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Synthesizing social and environmental sensing to monitor the impact of large-scale infrastructure development

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ABSTRACT

The booming development of large-scale infrastructure projects (LSIPs) facilitated by China's Belt and Road Initiative (BRI) has drawn global concern regarding the scale, pace, and potential impact. Studies have largely focused on the geopolitical impact (i.e., politics and international relations) but less is known about social and environmental impact. This is in large part because consistent, high-resolution, cross-boundary social and environmental data at large scales are rather limited. To address the knowledge gap, this research developed a novel Socio-Environmental Sensing (SES) approach by synthesizing remote sensing imagery and geotagged Twitter data to map the socio-environmental impact of LSIPs. We demonstrated the applicability of this approach using two BRI flagship projects, namely, the Mombasa-Nairobi Standard Gauge Railway (SGR) in Kenya and the China-Pakistan Economic Corridor (CPEC) in Pakistan. Our analysis shows that both projects have led to a substantial loss of natural land (e.g., 3.7 % loss of vegetation in Kenya, and 23.3 % reduction of the glacier in Pakistan) but gains in artificial land (e.g., 4.2 % increase in cropland in Kenya, and 34.6 % expansion of built-up land in Pakistan). In addition, the BRI-LSIPs have largely improved local economic development, because nighttime light imagery revealed that regions near the BRI-LSIP sites became much brighter than other regions. Regarding the social aspect, we found that public sentiment toward the projects was largely positive and improved over time, which contradicts the prevalent pessimism to BRI-LSIPs by critics. Nevertheless, sentiment also presented strong spatial heterogeneity – regions around the BRI transportation hubs (usually large cities) most showed more positive sentiment than other regions. By spatially joining the georeferenced sentiment scores with environmental indicators from remote sensing, we further found that positive sentiment improved more in more developed regions, but only changed slightly in other regions. This study provides a novel approach to assess the socio-environmental impact of large-scale projects, and the findings would be useful for informing the implementation of future BRI projects across the globe.

1. Introduction

In the last decade, large-scale infrastructure projects (LSIPs, e.g., railways, highways, ports, pipelines, and hydropower) have proliferated throughout the Global South. China's Belt and Road Initiative (BRI) is one especially noteworthy international finance-driving global development. Launched in 2013, this initiative plans to build a network of transportation and economic centers connecting more than 180 countries across East Asia, Europe, and Africa. To date, China has pledged an estimated US$1 trillion (7.7 % of China's GDP or 1.2 % of the world's GDP) for these projects worldwide, and many more are currently being planned. Projects at this scale have had a significant positive

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impact on transportation connectivity and economic development (Thacker et al., 2019), but there is also considerable concern regarding their socio-environmental impact (Ascensão et al., 2018; Isaksson and Kotsadam, 2018; Lechner et al., 2018; Narain et al., 2020). Earlier research suggests that large-scale construction can not only lead to substantial land-use change (e.g., deforestation, agricultural land expansions), but also can affect human livelihood and wellbeing (Forman et al., 2003; Karlson et al., 2014; Moran, 1993; Moran and Brondizio, 1998). It is, therefore, crucial to understand the potential widespread socio-environmental impact of infrastructure projects generally, but the scope of large-scale infrastructure projects elevates this importance as even individual projects have the potential to impact many more people and ecosystems.

In recognition of this heightened potential, considerable scholarly attention has been devoted to understanding the socio-environmental impact of major infrastructure projects, especially the BRI-LSIPs. However, the existing studies largely considered either the environmental aspect or the social aspect. Moreover, studies on environmental impact mostly focused on predicting potential impact rather than assessing the factual impact, which is essential for informed planning and decision-making. For example, some work predicted possible increases in energy consumption and pollution, enlarged carbon footprints, and encroachment on wildlife habitats (Hughes, 2019; Teo et al., 2019; WWF, 2017), but little is known about how LISPs have actually altered environmental conditions. For studies on the social aspect, rich literature explored the political and economic implications at the macro-level (Du and Zhang, 2018; Saud et al., 2019; Zhai, 2018), but perspectives from the local communities have been largely ignored. Incorporating the perspectives of local communities is crucial as these communities are the ones who were affected directly. In an endeavor to address this, some conducted fieldwork (e.g., interview and survey) to gather such data (Blair and Roessler, 2018). But these traditional methods are usually costly and time-consuming, which limit the research scope to small and local scales (Boonwattanopas, 2015; García-Herrero and Xu, 2019; Wissenbach and Wang, 2017), making them underrepresented and insufficiently positioned to speak to the international, national, and regional concerns. In short, existing studies are limited in two primary ways: most either (1) adopt a risk assessment perspective where they focus on the potential harm rather than investigating actual socio-environmental impact, or (2) fail to consider both aspects of social and environmental impact despite increasingly forceful calls for such analyses (Liu et al., 2007; Ostrom, 2009). In particular, the World Bank and the International Union for Conservation of Nature (IUCN) have recently called for Strategic Environmental and Social Assessments (SESAs) of BRI-LSIPs specifically to address this knowledge gap (Ascensão et al., 2018).

To advance the understanding of socio-environmental impact at large spatial scales and inform policy, this study proposes to integrate broadly available social media data and environmental remote sensing data to investigate the social and environmental impact of BRI-LSIPs (Fig. 1). These two data sources complement each other and provide more comprehensive indicators for both environmental and social aspects. Long-term, global remote sensing data have proven powerful for monitoring environmental changes on the Earth's surface. For example, Landsat images are used to detect land-use change (Linderman et al., 2005), while nighttime light images serve as indicators of socioeconomic change (Wulder et al., 2019). Similarly, social media data (e.g., Twitter) provides rich individual-level information (e.g., user-generated images, text, and videos). This kind of data is increasingly used to analyze the public sentiment in a variety of contexts (Arthur et al., 2018; Di Minin et al., 2019; Liu et al., 2015; Moore et al., 2019). Although both provide important contributions, environmental remote sensing and social sensing are often applied separately for different research purposes. To date, they have rarely been considered together within the same research effort to understand the socio-environmental impact of large-scale infrastructure development efforts.

In this paper, we first illustrated the novel Socio-Environmental Sensing (SES) approach that integrates remote sensing and social sensing. Then, we exemplified the approach by taking two BRI flagship projects – the Mombasa-Nairobi Standard Gauge Railway (SGR) projects in Kenya and the China-Pakistan Economic Corridor (CPEC) in Pakistan – as representative cases (see Geographic foci in Section 2.2). We aimed

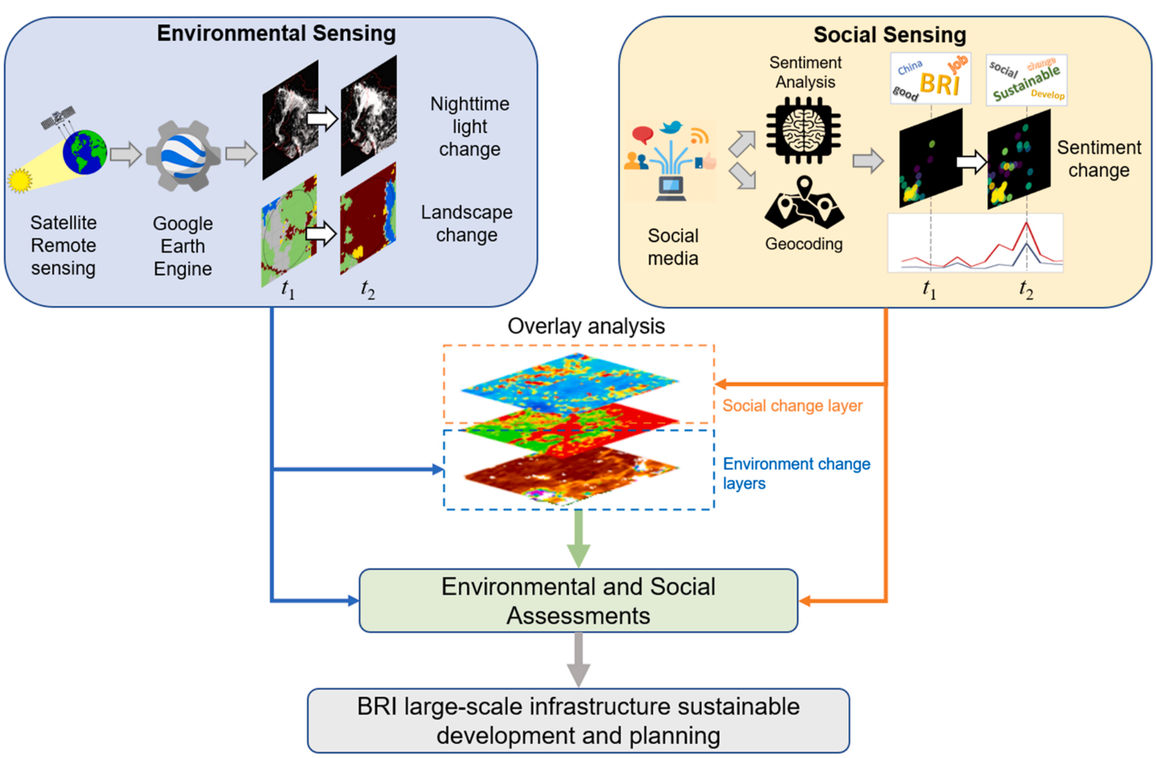

Fig. 1. The workflow of Socio-Environmental Sensing for impact assessment and LSIP sustainable development and planning.

to address three research questions. First, how did landscapes change with the development of BRI-LSIPs? Previous research focused on forest loss (BenYishay et al., 2016), but it is still not clear how other types of land use/land cover have changed. For instance, farmland expansion and rapid urbanization are very likely to happen in these developing countries under population growth and increasing globalization (Brondízio and Moran, 2012; Liu et al., 2020). Second, how did the general public perceive the BRI-LSIPs, and how did their sentiment change over time? Many environmental non-governmental organizations (NGOs), conservationists, journalists, and scholars criticized the nature, pace, and scale of China's overseas projects (BenYishay et al., 2016; Blair and Roessler, 2018; Laurance et al., 2015), but it would be more important to know how the general public and local community perceived those projects as they are the ones who experienced the actual impact. Lastly, is the public sentiment change associated with environmental change? We synthesized results from remote sensing and social sensing and hypothesize that there might be strong negative sentiment towards natural land loss. This study contributes to human-environment literature by providing a novel SES approach to enable socio-environment impact assessment to a large spatial extent. The findings provide valuable information for the planning, implementation, and monitoring of similar large-scale infrastructure projects globally.

2. Materials and methods

2.1. Socio-environmental sensing

The Socio-Environmental Sensing (SES) approach is a key extension of the *People and Pixels* foundation (National Research Council, 1998), which connects remotely sensed data and georeferenced social science data to advance empirical and theoretical understanding of human-environment interactions (Kugler et al., 2019). Remotely sensed satellite data have been widely applied in environmental monitoring, while the individual-level geotagged social media data is an emerging data source for capturing collective human behavior and individual-level sentiments (Di Minin et al., 2019; Liu et al., 2015). Adopting social and remote sensing data simultaneously provides a new way to investigate changes in complex socio-environmental systems and inform policymaking in a timely manner. Both data sources can be easily queried from databases at very low or no cost (Hasan et al., 2017). Remote sensing images at high spatial resolution (e.g., 10-m or 30-m) can be accessed weekly or biweekly, and social media data can be collected in real-time. These enable us to investigate the long-term environmental changes with detailed information and capture sentiment changes with social sensing technologies across a large region. Here, we took a commonly used Before-After (also called Pre-Post test) analysis to evaluate the impact (Christie et al., 2020) given there were few other projects at this large scale in the region. Each LSIP is divided into two stages: "before" the project implementation, and "after" the project was completed (See Table A.1 for the detailed timeline of each project). Referring to previous studies (Benítez-López et al., 2010; Isaksson and Kotsadam, 2018; Ng et al., 2020), we chose 50 km as the threshold distance to determine the project impact zone. Our SES approach builds on and advances previous studies by integrating emerging big data sources and novel tools (e.g., artificial intelligence, cloud computing) to enable human-environment research at a large spatial scale. In the following sections, we detail each sensing approach and how they complement each other for a more comprehensive impact assessment.

2.1.1. Environmental sensing

Remote sensing and its associated cloud computing technologies provide powerful datasets and tools to capture the landscape and environmental change over considerable time and space – a substantial advance to traditional field observation-based environmental research (Gorelick et al., 2017). For example, more than 46 years of Landsat imagery archive has enabled long-term global forest monitoring (Hansen et al., 2013), crop yield estimation (Huang et al., 2015), surface water mapping (Pekel et al., 2016), surface temperature estimation (Li et al., 2013), and more (Wulder et al., 2019). Similarly, Google Earth Engine's cloud-computing platform makes remote sensing more efficient in detecting and quantifying changes at large spatial scales (Gorelick et al., 2017). In this study, we focused on investigating changes in land use and nighttime light. This is because land-use change is often the most direct consequence of large-scale development (Brown et al., 2007; Lambin et al., 2001; Liu et al., 2010), and nighttime light brightness often is used as an indicator of economic growth and social-economic activity (Chen and Nordhaus, 2019; Wu et al., 2013).

2.1.2. Social sensing

Large-scale development can have a substantial impact on local communities. For some, infrastructure development projects create jobs and make transportation more convenient. For others, these projects invade protected areas and impact sacred landmarks (Giddens, 2013). These impacts can unfold over the course of the project as intended actions become unfeasible or unintended consequences become clear (Cohen et al., 2014; Jiang et al., 2016). Capturing this change traditionally relies on participatory mapping or questionnaire-based surveys. These approaches are useful for studies at the local scale but are limited for research at large spatial extents. The recent rapid development of social media platforms and Application Programming Interfaces (API) offers a more accessible and abundant data source over large spatial extents to fill the data gap (Bing et al., 2014). Social media platforms such as Twitter allow individual voices to be heard in an unprecedented way, bypassing news media which traditionally acts as the primary gatekeeper for the spread of the information (Bing et al., 2014; Seki, 2016; Tan et al., 2014; Vos, 2019). Put another way, Twitter allows for relatively unfiltered opinions to be expressed. Extensive studies show how individuals are more willing to give their honest opinion through online platforms, sharing feelings they would not share face-to-face or through a record associated with their name (e.g., some interviews and questionnaire-based surveys) (Black et al., 2016; Correa et al., 2015; Jones et al., 2020). As Twitter's prompt to post (i.e., "What's happening?") indicates, social media provides a temporally- and spatially-explicit rich mix of news and reactions, thus allowing for the efficient study of trends in public sentiment on a larger scale than was previously possible (Rajadesingan and Liu, 2014; Tavoschi et al., 2020).

In this study, we only used Twitter data because it is the only available and accessible data source that offers fine-scale spatial information (Arthur et al., 2018; Cai, 2021; Fu et al., 2018). Although information from local news and other media outlets is valuable, they mostly do not have specific spatial location information (only a few can be geocoded to a city or state level). Besides, opinions and attitudes in news reports are largely determined by the journalists, and even worse censored by the government or certain political parties. While a few Twitter accounts are run by governments and newspaper offices, a vast majority are owned by individuals. The advantage of using Twitter data is that we can collect diverse "voices" from a large body of individuals and use those data to identify the "emerging" pattern (Cai, 2021; Tan et al., 2014). Sentiment information derived from tweets might be sometimes less accurate than that from a well-designed survey, but as far as we know, Twitter is by far the most feasible data source we can use to estimate human sentiment and behaviors at a large spatial scale. In addition, Twitter data have been proven efficient in analyzing public sentiments to climate change (Moore et al., 2019), wildlife conservation (Di Minin et al., 2019), cultural ecosystem services (Johnson et al., 2019), urban planning (Cai, 2021), and disasters (Arthur et al., 2018).

2.1.3. Integrating environmental and social sensing analysis

Although remote sensing and social sensing data are useful on their own, integrating these two can provide us with complementary information to more comprehensively understand both the social and environmental impact of BRI-LSIPs and as well as their linkages.

In this study, after evaluating the environmental and social impact respectively (see details in Section 2.3), we then took information from the data layers of two sensing analyses and ran a regression analyses to test if public sentiment change was associated with environmental landscape change and socioeconomic change (Fig. 1). Specifically, we extracted evenly distributed points from the data layers of landscape naturalness (see details in Section 2.3.1), nighttime light brightness, and sentiment based on a 10 km x 10 km grid. Within the same grid unit, we assume the corresponding sentiment change could be observed if the grid area experienced environmental change (e.g., deforestation because of infrastructure development). In total, 4735 points were obtained for Kenya and 8193 points for Pakistan.

Overall, by linking environmental remote sensing and social sensing data, we aimed to provide a feasible way to narrow the gap in efficiently assessing the socio-environmental impact of LSIPs (Fig. 1).

2.2. Geographic foci

This study seeks to shed light on the impact of BRI-LSIPs through an investigation of the Mombasa-Nairobi Standard Gauge Railway (SGR) in Kenya, and the China-Pakistan Economic Corridor (CPEC) highway system in Pakistan. We selected these two projects for a few reasons. First, these two projects generally are representative of BRI-LSIPs in terms of their large spatial scale/coverage, geography, level of investment, and widespread media coverage (Laurance et al., 2014). There are also noteworthy concerns regarding the impacts of both projects given their overlap with environmentally important or ecologically fragile regions (WWF, 2017). Additionally, we selected transportation projects specifically because they account for over 60 % of all BRI-LSIPs that are currently planned (around 6200 projects; Fig. A.1) (AIDDATA, 2020; Strange et al., 2017). We chose projects in two continents to facilitate a multinational analysis (Carlson and Harris, 2020; Hu, 2018; Janowicz et al., 2012). Finally, we selected these sites because of the relatively strong availability of English-language Twitter posts (text in a common language is important for the analyses) and high-quality remote sensing data in those regions.

2.2.1. The mombasa-nairobi standard gauge railway

The Mombasa–Nairobi Standard Gauge Railway (SGR) is a flagship BRI project in East Africa. To date, it is the most expensive infrastructure project in Kenya's history, with a total cost of US$3.6 billion. The SGR is one of the earliest completed projects under the BRI with construction formally starting in December of 2015, passenger services opening in May of 2017, and freight rail services opening in January of 2018. The railway has greatly reduced the transportation cost between Mombasa and Nairobi, and facilitated regional tourism and other related businesses. Despite these benefits, concerns have been raised regarding increased national debt (Githaiga and Bing, 2019). Additionally, the SGR railway traverses several important ecological areas (e.g., Tsavo National Park, Nairobi National Park, Mombasa Mangrove Wetland Park) and there is concern that the project may offset previous conservation efforts or even aggravate environmental degradation (Kenneth and Zhao, 2020).

2.2.2. The China-Pakistan economic corridor

The China-Pakistan Economic Corridor (CPEC) is a flagship project of the BRI. CPEC was launched in April 2015 to upgrade Pakistan's transportation infrastructure, for which China has allocated financing for US$10.63 billion. Three primary corridors have been identified: (1) the Eastern Alignment through the heavily populated provinces of Sindh and Punjab, where most industries are located; (2) the Western Alignment through the less developed and more sparsely populated provinces of Khyber Pakhtunkhwa and Baluchistan; and (3) the future Central Alignment that will pass through Khyber Pakhtunkhwa, Punjab, and Baluchistan (Abid and Ashfaq, 2015). Most of these highway projects started in early 2016 and were completed in the second half of 2019 (see Table A.1 for the detailed timeline of each project). Together they have promoted regional economic development and interregional trade, but also brought considerable environmental concerns (e.g., loss of natural vegetation, increased glacial melting in the northern Pakistan region) (Kanwal et al., 2019).

2.3. Data collection and analysis

2.3.1. Environmental sensing data collection and analysis

We used freely available, high-resolution global land cover products derived from remote sensing imagery to investigate land-use change due to BRI-LSIP developments. GlobeLand30 – the 30-meter resolution global land cover data product for 2010 and 2020 – was used to analyze the land cover and land-use changes in Kenya and Pakistan. GlobeLand30 includes land cover classes such as cultivated land, forest, grassland, shrubland, wetland, water bodies, tundra, artificial surface, and bare land (Jun et al., 2014). This product has high-resolution, global coverage, and is constantly updated. The total accuracy of GlobeLand30 2010, as based on the validation of over 150,000 points in 80 of the total 853 tiles, is 83.50 % and the Kappa coefficient is 0.78. The total accuracy of GlobeLand30, 2020 is 85.72 % and the Kappa coefficient is 0.82 (GlobeLand30, 2020). Due to the data availability, we used the data in 2010 for estimating land cover "before projects" (i.e., in 2013), and 2020 for "after projects" (i.e., in 2019). This approximation may be a limitation but is widely used in other studies with the assumption that the changes in land use within adjacent years are usually small (Li et al., 2017; Liu et al., 2014). In addition, based on different land cover types from the GlobeLand30, we created a land cover naturalness index for later quantitative analysis (Machado, 2004). The index ranges from 0 to 100 percent, including different values for the 11 land-cover types. The more "natural" the land-cover type is, the higher the value. Here, we assigned 100 % to forest, shrubland, grassland, wetland, tundra, and snow/ice; 75 % to water; 50 % to agricultural land; 25 % to bare land; and 0 % to artificial land. We further categorized three naturalness levels: low (< 25 %), moderate (25 % ∼ 50 %), and high (> 50 %).

To address economic changes, we used the NASA Visible Infrared Imaging Radiometer Suite (VIIRS) nighttime light images at 15 arc seconds from 2014 to 2019 (https://viirsland.gsfc.nasa.gov/). Nighttime light imagery can approximate socioeconomic indicators (population and human activities) and is especially useful for areas that lack sufficient socioeconomic data (Elvidge et al., 2017; Yang et al., 2019). Similar to naturalness, we categorized the VIIRS nighttime light images to three brightness levels (in radiance units of nano-Watts/cm2/sr) for analysis: low (0 ∼ 2), moderate (2 ∼ 5), and high (> 5) (Levin and Zhang, 2017).

2.3.2. Social sensing data collection and analysis

This study used social media data to understand public sentiment towards the BRI-LSIPs. We chose Twitter because it is the social media platform with the broadest country user coverage (with 330 million users active monthly). Recent advanced artificial intelligence methods (e.g., text mining and sentiment analysis) provide ready-to-use packages for detecting topics and human sentiments from text information (Bing et al., 2014; Cai, 2021). In this study, a dictionary-based sentiment analysis *R* package (*sentimentr*) (Rinker, 2018) was applied to investigate public sentiment towards the project (see details in Appendix A). Additionally, we used the opinion mining method from Microsoft Azure's Cognitive Services to further locate the subject and the corresponding sentiment in a tweet (https://docs.microsoft.com/en-us/azure/cognitive-services/text-analytics/). For example, if a tweet says, "The railway is great, but the environmental impact is worrisome.", opinion mining will return the mapping relationship like "positive" sentiment to "railway", and "negative" sentiment to "environmental impact".

Twitter's Application Programming Interface (API) was used to extract the historical tweets from its full archive. As the BRI was formally initiated in September of 2013 when Chinese President Xi visited Pakistan, we filtered and requested Tweets posted between September 2013 and December 2019. We requested all tweets containing one of a list of keywords or hashtags (here we followed Twitter API searching rules and filtering guide, including Boolean operators, truncation, and wildcard): *'#bri OR #obor OR #silkroad OR beltandroad OR beltandroadinitiative OR beltroad OR "belt road" OR "silk road" OR onebeltoneroad OR "belt and road" OR ("one belt" "one road")'* (see detailed explanation in Supplementary Methods in Appendix A). For each specific project, we further reviewed local news media posts and a sample of tweets to identify additional search terms for each country. For Kenya, we added *'(China OR Chinese OR Beijing) (rail OR highway OR road OR train OR infrastructure) (SGR OR "standard gauge") place_country:KE'* (see detailed explanation in Supplementary Methods in Appendix A). For Pakistan, we added *'(China OR Chinese OR Beijing) (rail OR highway OR road OR train OR infrastructure) ("Economic Corridor" OR CPEC) place_country:PK'* to the general BRI search terms. The final dataset is the set of geotagged tweets between September 1, 2013, and the end of December 2019 (330 weeks, or 2313 days). The tweets, therefore, covered the periods before, during, and after the construction of both project cases in this study. The data include anonymous user profile information like fuzzy location and social identity, tweet locations and timestamps, and comments/replies in addition to the tweet content itself. Around 1.6 million tweets from around 0.4 million unique users were collected (replies and retweets are not included). Unnecessary symbols and noise, such as weblinks, mentions, punctuations, stop words (usually refers to the most common words in a language that have relational rather than content meaning, such as "a", "the" and "is"), were removed from the tweet texts before sentiment analysis and opinion mining (Cielen et al., 2016). Sentiment analysis was validated by manually screening 1000 tweets (Moore and Obradovich, 2020).

3. Results

3.1. Land use and land cover change

Infrastructure development through the BRI has resulted in considerable natural land loss and artificial land increases in both Kenya and Pakistan (Fig. 2). These changes are also reflected in the nighttime light images. We found human activities along the transportation infrastructure networks increased substantially after the projects, and regions close to the newly built railways and highways presented much brighter nighttime light than other regions (Fig. A2). These brighter regions in the satellite images presented a mostly linear pattern and aligned with the new transportation network obtained from the OpenStreetMap (https://www.openstreetmap.org/).

In Kenya, there was a net loss of forest within the project impact zone, but a large net increase outside the zone. Although the project impact zone only accounts for 22.3 % of the total land area of Kenya, the increase of agricultural land accounts for 62.0 % of the country's total increase. Specifically, land cover within the 50 km buffer zone of the Mombasa–Nairobi Standard Gauge Railway showed an increase in artificial land (by 13.7 %), agricultural land (by 4.2 %), and water (by 6.9 %) at the expense of wetland (by 12.2 %), shrubland (by 6.7 %), grassland (by 3.5 %), bare land (by 5.7 %), and forest (by 3.2 %) during 2010 and 2020 (Table A.2, Fig. 3A). In addition to a relatively large increase in artificial land because of the infrastructure development, there is a larger increase in agricultural land near the railway (Fig. 3C and D). The increase in artificial land and agricultural land was mainly due to transfer from natural lands, such as grassland, forest, and shrub (Fig. 3B; Table A3).

For Pakistan, land within the project impact zone has undergone much larger changes than regions without such projects, with over 65 % reduction in wetland, forest, agricultural land, shrubland, and grassland, and more than 80 % increases in artificial land and water bodies (Fig. 2). Specifically, the land cover within the 50 km buffer zone around the CPEC transportation networks showed an increase of artificial land (by 34.6 %), water (by 44.4 %), and wetland (by 6.6 %), mainly at the expense of snow/ice (by 23.3 %), shrubland (by 3.9 %), grassland (by 2.3 %), forest (by 1.0 %) (Table A4). Unlike Kenya, we found there was a much larger increase in artificial land and water bodies, and an alarming decrease (>20 %) in glaciers (snow and ice) in Pakistan (Fig. 4A). The increases in both water bodies and wetland were due to the land transfer from agricultural land, grassland, and bare land (Fig. 4 B and Table A5).

3.2. Sentiment change

3.2.1. Average sentiment towards the BRI-LSIPs

Of the 1.58 million Tweets collected from 415,770 unique users, 9,426 were attributed to Kenya, and 26,655 were attributed to Pakistan. Surprisingly, we found most of the public were more concerned about

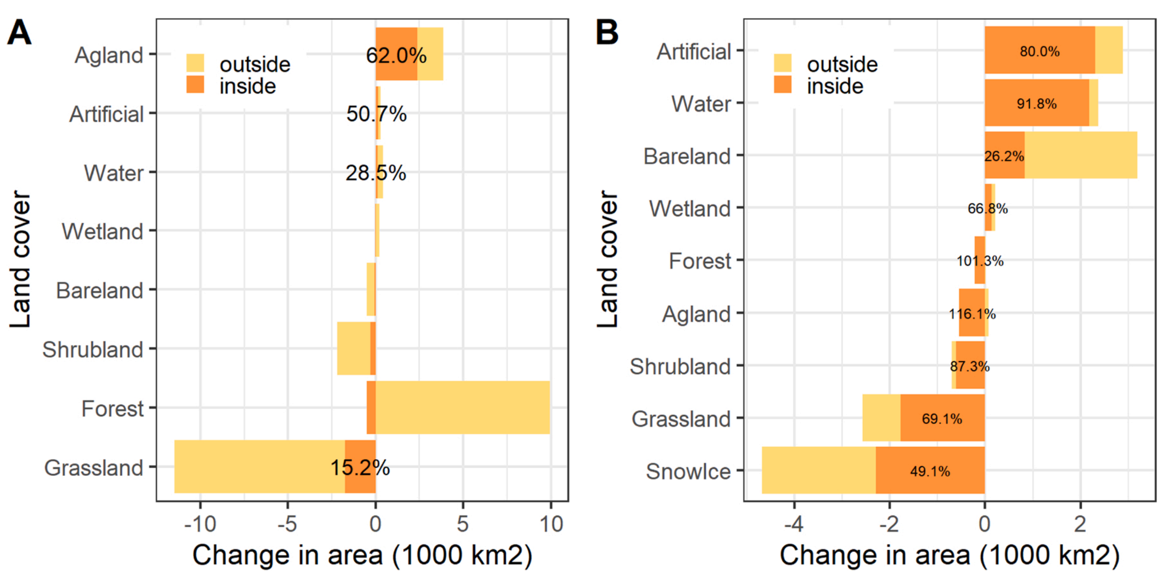

Fig. 2. Land area changes in each type (A. Kenya. B. Pakistan). Bars with darker color represents land cover change within the project impact zone, while bars with light color represent land-use change outside the zone. The percentage annotations show the percentage of change inside the impact zone to the total change in the country. Note, only percentages larger than 15 % are annotated in the figures.

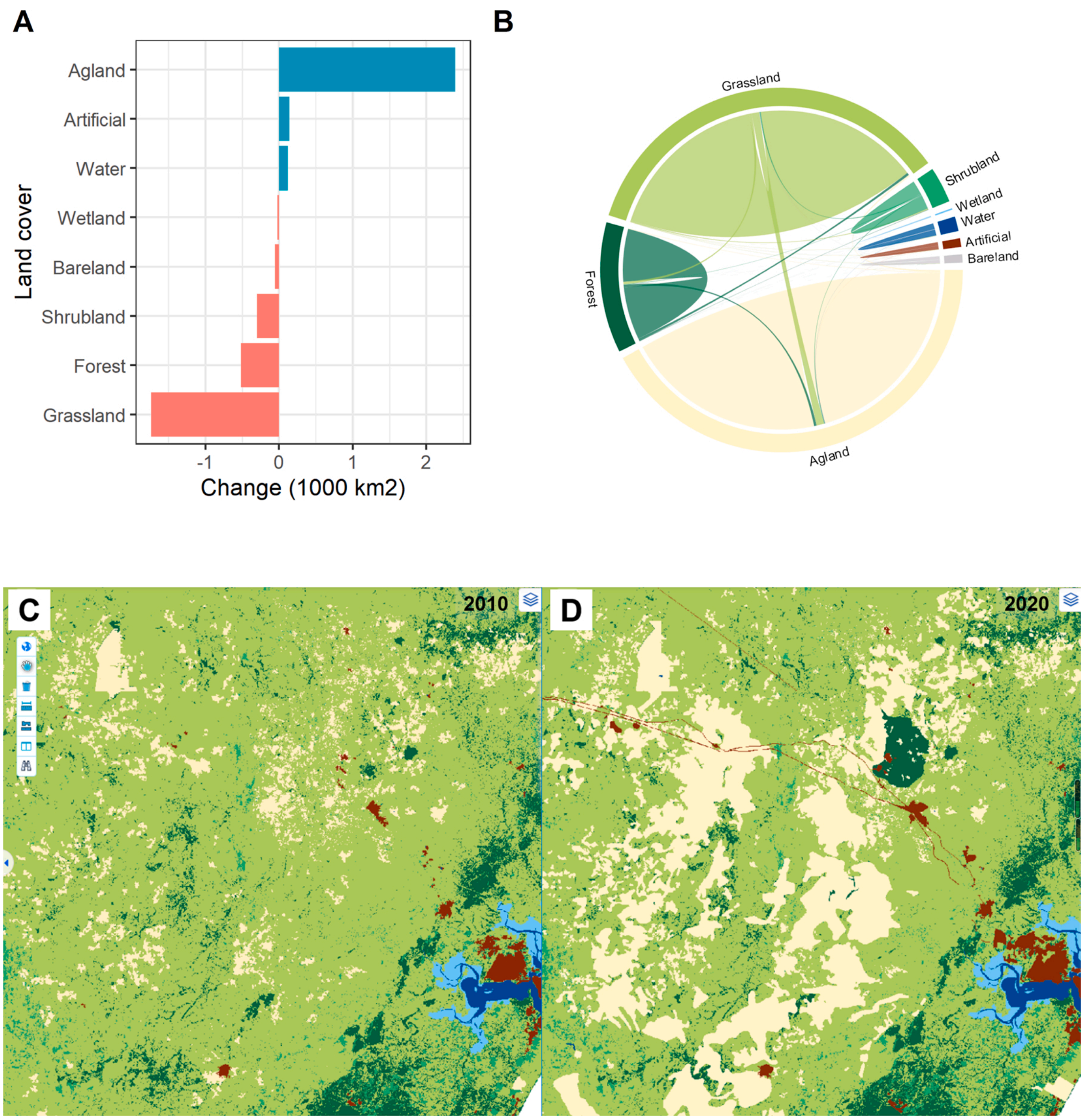

Fig. 3. Land cover change in Kenya. Net land cover changes after the project (A); Land cover change across all types (B) (The arc length of an outer circle indicates the sum of transfer-out and transfer-in in each land cover type. Ribbon colors suggest the land cover type being converted to other types); Zoom in to the land cover map in Samburu and Mombasa regions in 2010 (C) and in 2020 (D) (large increase in cropland and roads. C and D share the same color scheme with B). Land cover map credit: http://www.globallandcover.com/.

social and economic issues (e.g., “corruption”, “debt”, and “cooperation”) than the environment (see details in Section 3.3). In Kenya, the most common keyword in tweets is “sgr” (Fig. A2). Most of the negative sentiment is related to “corruption”, “debt”, and “scandal”, while positive sentiment is linked to “good” benefits of the “road” (Fig. 5A). In Pakistan, the keyword most used is “cpec” (Fig. A2). Similar to Kenya, Pakistan’s negative sentiment is also tied with “corruption” and “debt” (Fig. 5B); but unlike Kenya, another common negative sentiment is related to “India” (Fig. 5B). The positive sentiment in Pakistan focuses on the “cooperation” and “opportunity” by the “bri” and “road” (Fig. 5B).

In both Kenya and Pakistan, the local community’s sentiment towards BRI-LSIPs (measured as sentiment score) was mostly positive between 2013 and 2019 (Fig. 6). In Kenya, 60 of the 75 months evaluated had majority positive sentiments (80.0 %), while 15 months had majority negative sentiments (20.0 %) and the strongest negative sentiment occurred before the SGR construction (Fig. 6). In Pakistan, 72 of the 76 months measured had majority positive sentiments (94.7 %), while only 4 months had majority negative sentiments (5.3 %) and the strongest negative sentiment emerged before the CPEC as well (Fig. 6). The mean sentiment score in Kenya was +0.03, while the mean sentiment score in Pakistan was +0.12 (Fig. 6).

3.2.2. *Spatial-temporal change of sentiment change*

Although the sentiment towards BRI-LSIPs in both Kenya and Pakistan became more positive over time (Fig. 6), it varied largely across space (Fig. 7). Within Kenya, positive sentiments increased primarily in the southern half of the country (e.g., the Coast Province), as well as part of the central portions (e.g., Central Province) (Fig. 7A). These two regions also have the country’s largest city (i.e., Mombasa) and the national capital city (i.e., Nairobi), which are connected by the new SGR. Negative sentiments emerged and became worse in the northwest (e.g., northern Rift Valley county) and east of the Central Province of the country after the projects were completed.

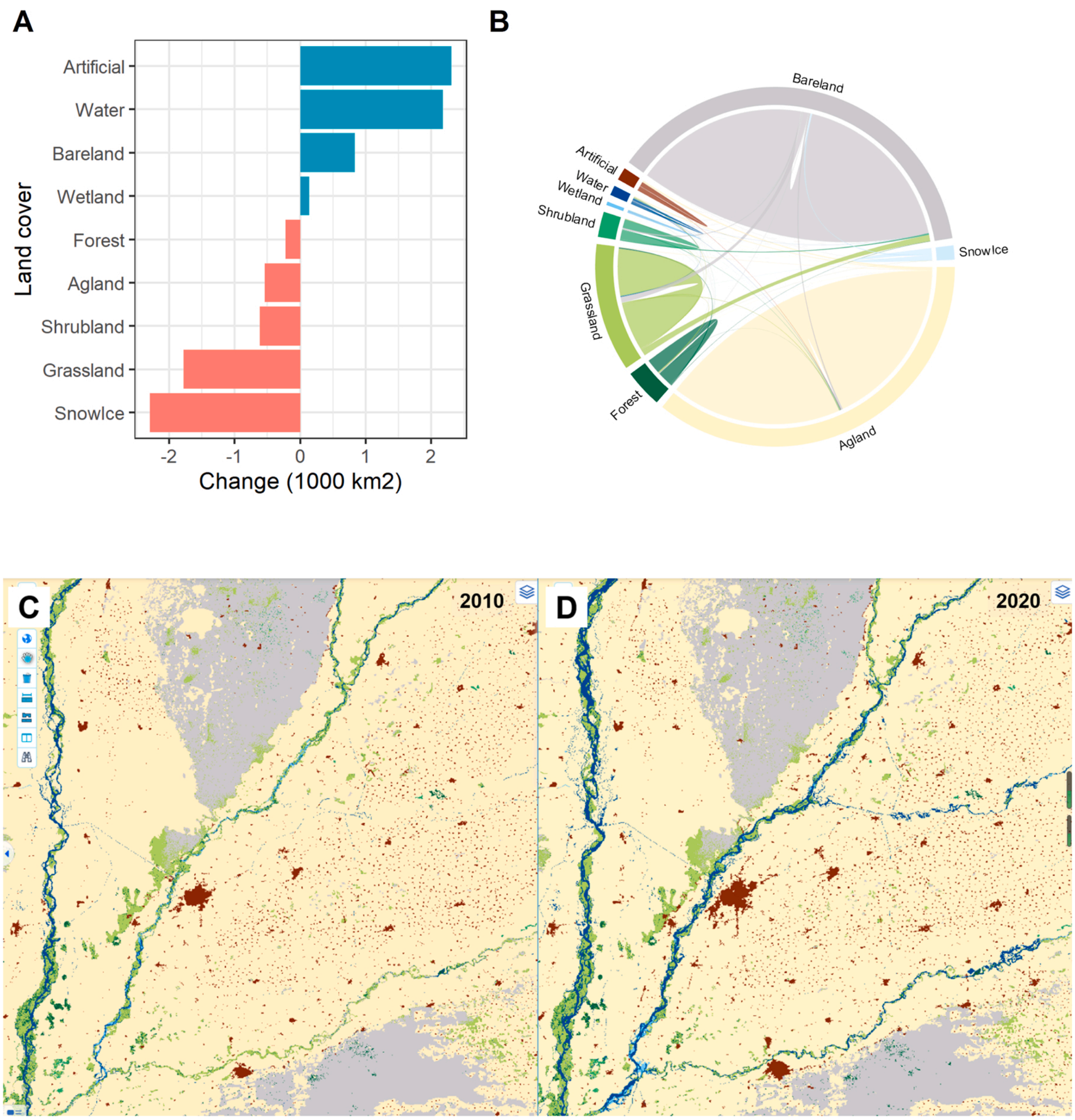

Fig. 4. Land cover change in Pakistan. Net land cover changes after the project (A); Land use change across all types (B) (The arc length of an outer circle indicates the sum of transfer-out and transfer-in in each land cover type. Ribbon colors suggest the land cover type being transferred out to other types); Zoom in to the land cover map in Multan and Bahawalpur regions in 2010 (C) and in 2020 (D) (visually observed increases in artificial land and water bodies. C and D share the same color scheme with B). Land cover map credit: http://www.globallandcover.com/.

A similar city-hub-dependent sentiment change was seen in Pakistan (Fig. 7B). Positive sentiment increased primarily in regions around the large cities, such as the southwestern region with Karachi (the largest city), the eastern region with Lahore (the second largest city), and the northern region with Islamabad (the national capital). Sentiment score decreased mostly in the northern parts of the country (i.e., the Gilgit–Baltistan region), which is regarded as a conflict zone at the junction of the three countries – Pakistan, India, and China. Infrastructure projects in such regions might require additional funding and efforts to ease social tensions and environmental challenges (Hughes et al., 2020).

3.3. Linkage between sentiment changes and environment changes

Three main environment-related subjects – "environment", "land", and "water" – in tweets were identified by using opinion analysis. Although it is not statistically significant, we observed that sentiments to these three subjects were generally negative before implementing the BRI projects, but became more positive after completing the projects in both countries (Fig. 8). This indicates that from the local perspectives, the BRI projects did not cause as many environmental concerns as envisioned at the beginning. However, it does not mean the BRI projects caused no negative environmental impact at all. A small portion of tweets did express concerns on the environmental impact, and the perception also varied across people from different regions within the country. For example, some worried about the negative impact on the Nairobi National Park because the SGR is passing the park; others warned of the alarming trend of glacier melting in Pakistan because of railway construction.

The relationship between sentiment changes and landscape changes was subtle for both projects. Other complex confounding factors, such as level of development and affluence, may also play a role in influencing human sentiment. Interestingly, we found that sentiment change has a negative relationship with landscape naturalness change in Kenya, while the relationship is positive in Pakistan (Fig. 9). Furthermore, we found

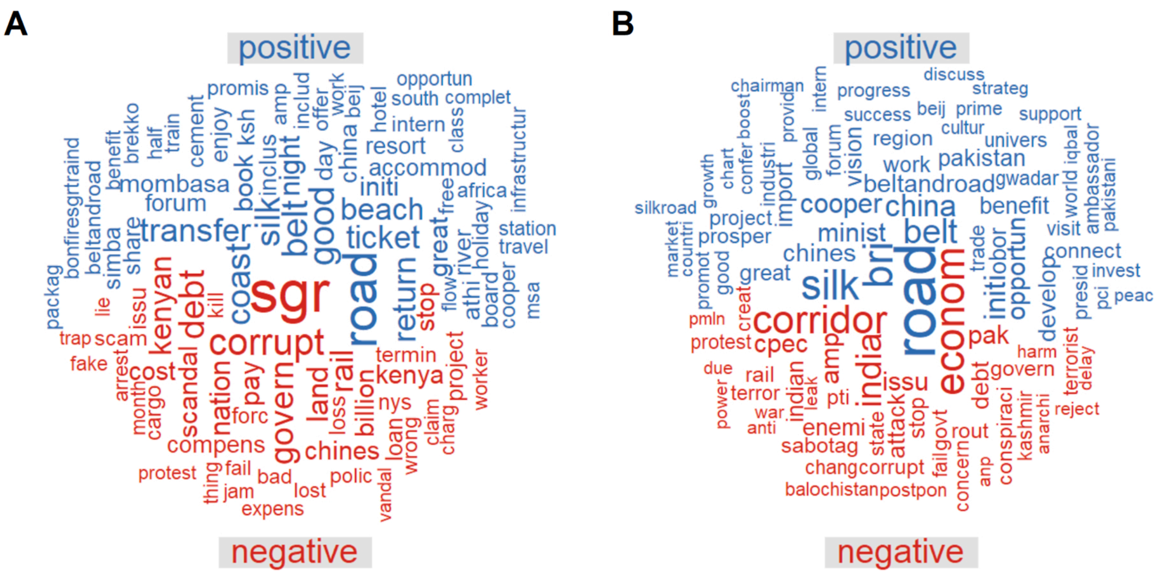

Fig. 5. Sentiments towards key topics of BRI projects in Kenya (A) and Pakistan (B). The word clouds only include the top frequent 100 words (large word size indicates high frequency).

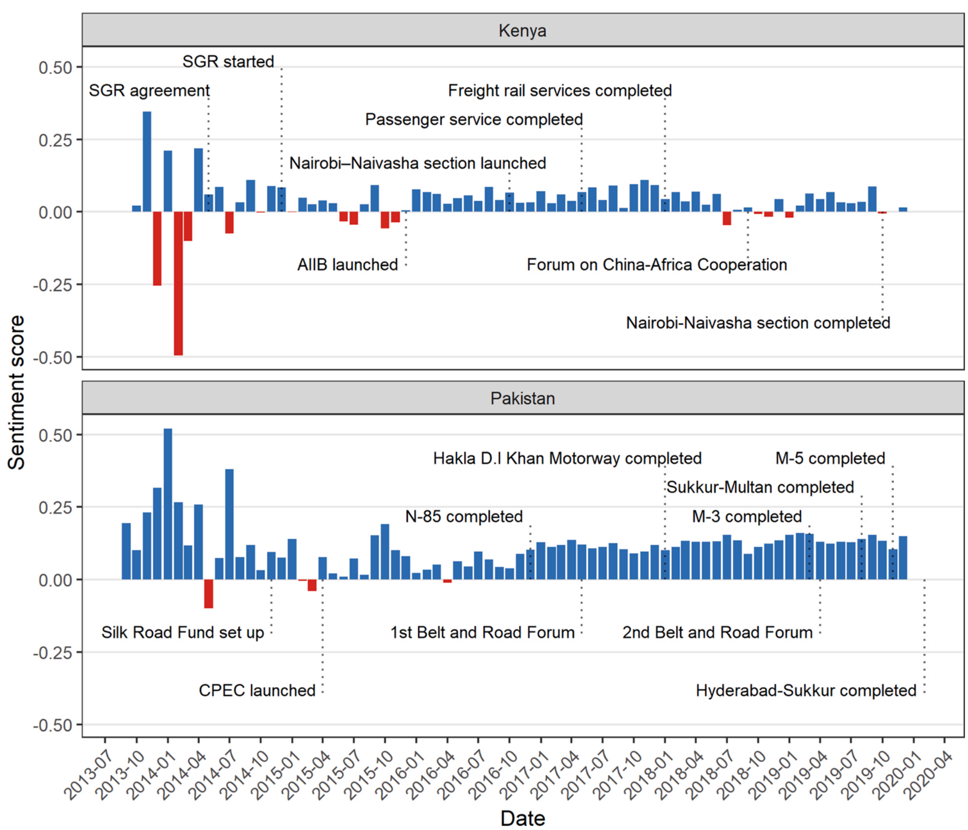

Fig. 6. Sentiments change over time (by month) with annotation of major events. See Table A.1 for the full name of each event.

that in both Kenya and Pakistan, people in the low naturalness region presented more positive sentiment after the BRI projects, while people in the high naturalness region shown more negative sentiment after the BRI projects (Fig. A.11). This implies people in the more urbanized region tended to have more positive sentiment to the projects, while people in the more rural region tended to have more negative sentiments. The positive relationship between sentiment score and nighttime light brightness further strengthens this argument, as nighttime lights are often used as proxies for population and economic affluence (Chen and Nordhaus, 2019; Proville et al., 2017). More importantly, we found that positive sentiment increased most in the brightest regions (i.e., more prosperous regions) after the projects were completed, but sentiment only changed slightly in less bright regions (Fig. A.11). This spatial heterogeneity is substantively important for understanding the relationship between sentiment change and environmental change, even though results from a regression analysis do not show statistical significance.

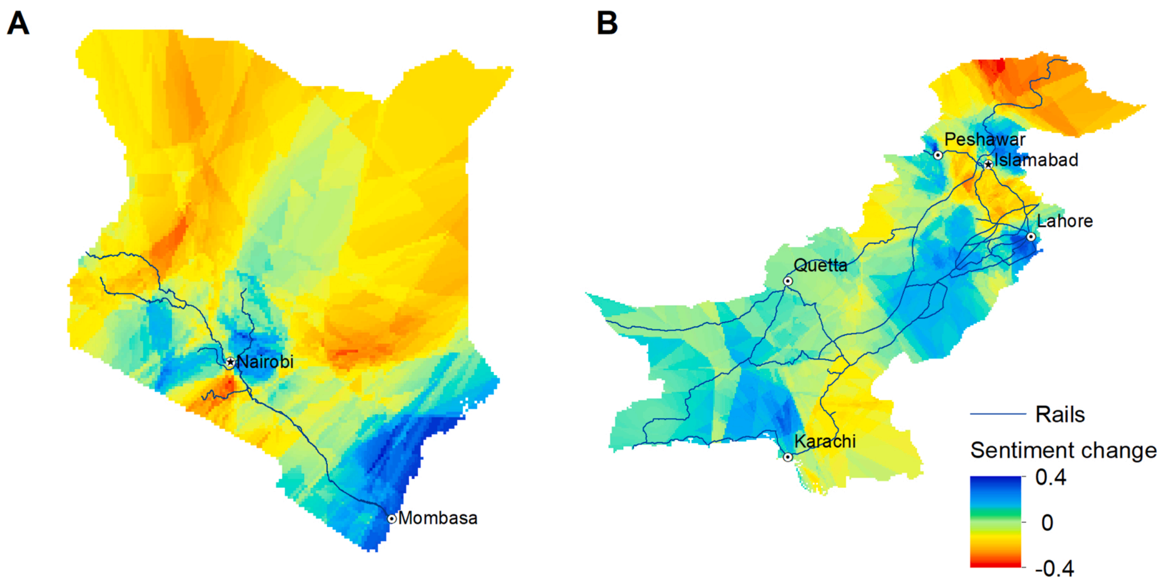

Fig. 7. Map of sentiment change regarding the BRI LSIPs in Kenya (A) and Pakistan (B).

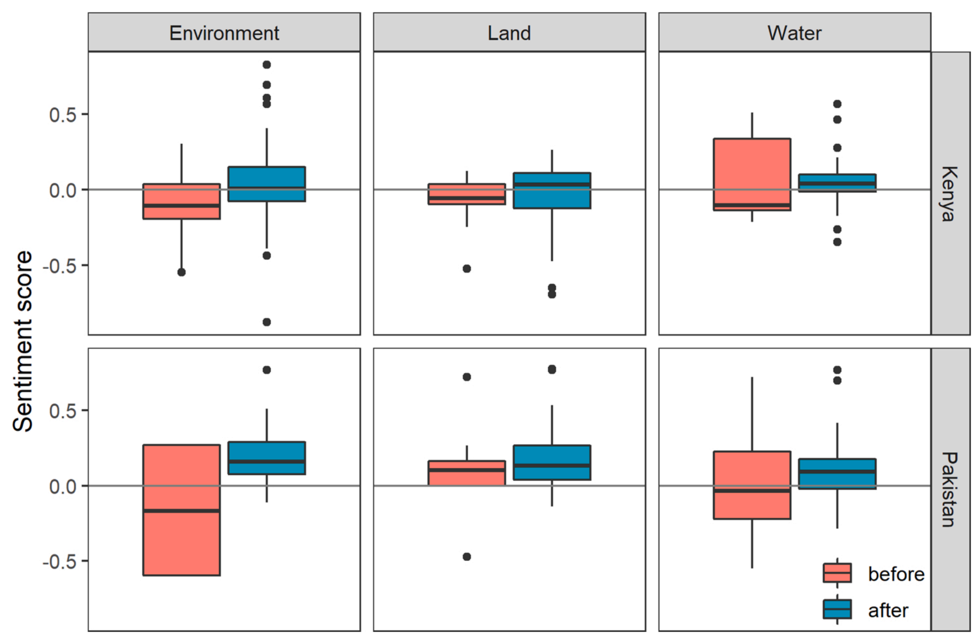

Fig. 8. Sentiment changes to main environment-related subjects in tweets.

4. Conclusion and discussion

This research developed and applied the novel Socio-Environmental Sensing (SES) approach to assess the environmental and social impact of large-scale infrastructure projects development in the Global South. This approach narrowed the data gaps in assessing socio-environmental impact at large spatial scales. We investigated two representative LSIPs (i.e., SGR in Kenya and CPEC in Pakistan) that were facilitated by the Belt and Road Initiative. We found both projects led to substantial land use and land cover changes, mainly reflecting on natural land loss and artificial land gains. Nighttime light imagery also confirmed this change and revealed that regions near the project sites became brighter than regions without such projects. This implies BRI-LSIPs have largely improved local economic development. In addition, our social sensing analysis found that the sentiment of local communities towards the BRI-LSIPs became more positive throughout the projects, which contradicts the prevalent pessimism by critics. Our integrated analysis found that there were fewer sentiments to environment impact than socioeconomic, and the relationship between sentiment and environment was not as strong as expected because of spatial heterogeneity across nation and region.

4.1. Unexpected landscape change and the potential impact

The two projects had a tremendous direct environmental impact on each country's landscape and economic development. Both Kenya and Pakistan experienced natural land loss and increases in artificial lands coinciding with increased human activities along with the project sites. Various natural lands were lost during the construction process for both countries. Specifically, Kenya lost a large amount of grassland, forest, and shrubland, in favor of increases in construction, agriculture, and water bodies. Pakistan lost even more (semi)natural lands, such as

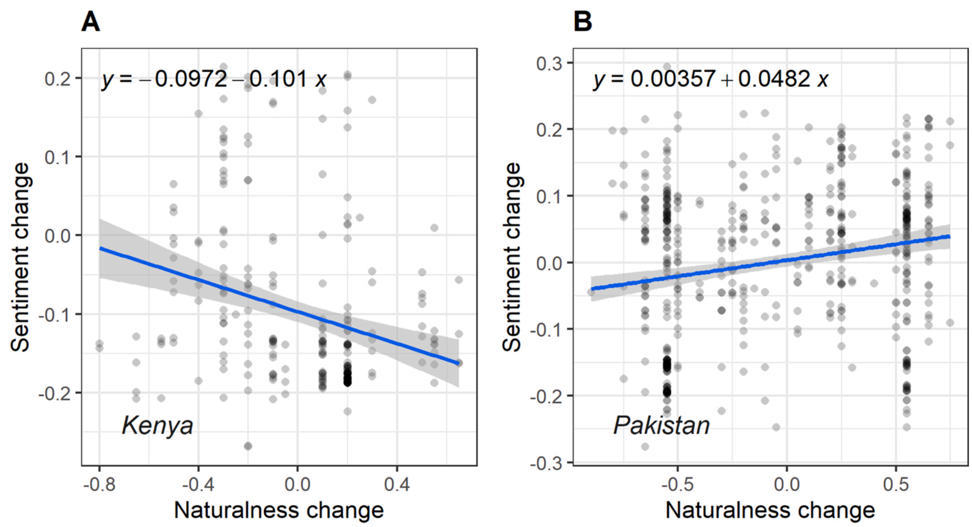

Fig. 9. Sentiment changes vs. naturalness changes. A - Kenya, B - Pakistan.

snow/ice, grassland, shrubland, forest, and agricultural land. These land types were primarily replaced by artificial land and water bodies.

It is worth noting that transportation construction can not only spur artificial land use but also propel agricultural activities along with the transportation network. Our analysis found there is a surge in agricultural land in southern Kenya (Fig. 3). This change might attribute to the convenient transportation that enables interregional food trade and promotes agricultural activities in the region. In addition, we surprisingly found an enormous amount of water body and wetland growth in Pakistan, while the snow and ice retreated (Fig. A.6). This finding is consistent with the warning from geologists who highlighted the potential for glacier melting in the upstream Indus River and the increase in High Asia's runoff (Lutz et al., 2014; Rathore et al., 2018). This arouses another layer of concern that human construction may compound the climate change effect and catalyze the glacial melting in the Himalayan region. The consequent impact on local ecosystems and beyond remains unknown and could be devastating (Kehrwald et al., 2008; Veh et al., 2020). Our findings thus suggest future LSIPs and road ecology studies should pay special attention to the usually ignored broader environmental impact of transportation (e.g., agricultural expansion, habitat fragmentation, and ecosystem degradation), in addition to the local effects (e.g., local land use transfer, and local air quality).

4.2. Sentiment trends

Although many negative comments on the BRI itself and BRI financed LSIPs in the news media, we found the overall sentiments in both Kenya and Pakistan were generally positive throughout the development process (Fig. 6). One potential explanation is the socio-economic benefits that come with such large-scale infrastructure projects (Thacker et al., 2019). Looking at the sentiment change over time by country, we identified a spike in positive sentiment before the project (when the project was under planning), and then there appeared to be more negative sentiment when approaching the actual launching of the project (Fig. 6). This can be confirmed with the fact that several LSIPs financed by the BRI were either suspended or terminated prior to the project implementation because of conflicting interests or opposition by different stakeholders. Future project planning should especially pay attention to these potential obstacles and impacts before implementing.

In terms of the spatial variation in sentiment within countries, we find parallels between locations. In Kenya, positive sentiment tended to be higher in the southern portion of the country where the Mombasa-Nairobi Standard Gauge Railway is located. While a similar pattern can be seen with the China-Pakistan Economic Corridor construction, we also found most of the regions that experienced LSIPs showed positive sentiment, though with a mix of few negative sentiments along the territory border in Pakistan. This indicates people in Pakistan tended to have positive sentiment towards the LSIPs overall, but concerned about geopolitical relations. Our keyword analysis confirmed this, as "India" is among the most frequently mentioned keywords on Twitter in Pakistan. This makes sense when placed in context with the conflicting interests among Pakistan, India, and China. It was reported that several CPEC projects are set to be conducted near disputed territory in the Himalayan Mountains near the Indian Ocean (Verma, 2020).

When looking at these country-wide sentiments, it is important to note the spatial heterogeneity of population centers. A higher concentration of sentiment data is found in higher population areas (Figs. A.7 and A.8), while a lower concentration of sentiment data was in low-population areas. This makes sense as these populous areas are often relative wealthy cities, while low-population areas are often less-affluent rural regions (where the residents may not have access to mobile devices or have limited usage of Twitter app). One way to gather more sentiment data from a greater portion of the population would be to incorporate other social media data sources (such as Facebook and Instagram) or multimedia news to expand the sample size (e.g., the Global Database of Events, Language, and Tone Project [aka, GDELT], which collects the world's broadcast, print, and web news from nearly every corner of every country; https://www.gdeltproject.org/). However, it has been extremely challenging to obtain Facebook data since its API changes in 2018, and cleaning the GDELT mixed text data is complicated. Our sentiment analysis using Twitter data, although with a potential data gap in less developed regions within a country, can help provide a timely sense of how local response to such large-scale infrastructure development across a country.

4.3. Complex socio-environmental interactions

Social-environmental impact and their interactions across scales and locations are complex, and depicting the complexity is challenging but beneficial. For example, Kenya has a negative relationship between sentiment and landscape naturalness, while Pakistan has a positive one. However, both countries share the common trend of positive relationships between sentiment and nighttime light brightness (an indicator of economic growth). According to the World Bank data, Pakistan's GDP per capita PPP (i.e., purchasing power parity) ($4,690 in 2019) is slightly higher than Kenya's ($4,330 in 2019). What we found from this study might be relevant to the Environmental Kuznets Curve (EKC) held by neoliberal economics, maintaining that poorer people and poorer governments would not care about the environment until after a certain economic threshold is reached (Broad and Cavanagh, 2015; Grossman and Krueger, 1995). Although it is challenging to draw a universal conclusion on the relations across countries, it otherwise informs us that the assessment of environmental and social impact should be country-wide, and that decision-making should be context-specific. Future research should include more BRI countries to test the EKC hypothesis.

Of note, our analysis revealed that positive sentiment increased most in regions with less natural land and brighter nighttime light, but only changed slightly in other regions with high naturalness land. Generally, areas with high naturalness land are considered as the rural, remote, and often poor regions in developing countries. Our findings thus suggest LSIPs may benefit developed regions more than less developed regions. Therefore, how to support the poor population and address the inequality in development should be put into the agenda of future LSIPs planning and implementation.

The integrated analysis of environmental and social impact can provide better information for future policymaking, catering to both environmental and social considerations. By doing so, potential synergies and trade-offs of policy impact could achieve the optimization of policy effectiveness and minimize unnecessary cost. For example, less developed regions could benefit from well-planned infrastructure development and thus become prosperous. Incorporating social development consideration into the planning of infrastructure development could be applauded by most stakeholders with an overall positive sentiment in the area. On the other hand, a large trade-off between environmental and social impact would alert decision-makers in implementing policies with careful consideration. With a better understanding of the strengths and drawbacks of implementing a project, decision-making would be more robust and engaged with more different stakeholders.

4.4. Study limitations

While social media provides a channel for a diverse population to provide individual sentiment expression, due to the various socioeconomic-cultural status in the study regions, people in part of the study regions may not use social media or may not speak English. This may lead to biased estimates in our sentiment analysis. Thus, some countries or regions with less sufficient social media data may face challenges in applying the SES approach.

Future research needs to combine more diverse social media data sources and community engagement scholarship to fully understand the social impact of LSIPs financed by international agencies. To the best of our knowledge, the broad coverage and substantial user group of Twitter throughout the world provide us with the most comprehensive individual-level data samples by far, and such information thus can help us capture the best estimate of people's sentiment and the change over time and across space. Additionally, although language differences across countries might add difficulty to generalize this approach, recent rapid developments in machine learning techniques are more capable of addressing this by translating text in different languages into a designated language (e.g., English) for sentiment analysis.

In all, this SES approach fosters timely and prompt socioeconomic-environmental monitoring across scales with fine resolutions by integrating social media data and remote sensing data. The findings will also help stakeholders be aware of the potential socio-environmental impact of implementing large-scale infrastructure projects and facilitate sustainable infrastructure development.

4.5. Future research and implications

Future research can apply this SES approach to other countries that have experienced rapid development of LSIPs. As of January 2020, 138 countries had joined the Belt and Road Initiative (https://www.yidaiyilu.gov.cn/) and many more LSIPs under the BRI are either under construction or under planning (https://green-bri.org/). Some of those infrastructure projects incurred doubt and dispute. For example, the Kunming-Singapore railway corridor is currently suspended in Malaysia because of political and funding conflicts; for the Budapest-Belgrade railway case, despite not having been started yet, it already shows social concerns about the environmental impact. It is important for investors and project managers to conduct a rigorous and transparent environmental impact assessment first before project planning, and draw insights and develop media strategies from public sentiment analysis to help mitigate the potential challenges in implementing those projects. In this study, we took land use/land cover change and nighttime light change as indicators of the environmental and economic impact, and took sentiment on BRI-LSIPs from the social media platform Twitter as an indicator of the social impact. Future research could incorporate more comprehensive social media data and recently developed remote sensing environmental indicators – such as concentration of air pollutants from the Sentinel-5 Precursor TROPOMI multispectral sensor (Guo, 2017; Veefkind et al., 2012), freshwater stress derived from the Gravity Recovery and Climate Experiment (GRACE) satellites (Richey et al., 2015; Rodell et al., 2018), and the land surface temperature detected from Landsat images (Ranagalage et al., 2017) – into investigating transportation-related LSIPs and many other types of LSIPs (such as power plants, ports, water supply pipelines).

In addition, since countries are more connected than ever before in this increasingly globalized world, collaborations will be the key to achieving multilateral win-win development and sustainability. With the interactions among countries extending from nearby partnerships to more distant ones, LSIPs in the Global South are increasingly supported by international finance, like the BRI. However, differences in cultural, social, and environmental conditions may incur many unexpected impacts and conflicts. In the meantime, large-scale infrastructure projects – such as transportation, pipelines, power plants, and dam constructions – may benefit a certain group of people at the cost of others. For instance, the transportation network by CPEC made interregional trade more convenient in northern Pakistan, but unintentionally led to the melting of glaciers and consequently flooding downstream. Dam constructions may help people in the upper stream enjoy more abundant water and more affordable electricity, but would generate unexpected impact on the livelihoods of the downstream communities (Golden et al., 2019; Latrubesse et al., 2017; Moran et al., 2018). Further study needs to consider human-nature interactions across scales and over distances (e.g., internally, nearby, and far away) by applying the integrated metacoupling framework (Liu, 2017). With these integrated efforts, we hope information from comprehensive assessment like this study can help inform decision-makers in future LSIP planning and implementation to address the potential socio-environmental impact, and help countries to fulfill the United Nations' Sustainable Development Goals (SDGs) (Sachs et al., 2019; Xu et al., 2020), particularly SDG 9 (to build resilient infrastructure and promote inclusive and stable industrialization) and SDG 17 (Partnerships to achieve the Goal).

Authorship contribution statement

Yingjie Li: Conceptualization, Methodology, Data curation, Investigation, Formal analysis, Visualization, Writing - original draft, Writing - review & editing, Funding acquisition, Project administration. **Yuqian Zhang:** Conceptualization, Methodology, Investigation, Formal analysis, Writing - original draft, Writing - review & editing. **Leigh Anne Tiffany:** Methodology, Investigation, Formal analysis, Writing - original draft, Writing - review & editing. **Ruishan Chen:** Conceptualization, Writing - review & editing, Funding acquisition. **Meng Cai:** Data curation, Formal analysis, Writing - review & editing. **Jianguo Liu:** Conceptualization, Writing - review & editing, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.envsci.2021.07.020.

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