerning health-related problems.

| | 2013 | 2014 | 2015 | 2016 | 2017 | Total |
|---|---|---|---|---|---|---|
| Factors for disease distribution | | | 1 | 1 | 3 | 5 |
| Disease risk mapping | | 2 | | | | 2 |
| Urban health assessment | | | | | 1 | 1 |
| Total | 0 | 2 | 1 | 1 | 4 | 8 |

**Table 12**
Number of GEE publications concerning human-activity-related problems.

| | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Total |
|---|---|---|---|---|---|---|---|
| Human's impact on environment | | | | 1 | 1 | | 2 |
| Change of human activity | | | | 1 | | | 1 |
| Total | 0 | 0 | 0 | 2 | 1 | 0 | 3 |

## 4. Discussion

The GEE-related literatures before April 2018 show that RSE studies arise earlier and quickly gain more attention than RSS studies. In contrast, it should be remarked that our special issue published a larger portion of RSS papers than those of RSE, indicating the RSS studies begin to take off in the recent years. Therefore, it is intriguing to reveal the respective path that RSE and RSS has gone through and hopefully shed light on their future developments. To this end, this section provides a holistic synthesis of the review presented in Sections 2 and 3. More specifically, in Sections 4.1 and 4.2, we traverse the evolution within RSE and RSS domains, respectively; in Section 4.3, we attribute the various developments to four major aspects and strive for identifying potential research directions.

### *4.1. Remote sensing of environment (RSE)*

RSE aims to uncover the environmental changes resulted from natural factors. Since the GEE work commenced in RSE, three distinctive patterns of analyses are gradually unfolded in RSE: burst of mapping and change quantification, transition from mapping to modeling, and refinements of algorithm and accuracy.

Driven by the fact that GEE provides free access to a wide spectrum of multi-temporal and global coverage datasets, the first group of research focused on mapping and quantifying different land cover changes. For example, global forest was mapped with GEE-based on widely applied vegetation indices (e.g., Normalized Difference Vegetation Index ) (Hansen et al., 2013). Along the same line, water mapping with GEE was developed owing to the fact that water body is relatively easy to be differentiated from other land cover types (Pekel et al., 2016). Subsequently, mapping and change analysis were spread to other land cover types, such as wetland (e.g., (Alonso et al., 2016)) and soil (e.g., (Padarian et al., 2015)).

The second pattern we perceived is the transition of analysis from mapping to modeling. Inheriting the success of various land cover mapping and change quantification, substantial modeling efforts have been invested in order to probe the driving factors to the quantified changes. For example, investigation on the coupling of vegetation changes and various environmental factors (e.g., oil and gas locations, animal species distribution) led to the development of ecosystem and biodiversity research using GEE (Allred et al., 2015; Lewis et al., 2017). On the other hand, the modeling of climate and temperature lagged behind their ecosystem counterpart (Attermeyer et al., 2016; Fick and Hijmans, 2017), likely due to its relative complication compared to mapping studies.

Adjoining the early efforts on mapping and modeling, a third thread of analysis emerged with a focus on refining the algorithm and accuracy. Examples of such endeavors include (1) expanding data source from coarse spatial resolution (e.g., MODIS) to medium and high resolutions (e.g., Landsat and Sentinel), from solely optical imagery to fusion with radar and other ancillary data; (2) restricting the geographic extent from global to regional so that the algorithms can be better customized. These attempts, in turn, would further benefit the mapping and modeling studies.

### *4.2. Remote sensing of society (RSS)*

Unlike RSE, RSS aims to understand land changes primarily induced by human activities. Given the complication of the reconnaissance of human-related variables, RSS emerged later than RSE. Among the limited RSS works, three different clusters have been revealed: detection of human-induced environmental change, examination of environmental impact on society, and direct observation of human activity.

The predominant RSS publications fall in the detection of human-induced environmental change, mostly residing in three RSS domains: agriculture, LULC, and urban. This is partially attributed to the progress made with its counterpart in RSE. Leveraging the massive data repository of GEE, new mapping methods were developed to incorporate vegetation phenology in distinguishing the human-induced land cover change. For example, based on time-series Landsat images, pixel-based indices were proposed to map paddy rice areas (Dong et al., 2016), LULC in protected areas (Simonetti et al., 2015), and global urban extent (Liu et al., 2018). Furthermore, new modeling methods took place drawing upon the fusion of multiple sources of data on GEE, e.g., for crop yield estimation (Lobell et al., 2015) and for urban population estimation (Li and Lu, 2016).

The second thrived cluster of work in RSS focuses on the examination of the environmental impact on society. Two primary RSS domains, hazard and health, have reported some preliminary efforts using GEE. Interestingly, instead of applying conventional methods universally on a global scale, studies in this category have leaned toward developing new mapping methods that can be adapted to a local or regional scale. For example, scholars leveraged multi-source data to map deforestation due to wildfire (Reddington et al., 2015) and to model health-related environmental factors (Tatem et al., 2014). Progressively, more exclusive GEE-based methods were developed to yield a higher accuracy for quantifying the various environmental impacts (Coltin et al., 2016; Verhegghen et al., 2016).

More recently, the research on direct observation of human activity have started to emerge yet understudied. Amid the limited works, they attempted to expose human activity from infrastructure changes and nighttime light use. The underdevelopment is due to the fact that the GEE datasets (e.g., 30-m Landsat images (Elhacham and Alpert, 2016), 10-m Sentinel-1 SAR data (Wong et al., 2019), 1-km NTL data (Benz et al., 2017)) have rather coarser resolution than what is imperative for diagnosing human activity. Since human activity can be highly heterogeneous over space and time, these works could potentially benefit from higher resolution data such as DigitalGlobe images (sub-meter) (Chaussard and Kerosky, 2016) and Jilin1-03 NTL data (0.92 m) (Du et al., 2018). Therefore, we envision the future developments of human activity using GEE is contingent upon both the availability of high-spatial-resolution observations and the development of effective methods such as object-based image analysis and artificial intelligence algorithms on GEE.

### *4.3. Future prospect*

Despite the strides that both RSE and RSS have been progressing in their own courses of directions, it would be intriguing to examine the existing works under universal trends of analyses, based on which potential research directions can be inferred. Our special issue on GEE occurred at a turning point when various applications started to flourish. Along with the publicity of GEE, a large user community has been nurtured to foster GEE in their respective fields of studies. As a result, the pressing user demands have driven the types of analyses from basic data acquisition, to intermediate data processing, and ultimately to sophisticated modeling. Therefore, we propose the following to examine all the works under the umbrella of four universal trends of analyses (Table 13): from temporally static to dynamic, from mapping to modeling, from single data source to multiple data sources, and from using GEE for data retrieval to using GEE to articulate new science questions.

Table 13 details how the four proposed universal trends of analyses progressed in each science domain as included in RSE and RSS. In the table, two different symbols are adopted to represent two distinctive development status, i.e., checked items indicate that the developments have occurred, while the unchecked ones signal that no developments exist. We have discerned two seeming trends as follows.

First, in general, more checked items have shown up in RSE than in RSS, which resembles our earlier statements that RSE was more established than RSS. More specifically, studies on forest & rangeland in

**Table 13**
Domains development trend using GEE. "-" means "not applicable".

| Trends domains | | Temporal dimension: static to dynamic | Methodology: mapping to modeling | Data source: single to multiple | Role of GEE: platform to driver |
|---|---|---|---|---|---|
| Remote sensing of environment (RSE) (refer to Sections 2.1 and 3.1) | Forest & Rangeland | √ | √ | √ | √ |
| | Water | √ | √ | √ | |
| | Ecosystem & Biodiversity | √ | √ | √ | |
| | Climate & Temperature | √ | – | √ | |
| | Wetland | √ | √ | √ | |
| | Soil | | √ | √ | |
| Remote sensing of society (RSS) (refer to Sections 2.2 and 3.2) | Agriculture | √ | √ | √ | |
| | LULC | √ | √ | √ | √ |
| | Urban | √ | √ | √ | |
| | Hazard | √ | √ | √ | |
| | Health | √ | – | √ | |
| | Human Activity | | √ | √ | |

RSE and LULC in RSS have prevailed in existing GEE research as evidenced by all the four trends checked. Conversely, studies on soil and human activities trailed behind their main-stream cohorts as evidenced by only two out of the four trends checked. We infer that a possible impetus for the disparate developments is data adequacy, i.e., if the data demanded by a science domain can be largely satisfied by GEE exclusively, then the development is naturally populated; alternatively, if additional domain-specific data is requested beyond what is provided by GEE, then the development is encumbered.

Second, the four universal trends unveiled at different paces of adaptation in different science domains. 1) In 10 out of the 12 science domains in RSE and RSS, analyses have been migrated from spotting single-time static status to monitoring multi-temporal dynamics, thanks to the time-series datasets housed by GEE. The two domains lingering with static analysis are soil and human activity. This can likely be attributed to data availability. More specifically, soil studies often engage underground measurements while human activity is desired to be portrayed with meter-level data. However, the datasets catered by GEE are mostly satellite observations of the earth surface, which remain too coarse in spatial resolution for the two domains' experts to resolve their questions. Therefore, we anticipate that studies on soil and human activity using GEE can be expanded to dynamic analyses if refined datasets can be assimilated in GEE. 2) Nearly all domains have practiced a transition from mapping to modeling. The only exceptions are climate & temperature and health, in which modeling is indispensable in the beginning. It should be noted that although GEE provides a ready computing facility to facilitate modeling efforts, most existing work is still in its infancy as only simple regression is adopted. More sophisticated mathematical forms are desired to be included in future model developments to fully embrace the GEE potential. 3) All domains have transitioned from using single data source to using multiple data sources because of vast efforts toward full exploitation of GEE. Nevertheless, as more and more datasets are assessed on GEE, a potential route of refinement can be the combined use of datasets that encompass different spatial, temporal, and spectral resolutions. 4) Lastly, nearly in all the science domains, GEE was primarily adopted for expanding spatial and temporal coverage of a prevailing research question pre-existing in the domain. The two domains that have pioneered in this transition trend are forest & rangeland and LULC. In the forest & rangeland domain, an exemplified question is to examine how the vegetation worldwide is affected by various natural and anthropogenic factors such as climate change (Bunting et al., 2019) and human population (Bunting et al., 2019; Tracewski et al., 2016). In LULC, researchers have started to scrutinize the unparalleled large-spatial-scale and long-temporal patterns of LULC change as a testimony to the effectiveness of a policy (Ge et al., 2019). As a significant number of GEE research starts to unfold, we envision that new suites of science questions will be cultivated that can seamlessly integrate the data and computing potential indigenous in GEE in advancing the respective RSE and RSS domains.

## 5. Conclusions

This paper provides a summary to our special issue on land change science with GEE, which has published in total 19 research articles. Rooted in the two broadly-defined science domains, i.e., RSE and RSS, we summarized the various contributions achieved by these articles. In addition, embracing the special issue as an anchor point, we analyzed the historical developments before the special issue, and provided a prospect of the future developments after the special issue. Finally, we envision that GEE will equip the broad science community with better cutting-edge tools and free access to wider spectrum of remote sensing data, and thus utterly stimulate the emergence of transformative research questions in land change science.

## References


Allred, B.W., Smith, W.K., Twidwell, D., Haggerty, J.H., Running, S.W., Naugle, D.E., Fuhlendorf, S.D., 2015. Ecosystem services lost to oil and gas in North America. Science 348, 401–402.

Alonso, A., Muñoz-Carpena, R., Kennedy, R.E., Murcia, C., 2016. Wetland landscape spatio-temporal degradation dynamics using the new Google Earth Engine cloud-based platform: opportunities for non-specialists in remote sensing. Trans. ASABE 59, 1331–1342.

Alonso, A., Rafael, M.-C., David, K., 2017. Combining field monitoring with remote sensing to reconstruct historical hydroperiod in a degrading tropical wetland. In: AGU Book of Abstracts, pp. H54G.

Asner, G.P., Brodrick, P.G., Philipson, C., Vaughn, N.R., Martin, R.E., Knapp, D.E., Heckler, J., Evans, L.J., Jucker, T., Goossens, B., 2018. Mapped aboveground carbon stocks to advance forest conservation and recovery in Malaysian Borneo. Biol. Conserv. 217, 289–310.

Attermeyer, K., Flury, S., Jayakumar, R., Fiener, P., Steger, K., Arya, V., Wilken, F., Van Geldern, R., Premke, K., 2016. Invasive floating macrophytes reduce greenhouse gas emissions from a small tropical lake. Sci. Rep. 6, 20424.

Azzari, G., Lobell, D., 2017. Landsat-based classification in the cloud: an opportunity for a paradigm shift in land cover monitoring. Remote Sens. Environ. 202, 64–74.

Badgley, G., Field, C.B., Berry, J.A., 2017. Canopy near-infrared reflectance and terrestrial photosynthesis. Sci. Adv. 3, e1602244.

Battles, J.J., Cleavitt, N.L., Saah, D.S., Poling, B.T., Fahey, T.J., 2017. Ecological impact of a microburst windstorm in a northern hardwood forest. Can. J. For. Res. 47, 1695–1701.

Benz, S.A., Bayer, P., Blum, P., 2017. Identifying Anthropogenic Anomalies in Air, Surface and Groundwater Temperatures in Germany. 584. Science of the Total Environment, pp. 145–153.

Bey, A., Jetimane, J., Lisboa, S.N., Ribeiro, N., Sitoe, A., Meyfroidt, P., 2020. Mapping smallholder and large-scale cropland dynamics with a flexible classification system and pixel-based composites in an emerging frontier of Mozambique. Remote Sens. Environ. 239, 111611.

Bunting, E.L., Munson, S.M., Bradford, J.B., 2019. Assessing plant production responses to climate across water-limited regions using Google Earth Engine. Remote Sens. Environ. 233, 111379.

Byrd, K.B., Ballanti, L., Thomas, N., Nguyen, D., Holmquist, J.R., Simard, M., Windham-Myers, L., 2018. A remote sensing-based model of tidal marsh aboveground carbon

stocks for the conterminous United States. ISPRS J. Photogramm. Remote Sens. 139, 255–271.
Cao, W., Zhou, Y., Li, R., Li, X., 2020. Mapping changes in coastlines and tidal flats in developing islands using the full time series of Landsat images. Remote Sens. Environ. 239, 111665.
Chaussard, E., Kerosky, S., 2016. Characterization of Black Sand Mining Activities and Their Environmental Impacts in the Philippines Using Remote Sensing. 8. Remote Sens., pp. 100.
Coltin, B., McMichael, S., Smith, T., Fong, T., 2016. Automatic boosted flood mapping from satellite data. Int. J. Remote Sens. 37, 993–1015.
Crowley, M.A., Cardille, J.A., White, J.C., Wulder, M.A., 2019. Generating intra-year metrics of wildfire progression using multiple open-access satellite data streams. Remote Sens. Environ. 232, 111295.
Deines, J.M., Kendall, A.D., Crowley, M.A., Rapp, J., Cardille, J.A., Hyndman, D.W., 2019. Mapping three decades of annual irrigation across the US High Plains Aquifer using Landsat and Google Earth Engine. Remote Sens. Environ. 233, 111400.
DeVries, B., Huang, C., Armston, J., Huang, W., Jones, J.W., Lang, M.W., 2020. Rapid and robust monitoring of flood events using Sentinel-1 and Landsat data on the Google Earth Engine. Remote Sens. Environ. 240, 111664.
Diek, S., Fornallaz, F., Schaepman, M.E., De Jong, R., 2017. Barest Pixel Composite for Agricultural Areas Using Landsat Time Series. 9. Remote Sens., pp. 1245.
Dong, J., Xiao, X., Menarguez, M.A., Zhang, G., Qin, Y., Thau, D., Biradar, C., Moore III, B., 2016. Mapping paddy rice planting area in northeastern Asia with Landsat 8 images, phenology-based algorithm and Google Earth Engine. Remote Sens. Environ. 185, 142–154.
Du, M., Wang, L., Zou, S., Shi, C., 2018. Modeling the census tract level housing vacancy rate with the Jilin1-03 satellite and other geospatial data. Remote Sens. 10, 1920.
Eberle, J., Urban, M., Homolka, A., Hüttich, C., Schmullius, C., 2016. Multi-source data integration and analysis for land monitoring in Siberia. In: Novel Methods for Monitoring and Managing Land and Water Resources in Siberia. Springer, pp. 471–487.
Elhacham, E., Alpert, P., 2016. Impact of Coastline-Intensive Anthropogenic Activities on the Atmosphere From Moderate Resolution Imaging Spectroradiometer (MODIS) Data in Dubai (2001–2014). 4. Earth's Future, pp. 54–61.
Farda, N., 2017. Multi-temporal land use mapping of coastal wetlands area using machine learning in Google Earth Engine. In: IOP Conference Series: Earth and Environmental Science. IOP Publishing, pp. 012042.
Fick, S.E., Hijmans, R.J., 2017. WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. Int. J. Climatol. 37, 4302–4315.
Garcia-Martí, I., Zurita-Milla, R., Swart, A., van den Wijngaard, K.C., van Vliet, A.J.H., Bennema, S., Harms, M., 2017. Identifying environmental and human factors associated with tick bites using volunteered reports and frequent pattern mining. Trans. GIS 21, 277–299.
Ge, Y., Hu, S., Ren, Z., Jia, Y., Wang, J., Liu, M., Zhang, D., Zhao, W., Luo, Y., Fu, Y., 2019. Mapping annual land use changes in China's poverty-stricken areas from 2013 to 2018. Remote Sens. Environ. 232, 111285.
Goldblatt, R., You, W., Hanson, G., Khandelwal, A.K., 2016. Detecting the Boundaries of Urban Areas in India: A Dataset for Pixel-based Image Classification in Google Earth Engine. 8. Remote Sensing, pp. 634.
Goldblatt, R., Stuhlmacher, M.F., Tellman, B., Clinton, N., Hanson, G., Georgescu, M., Wang, C., Serrano-Candela, F., Khandelwal, A.K., Cheng, W.H., Balling Jr, R.C., 2018. Using Landsat and Nighttime Lights for Supervised Pixel-based Image Classification of Urban Land Cover. 205. Remote Sens. Environ., pp. 253–275.
Gong, P., Li, X., Wang, J., Bai, Y., Chen, B., Hu, T., Liu, X., Xu, B., Yang, J., Zhang, W., Zhou, Y., 2020. Annual Maps of Global Artificial Impervious Area (GAIA) Between 1985 and 2018. 236. Remote Sens. Environ., pp. 111510.
Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google Earth Engine: planetary-scale geospatial analysis for everyone. Remote Sens. Environ. 202, 18–27.
Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S., Goetz, S.J., Loveland, T.R., 2013. High-resolution global maps of 21st-century forest cover change. Science 342, 850–853.
Hird, J.N., DeLancey, E.R., McDermid, G.J., Kariyeva, J., 2017. Google earth engine, open-access satellite data, and machine learning in support of large-area probabilistic wetland mapping. Remote Sens. 9, 1315.
Huang, C., Yang, J., Lu, H., Huang, H., Yu, L., 2017. Green spaces as an indicator of urban health: evaluating its changes in 28 mega-cities. Remote Sens. 9, 1266.
Jin, Z., Azzari, G., You, C., Di Tommaso, S., Aston, S., Burke, M., Lobell, D.B., 2019. Smallholder maize area and yield mapping at national scales with Google Earth Engine. Remote Sens. Environ. 228, 115–128.
Johnson, D.M., 2019. Using the Landsat archive to map crop cover history across the United States. Remote Sens. Environ. 232, 111286.
Johnson, B.A., Iizuka, K., 2016. Integrating OpenStreetMap crowdsourced data and Landsat time-series imagery for rapid land use/land cover (LULC) mapping: case study of the Laguna de Bay area of the Philippines. Appl. Geogr. 67, 140–149.
Joshi, A.R., Dinerstein, E., Wikramanayake, E., Anderson, M.L., Olson, D., Jones, B.S., Seidensticker, J., Lumpkin, S., Hansen, M.C., Sizer, N.C., 2016. Tracking changes and preventing loss in critical tiger habitat. Sci. Adv. 2, e1501675.
Knox, S.H., Dronova, I., Sturtevant, C., Oikawa, P.Y., Matthes, J.H., Verfaillie, J., Baldocchi, D., 2017. Using digital camera and Landsat imagery with eddy covariance data to model gross primary production in restored wetlands. Agric. For. Meteorol. 237, 233–245.
Larsen, D.A., Ngwenya-Kangombe, T., Cheelo, S., Hamainza, B., Miller, J., Winters, A., Bridges, D.J., 2017. Location, location, location: environmental factors better predict malaria-positive individuals during reactive case detection than index case demographics in Southern Province, Zambia. Malar. J. 16, 18.
Lewis, J.S., Farnsworth, M.L., Burdett, C.L., Theobald, D.M., Gray, M., Miller, R.S., 2017. Biotic and abiotic factors predicting the global distribution and population density of an invasive large mammal. Sci. Rep. 7, 44152.
Li, L., Lu, D., 2016. Mapping Population Density Distribution at Multiple Scales in Zhejiang Province Using Landsat Thematic Mapper and Census Data. 37. International Journal of Remote Sensing, pp. 4243–4260.
Li, X., Zhou, Y., Asrar, G.R., Meng, L., 2017. Characterizing Spatiotemporal Dynamics in Phenology of Urban Ecosystems Based on Landsat Data. 605. Science of the Total Environment, pp. 721–734.
Liu, X., Hu, G., Chen, Y., Li, X., Xu, X., Li, S., Pei, F., Wang, S., 2018. High-resolution Multi-temporal Mapping of Global Urban Land Using Landsat Images Based on the Google Earth Engine Platform. 209. Remote Sens. Environ., pp. 227–239.
Liu, T., Mickley, L.J., Marlier, M.E., DeFries, R.S., Khan, M.F., Latif, M.T., Karambelas, A., 2020. Diagnosing spatial biases and uncertainties in global fire emissions inventories: Indonesia as regional case study. Remote Sens. Environ. 237, 111557.
Lobell, D.B., Thau, D., Seifert, C., Engle, E., Little, B., 2015. A scalable satellite-based crop yield mapper. Remote Sens. Environ. 164, 324–333.
Luo, H., Zhou, T., Wu, H., Zhao, X., Wang, Q., Gao, S., Li, Z., 2016. Contrasting responses of planted and natural forests to drought intensity in Yunnan, China. Remote Sens. 8, 635.
Meerow, S., Newell, J.P.J.L., Planning, U., 2017. Spatial Planning for Multifunctional Green Infrastructure: Growing Resilience in Detroit. 159. pp. 62–75.
Méndez-Lázaro, P., Muller-Karger, F.E., Otis, D., McCarthy, M.J., Rodríguez, E., 2018. A heat vulnerability index to improve urban public health management in San Juan, Puerto Rico. Int. J. Biometeorol. 62, 709–722.
Miettinen, J., Shi, C., Liew, S.C., 2016. Land cover distribution in the peatlands of Peninsular Malaysia, Sumatra and Borneo in 2015 with changes since 1990. Glob. Ecol. Conserv. 6, 67–78.
Obrist, D., Pearson, C., Webster, J., Kane, T., Lin, C.-J., Aiken, G.R., Alpers, C.N., 2016. A Synthesis of Terrestrial Mercury in the Western United States: Spatial Distribution Defined by Land Cover and Plant Productivity. 568. Science of the Total Environment, pp. 522–535.
Padarian, J., Minasny, B., McBratney, A.B., 2015. Using Google's cloud-based platform for digital soil mapping. Comput. Geosci. 83, 80–88.
Padarian, J., Minasny, B., McBratney, A.B., 2017. Chile and the Chilean Soil Grid: A Contribution to GlobalSoilMap. 9. Geoderma Regional, pp. 17–28.
Parente, L., Ferreira, L., 2018. Assessing the spatial and occupation dynamics of the Brazilian pasturelands based on the automated classification of MODIS images from 2000 to 2016. Remote Sens. 10, 606.
Parente, L., Mesquita, V., Miziara, F., Baumann, L., Ferreira, L., 2019. Assessing the pasturelands and livestock dynamics in Brazil, from 1985 to 2017: a novel approach based on high spatial resolution imagery and Google Earth Engine cloud computing. Remote Sens. Environ. 232, 111301.
Patel, N.N., Angiuli, E., Gamba, P., Gaughan, A., Lisini, G., Stevens, F.R., Tatem, A.J., Trianni, G., 2015. Multitemporal Settlement and Population Mapping From Landsat Using Google Earth Engine. 35. International Journal of Applied Earth Observation and Geoinformation, pp. 199–208.
Pekel, J.-F., Cottam, A., Gorelick, N., Belward, A.S., 2016. High-resolution mapping of global surface water and its long-term changes. Nature 540, 418.
Petrakis, R.E., Villarreal, M.L., Wu, Z., Hetzler, R., Middleton, B.R., Norman, L.M., 2018. Evaluating and monitoring forest fuel treatments using remote sensing applications in Arizona, USA. For. Ecol. Manag. 413, 48–61.
Pratihast, A.K., DeVries, B., Avitabile, V., de Bruin, S., Kooistra, L., Tekle, M., Herold, M., 2014. Combining satellite data and community-based observations for forest monitoring. Forests 5, 2464–2489.
Proville, J., Zavala-Araiza, D., Wagner, G., 2017. Night-time Lights: A Global, Long Term Look at Links to Socio-economic Trends. 12. PloS one, pp. e0174610.
Reddington, C.L., Butt, E.W., Ridley, D.A., Artaxo, P., Morgan, W.T., Coe, H., Spracklen, D.V., 2015. Air quality and human health improvements from reductions in deforestation-related fire in Brazil. Nat. Geosci. 8, 768.
Sanderman, J., Hengl, T., Fiske, G., Solvik, K., Adame, M.F., Benson, L., Bukoski, J.J., Carnell, P., Cifuentes-Jara, M., Donato, D., Duncan, C., 2018. A Global Map of Mangrove Forest Soil Carbon at 30 M Spatial Resolution. 13. Environmental Research Letters, pp. 055002.
Savory, D.J., Andrade-Pacheco, R., Gething, P.W., Midekisa, A., Bennett, A., Sturrock, H.J., 2017. Intercalibration and Gaussian Process Modeling of Nighttime Lights Imagery for Measuring Urbanization Trends in Africa 2000–2013. 9. Remote Sens., pp. 713.
Shao, Z., Fu, H., Li, D., Altan, O., Cheng, T., 2019. Remote Sensing Monitoring of Multi-scale Watersheds Impermeability for Urban Hydrological Evaluation. 232. Remote Sens. Environ., pp. 111338.
Simonetti, D., Simonetti, E., Szantoi, Z., Lupi, A., Eva, H., 2015. First results from the phenology-based synthesis classifier using Landsat 8 imagery. IEEE Geosci. Remote Sens. Lett. 12, 1496–1500.
Smith, J.L., Auala, J., Haindongo, E., Uusiku, P., Gosling, R., Kleinschmidt, I., Mumbengegwi, D., Sturrock, H.J.W., 2017. Malaria risk in young male travellers but local transmission persists: a case–control study in low transmission Namibia. Malar. J. 16, 70.
Soulard, C., Albano, C., Villarreal, M., Walker, J., 2016. Continuous 1985–2012 landsat monitoring to assess fire effects on meadows in Yosemite National Park, California. Remote Sens. 8, 371.
Soulard, C.E., Walker, J.J., Griffith, G.E., 2017. Forest harvest patterns on private lands in the Cascade Mountains, Washington, USA. Forests 8, 383.
Sturrock, H.J.W., Cohen, J.M., Keil, P., Tatem, A.J., Le Menach, A., Ntshalintshali, N.E., Hsiang, M.S., Gosling, R.D., 2014. Fine-scale malaria risk mapping from routine aggregated case data. Malar. J. 13, 421.

Tamiminia, H., Salehi, B., Mahdianpari, M., Quackenbush, L., Adeli, S., Brisco, B., 2020. Google Earth Engine for geo-big data applications: a meta-analysis and systematic review. ISPRS J. Photogramm. Remote Sens. 164, 152–170.
Tang, Z., Li, Y., Gu, Y., Jiang, W., Xue, Y., Hu, Q., LaGrange, T., Bishop, A., Drahota, J., Li, R., 2016. Assessing Nebraska playa wetland inundation status during 1985–2015 using Landsat data and Google Earth Engine. Environ. Monit. Assess. 188, 654.
Tatem, A.J., Huang, Z., Narib, C., Kumar, U., Kandula, D., Pindolia, D.K., Smith, D.L., Cohen, J.M., Graupe, B., Uusiku, P., Lourenço, C., 2014. Integrating rapid risk mapping and mobile phone call record data for strategic malaria elimination planning. Malar. J. 13, 52.
Thieme, A., Yadav, S., Oddo, P.C., Fitz, J.M., McCartney, S., King, L., Keppler, J., McCarty, G., Hively, W.D., 2020. Using NASA earth observations and Google Earth Engine to map winter cover crop conservation performance in the Chesapeake bay watershed. Remote Sens. Environ. 248, 111943.
Tian, J., Wang, L., Yin, D., Li, X., Diao, C., Gong, H., Shi, C., Menenti, M., Ge, Y., Nie, S., 2020. Development of spectral-phenological features for deep learning to understand Spartina alterniflora invasion. Remote Sens. Environ. 242, 111745.
Tracewski, Ł., Butchart, S.H., Di Marco, M., Ficetola, G.F., Rondinini, C., Symes, A., Wheatley, H., Beresford, A.E., Buchanan, G.M., 2016. Toward quantification of the impact of 21st-century deforestation on the extinction risk of terrestrial vertebrates. Conserv. Biol. 30, 1070–1079.
Trianni, G., Lisini, G., Angiuli, E., Moreno, E., Dondi, P., Gaggia, A., Gamba, P., 2015. Scaling up to national/regional urban extent mapping using Landsat data. 8. Journal of Selected Topics in Applied Earth Observations and Remote Sensing, pp. 3710–3719.
Turner, B.L., Lambin, E.F., Reenberg, A., 2007. The emergence of land change science for global environmental change and sustainability. Proc. Natl. Acad. Sci. 104, 20666–20671.
Verhegghen, A., Eva, H., Ceccherini, G., Achard, F., Gond, V., Gourlet-Fleury, S., Cerutti, P.O., 2016. The potential of Sentinel satellites for burnt area mapping and monitoring in the Congo Basin forests. Remote Sens. 8, 986.
Weiss, D.J., Nelson, A., Gibson, H., Temperley, W., Peedell, S., Lieber, A., Hancher, M., Poyart, E., Belchior, S., Fullman, N., Mappin, B., 2018. A Global Map of Travel Time to Cities to Assess Inequalities in Accessibility in 2015. 553. Nature, pp. 333–336.
Wong, B.A., Thomas, C., Halpin, P., 2019. Automating Offshore Infrastructure Extractions Using Synthetic Aperture Radar & Google Earth Engine. 233. Remote Sens. Environ., pp. 111412.
Wright, J.S., Fu, R., Worden, J.R., Chakraborty, S., Clinton, N.E., Risi, C., Sun, Y., Yin, L., 2017. Rainforest-initiated wet season onset over the southern Amazon. Proc. Natl. Acad. Sci. 114, 8481–8486.
Wu, Q., Lane, C.R., Li, X., Zhao, K., Zhou, Y., Clinton, N., DeVries, B., Golden, H.E., Lang, M.W., 2019. Integrating LiDAR data and multi-temporal aerial imagery to map wetland inundation dynamics using Google Earth Engine. Remote Sens. Environ. 228, 1–13.
Xie, Z., Phinn, S.R., Game, E.T., Pannell, D.J., Hobbs, R.J., Briggs, P.R., McDonald-Madden, E., 2019. Using Landsat observations (1988–2017) and Google Earth Engine to detect vegetation cover changes in rangelands-a first step towards identifying degraded lands for conservation. Remote Sens. Environ. 232, 111317.
Ying, Q., Hansen, M.C., Potapov, P.V., Tyukavina, A., Wang, L., Stehman, S.V., Moore, R., Hancher, M., 2017. Global bare ground gain from 2000 to 2012 using Landsat imagery. Remote Sens. Environ. 194, 161–176.
Yu, M., Gao, Q., Gao, C., Wang, C., 2017. Extent of night warming and spatially heterogeneous cloudiness differentiate temporal trend of greenness in mountainous tropics in the new century. Sci. Rep. 7, 41256.
Zhang, Q., Li, B., Thau, D., Moore, R., 2015. Building a Better Urban Picture: Combining Day and Night Remote Sensing Imagery. 7. Remote Sens., pp. 11887–11913.
Zhou, B., Okin, G.S., Zhang, J., 2020. Leveraging Google Earth Engine (GEE) and machine learning algorithms to incorporate in situ measurement from different times for rangelands monitoring. Remote Sens. Environ. 236, 111521.

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