Vegetation grows more luxuriantly in Arctic permafrost drained lake basins

Yating Chen1,2 | Aobo Liu1,2 | Xiao Cheng2

1State Key Laboratory of Remote Sensing Science, and College of Global Change and Earth System Science, Beijing Normal University, Beijing, China
2School of Geospatial Engineering and Science, Sun Yat-Sen University, Zhuhai, China

Abstract

As Arctic warming, permafrost thawing, and thermokarst development intensify, increasing evidence suggests that the frequency and magnitude of thermokarst lake drainage events are increasing. Presently, we lack a quantitative understanding of vegetation dynamics in drained lake basins, which is necessary to assess the extent to which plant growth in thawing ecosystems will offset the carbon released from permafrost. In this study, continuous satellite observations were used to detect thermokarst lake drainage events in northern Alaska over the past 20 years, and an advanced temporal segmentation and change detection algorithm allowed us to determine the year of drainage for each lake. Quantitative analysis showed that the greenness (normalized difference vegetation index [NDVI]) of tundra vegetation growing on wet and nutrient-rich lake sediments increased approximately 10 times faster than that of the peripheral vegetation. It takes approximately 5 years (4–6 years for the 25%–75% range) for the drainage lake area to reach the greenness level of the peripheral vegetation. Eventually, the NDVI values of the drained lake basins were 0.15 (or 25%) higher than those of the surrounding areas. In addition, we found less lush vegetation in the floodplain drained lake basins, possibly due to water logging. We further explored the key environmental drivers affecting vegetation dynamics in and around the drained lake basins. The results showed that our multivariate regression model well simulated the growth dynamics of the drainage lake ecosystem ($R^2_{adj} = .73$, $p < .001$) and peripheral vegetation ($R^2_{adj} = .68$, $p < .001$). Among climate variables, moisture variables were more influential than temperature variables, indicating that vegetation growth in this area is susceptible to water stress. Our study provides valuable information for better modeling of vegetation dynamics in thermokarst lake areas and provides new insights into Arctic greening and carbon balance studies as thermokarst lake drainage intensifies.

Keywords
greenness, lake drainage, northern Alaska, permafrost, remote sensing, thermokarst, tundra vegetation
Arctic temperatures are rising well above the global average due to the Arctic amplification effect (Box et al., 2019). The positive feedback loop between permafrost carbon and climate makes permafrost thaw one of the world’s most pressing climate issues (Koven et al., 2017; MacDougall et al., 2012; Schaefer et al., 2014; Schuur et al., 2015). Recent model assessments suggest that the response of permafrost to climate change remains highly uncertain (Burke et al., 2020; Chen et al., 2020), partly because of a lack of understanding of the thermokarst processes (Burke et al., 2020; Nitzbon et al., 2020; Schuur et al., 2015). Thermokarst processes manifest as landscape changes caused by abrupt thawing of excess ground ice, such as subsidence, thaw slumps, active layer detachments, and large-scale alterations in the hydrological cycle (Grosse et al., 2013; Kokelj & Jorgenson, 2013; Liljedahl et al., 2016; Nitzbon et al., 2020). Among these, thermokarst lake drainage events have a notable impact on permafrost degradation and greenhouse gas emissions (Anthony et al., 2018; Turetsky et al., 2019) and may trigger an “Arctic hazard” (Arp et al., 2020; Nitze et al., 2020).

As climate change intensifies, increasing evidence points to an increase in the frequency and magnitude of thermokarst lake drainage events in the Arctic and sub-Arctic regions (Grosse et al., 2013; Hinkel et al., 2007; Jones & Arp, 2015; Jones et al., 2020; Nitze et al., 2020; Smith, 2005). Long-term monitoring of Arctic permafrost lake dynamics can be achieved through satellite remote sensing (Hinkel et al., 2007; Nitze & Grosse, 2016; Nitze et al., 2018; Olthof et al., 2015). However, previous studies have generally focused on overall changes in lake extent (Jones et al., 2011; Lantz & Turner, 2015; Lindgren et al., 2021; Nitze et al., 2020). Little attention has been paid to the quantification of vegetation growth dynamics following drainage events (Magnússon et al., 2020). As suggested by Turetsky et al. (2019), researchers need to monitor how thawed ecosystems evolve to assess the extent to which plant growth will offset the carbon released from the permafrost. Lake drainage is often accompanied by the invasion of wetland plants (Grosse et al., 2013; Jorgenson & Shur, 2007), which helps to reduce permafrost thaw (Natali et al., 2019; Schuur et al., 2015) and stabilize soil carbon (Anthony et al., 2014; Jones et al., 2011). In addition, biomass accumulated by vegetation can partially offset the carbon release during abrupt thaws (Turetsky et al., 2020). Our current understanding of vegetation growth dynamics and successional patterns in drained lake basins is limited because factors such as CO₂ and nutrient concentrations, length of growing seasons, and changing soil moisture levels affect vegetation growth rates.

The aim of this study was to explore the vegetation growth dynamics of the drained lake ecosystems in the Arctic permafrost region. In this study, all available high-quality Landsat satellite images with long period records were used to detect the permafrost lake drainage events that have occurred in northern Alaska (a region dominated by thermokarst lake landscapes) since 2000. The rate of vegetation growth and stabilization in the drained lake basins was then quantitatively assessed based on a time-series analysis of satellite images. We further compared the differences in growth dynamics between the drained lake ecosystem and peripheral vegetation and explored their response to key environmental drivers. Our study provides valuable information for better modeling of vegetation dynamics after thermokarst lake drainage and may also contribute to the understanding of Arctic greening and the estimation of carbon balance in permafrost ecosystems.
topography and shallow bedrock that helps retain groundwater (Arp & Jones, 2009). This area has experienced significant warming over the last few decades, which is reflected in the occurrence of multiple types of permafrost disturbances and thermokarst processes. Along the coastline to the south, the terrain gradually rises, with a roughly three-stage gradient: coastal plain, foreland basin, and foothill, whose main vegetation types are wet meadow tundra and tussock tundra (Smardon, 2014; Weintraub & Schimel, 2005), polar grassland-lichen-moss (Yang et al., 2018), and sedge and shrub tundra (Kelsey et al., 2021; Nowacki et al., 2002; Tape et al., 2006), respectively.

2.2 | Image acquisition and preprocessing

This study provides a dynamic detection and trend analysis of thermokarst lake drainage events in northern Alaska based on a long time-series Landsat image archive. Remote sensing data acquisition and preprocessing were performed on the Google Earth Engine cloud platform (Gorelick et al., 2017). Complete coverage data spanned 2000–2020, with available sensors including L5-Thematic Mapper (TM), L7-Enhanced Thematic Mapper+ (ETM+), and L8-Observation Land Imager (OLI). Six multispectral bands of Landsat 5, 7, and 8 (blue, green, red, NIR, SWIR1, and SWIR2) were used for the analysis of lake and vegetation dynamics, all with a spatial resolution of 30 m. For consistent assessment of tundra vegetation growth, only Landsat images acquired during the peak growing season, that is, between July 1 and August 31 (Pastick et al., 2019; Raynolds et al., 2013), were used. Given the subtle differences between the sensors, OLI data were processed with a statistical transformation function (Roy et al., 2016) to improve the spectral continuity with TM and ETM+ data. Images with a cloud coverage of more than 50% were excluded, and the CFMASK algorithm (Foga et al., 2017) was used to mask clouds, snow, and shadow based on the quality assessment band of the Landsat SR product. Gaps in the Landsat-7 Scan Line Corrector failed images were filled using images from adjacent months or years. Finally, annual composite images (2000–2020) were created on the basis of the filtered Landsat image set using a median filter.

2.3 | Detected thermokarst lake drainage events

It is a challenging task to identify thermokarst lake drainage events from hundreds of thousands of lakes in the study area and to determine their year of occurrence. In this study, we used an advanced temporal segmentation and change detection algorithm, LandTrendr (Landsat-based detection of Trends in Disturbance and Recovery; Kennedy et al., 2010, 2018), to detect thermokarst lake drainage events from the annual composite images (2000–2020) and to identify time-series breakpoints. The LandTrendr algorithm has been widely used for the detection of forest disturbances (Cohen et al., 2018; Fragal et al., 2016), and it has also performed well in monitoring water dynamics (He et al., 2020). Based on the spectral trajectories of land surface change extracted from a year-by-year stack of Landsat image series, the LandTrendr algorithm can determine the year of occurrence, magnitude, duration, and recovery of various disturbance events. However, since the LandTrendr algorithm is very sensitive to disturbances, interannual fluctuations in the lake area may lead to noisy signals (He et al., 2020; Nitze et al., 2020). Therefore, we drew on existing studies and adopted the Theil–Sen regression model (Fraser et al., 2014; Nitze & Grosse, 2016; Othof & Fraser, 2014) and an object-based approach for the analysis of lake dynamics (Nitze et al., 2017) to filter the disturbances detected by the LandTrendr algorithm. In our study area, a total of 90 thermokarst drainage lakes larger than 5 ha in size were identified (Figure 1b).

2.4 | Analysis of vegetation dynamics in the drained lake basins

We screened the detected thermokarst lake drainage events (Figure 1b), and the lakes that were partially drained or not invaded

| Table 1 Candidate explanatory variables for multivariate linear regression models |
|-----------------|---------------------------------|-----------------|
| Variable        | Description                      | Data source     |
| MAAT            | Mean annual air temperature (K)  | ERA5-LAND       |
| MSAT            | Mean annual air temperature (K)  | ERA5-LAND       |
| MAE             | Mean annual evaporation (m)      | ERA5-LAND       |
| MSE             | Mean annual evaporation (m)      | ERA5-LAND       |
| Snowfall        | Annual snowfall (m)              | ERA5-LAND       |
| MAST            | Mean annual soil temperature (K) | ERA5-LAND       |
| MSST            | Mean summer soil temperature (K) | ERA5-LAND       |
| TAP             | Total annual precipitation (m)   | ERA5-LAND       |
| TSP             | Total summer precipitation (m)   | ERA5-LAND       |
| TASR            | Total annual solar radiation (J·m⁻²) | ERA5-LAND |
| TSSR            | Total summer solar radiation (J·m⁻²) | ERA5-LAND |
| MASW            | Mean annual soil water (m³·m⁻³)  | ERA5-LAND       |
| MSSW            | Mean annual soil water (m³·m⁻³)  | ERA5-LAND       |
| MASKT           | Mean annual skin temperature (K) | ERA5-LAND       |
| MSSkT           | Mean summer skin temperature (K) | ERA5-LAND       |
| SoilC           | Soil carbon content (kg/m³)      | NCSCDv2         |
| Elevation       | Elevation (m)                    | ArcticDEM       |
| Slope           | Slope (degree)                   | ArcticDEM       |
| Aspect          | Aspect (degree)                  | ArcticDEM       |
| Hillshade       | Hillshade                        | ArcticDEM       |
| Thermal         | Thermal infrared band            | Landsat 5/7/8   |
| TCW             | Tasseled cap wetness             | Landsat 5/7/8   |
| YSLD            | Year since lake drainage         | LandTrendr      |
by vegetation were excluded. To quantify the growth dynamics of vegetation following lake drainage, we calculated the inter-annual variation in vegetation spectral indices within the drained lake basin on a pixel-by-pixel basis. A variety of vegetation spectral indices, including tasseled cap greenness (Crist, 1985), normalized difference vegetation index (NDVI; Townshend & Justice, 1986), modified NDVI (Jurgens, 1997), and soil adjusted vegetation index (Huete, 1988) were tested, and similar trends in vegetation dynamics were found. We chose NDVI as a measure of vegetation growth in and around the drained lake basins for two reasons: (1) it is widely employed in Arctic tundra studies (Jia et al., 2006; Macias-Fauria et al., 2012; Myers-Smith et al., 2020; Pastick et al., 2019; Reichle et al., 2018) and (2) it is a good indicator of tundra plant productivity and above-ground biomass (Berner et al., 2018, 2020). We compared trends in NDVI for the vegetation growing in the drained lake basin with those of the peripheral vegetation. Peripheral vegetation was defined as the area within a 1 km buffer zone around the drained lake after masking off the water body. All calculations were performed on a pixel scale and were used to derive the quartiles and the 5 and 95 percentiles.

2.5 Regression analysis

We selected 23 candidate explanatory variables (Table 1) to explore the factors influencing vegetation growth dynamics in and around the drained lakes. These include climate variables such as air and soil temperature, precipitation, evaporation, and solar radiation from the ERA5-Land reanalysis data (Muñoz-Sabater et al., 2021), with a spatial resolution of approximately 9 km. Soil organic carbon content from the Northern Circumpolar Soil Carbon Database (NCSCD V2; Hugelius et al., 2013) has a spatial resolution of approximately 1 km. Compared to the 30 m resolution of the Landsat data, these two kilometer-scale data sources cannot distinguish between pixel differences, but they can still be used for the analysis of inter-lake and inter-annual differences. In addition, we generated seven variables from remotely sensed data sources that reflect inter-pixel differences, including elevation and topographic information from the ArcticDEM product (Porter et al., 2018), spectral information representing temperature and humidity, and the year since lake drainage derived using LandTrendr.

We then developed a multivariate linear regression model that included all candidate variables and removed non-significant variables in a stepwise manner. We followed the Akaike information criterion (Burnham & Anderson, 2004) to evaluate combinations of variables until the best-fitting model was found (Chen et al., 2021; Sun et al., 2012). The variables retained were all significant factors (p < .001) for our response variable (NDVI value) and passed the multicollinearity test. Vegetation growth trends in the drained lake and surrounding areas differed significantly. Therefore, we used two independent regression models to describe the predictors of vegetation change. Pearson correlation coefficients (r) were calculated between the response variable and the predictors retained in the final model. The adjusted coefficient of determination (R²adj) was used to determine the explanatory power of the model.

3 RESULTS

Figure 2 demonstrates a thermokarst lake drainage event with a lake area of approximately 100 ha (1 km²). According to the results of the LandTrendr algorithm, this lake started to drain gradually in 2003 and disappeared completely in 2005. After the lake was completely drained, the tundra vegetation invaded the lake drainage basin and completely covered the original lake extent. Moreover, according to the vegetation greenness index (NDVI), the vegetation growing in the drained lake basin became more luxuriant than in the surrounding area over time. The time series of greenness changes in

![FIGURE 2 Landsat color infrared images (NIR-R-G) showing (a) a thermokarst lake; (b) the thermokarst lake after drainage (2005); (c) the thermokarst lake covered by vegetation (2020). The vegetation has high reflectance in the NIR band, so the dark red color represents more lush vegetation; (d) year of disturbance; (e) disturbance magnitude of the thermokarst lake drainage event detected by the LandTrendr algorithm; and (f) vegetation greenness (NDVI) in 2020. NDVI, normalized difference vegetation index](https://wileyonlinelibrary.com)
the drainage lake area and peripheral vegetation showed differences between the non-floodplains (Figure 3) and floodplains (Figure 4). Overall, vegetation in non-floodplain lakes grew rapidly after drainage, and their NDVI values reached the surrounding average in about 5 years and gradually showed higher levels of greenness. In contrast, vegetation in drained lake basins near rivers grew more slowly due to flooding, reaching the surrounding average in approximately 14 years. For the vegetation around the drainage lake area, vegetation greenness showed a slightly increasing trend between 2000 and 2020. The NDVI values of non-floodplain vegetation were approximately 0.45–0.65 while those of floodplain vegetation were approximately 0.1 lower. Before the thermokarst lakes were drained, the NDVI values were stable at negative values. Some lakes with growing wetland plants exhibited positive NDVI values, which were reflected in the whisker lines of the boxes (Figures 3a and 4a). In the year of thermokarst lake drainage events, NDVI values changed from negative to positive, representing a shift from water to bare ground.

For the non-floodplain drained lakes (Figure 3), the change in vegetation greenness was approximately +0.10 per year (25%–75% range: 0.09–0.11) during the first 5 years after the drainage event. Meanwhile, the change in surrounding vegetation was approximately +0.01 per year (25%–75% range: 0.01–0.01). Thus, the vegetation in the drainage lake area was greening up about 10 times faster than the peripheral vegetation during this period. Between 5 and 15 years after the drainage events, the vegetation greenness in the drainage lake area changed by approximately +0.02 per year (25%–75% range: 0.01–0.03) while the peripheral vegetation greenness showed a slight upward and then downward trend. On a lake-by-lake basis, we calculated the annual differences in NDVI values

FIGURE 3 (a) Time series of greenness changes in the drainage lake area (orange) and peripheral vegetation (green) in non-floodplains. Statistical information for all pixels is reflected in the boxes. Whiskers: 5%–95% range; boxes: 25%–75% range; horizontal lines: median. (b) Inter-annual variation in NDVI differences between the drainage lake area and peripheral vegetation. Negative values on the x-axis represent the number of years before the occurrence of lake drainage. NDVI, normalized difference vegetation index
between the vegetation in the drained lakes and the peripheral vegetation (Figure 3b). According to the median and confidence intervals, vegetation in the drainage lake area reached the greenness level of surrounding vegetation in approximately 5 years (4–6 years for the 25%–75% range, and 3–11 years for the 5%–95% range). In the 15th year after the drainage events, the vegetation greenness in the drainage lake area was about 25% higher than the surrounding vegetation with an absolute difference of 0.15 (25%–75% range: 0.12–0.19).

Compared to drainage lake areas that were not near the river (Figure 3), vegetation in the floodplain drained lake basins grew more slowly and did not exhibit significantly higher levels of greenness than peripheral vegetation throughout the study period (Figure 4). During the 15 years after the occurrence of lake drainage, the vegetation greenness in the drainage lake area near the river showed an approximately linear increase at a rate of about $+0.02$ (25%–75% range: 0.01–0.03) per year. Hence, the difference in the growth rate of vegetation in the drainage lake area near and not near the river can be up to five times within 5 years after drainage. Based on the inter-annual variation of NDVI differences (Figure 4b), the vegetation in the drained lake area reached the level of the surrounding vegetation approximately 14 years after the drainage occurred. It should be noted that the growth rate of vegetation in the drained lakes varied greatly, and the confidence interval (Figure 4b) showed that approximately 5% of the drainage lake area reached the greenness level of the surrounding vegetation in approximately 3 years. This also explains the large span of the blue boxes in Figure 4a and the fact that the median is close to the lower quartile.

The results showed that our multivariate regression models captured the majority of the variability in vegetation in and around the

**FIGURE 4** (a) Time series of greenness changes in the drainage lake area (blue) and peripheral vegetation (green) in floodplains. Statistical information for all pixels is reflected in the boxes. Whiskers: 5%–95% range; boxes: 25%–75% range; horizontal lines: median. (b) Inter-annual variation in NDVI differences between the drainage lake area and peripheral vegetation. Negative values on the x-axis represent the number of years before the occurrence of lake drainage. NDVI, normalized difference vegetation index.
drainage lakes (Figure 5). Vegetation in the drainage lake area near and not near the river, although exhibiting different growth rates, could be well explained by the same multivariate regression model (Figure 5a) with an $R^2_{adj}$ of 0.73 ($p < 0.0001$). Exploratory analysis indicated that the vegetation greenness was determined by the five most influential variables, namely, year since lake drainage (YSLD, $r = 0.60$, $p < .001$), elevation ($r = 0.49$, $p < .001$), total annual precipitation (TAP, $r = 0.58$, $p < .001$), mean annual soil water (MASW, $r = 0.57$, $p < .001$), and mean annual air temperature (MAAT, $r = 0.38$, $p < .001$), which accounted for 32.1%, 26.3%, 17.2%, 16.0%, and 8.4% of the explained variance of vegetation greenness, respectively. Meanwhile, the multivariate regression model (Figure 5b) for vegetation around the drainage lake showed that approximately 68% of the variation in vegetation greenness could be explained by three variables ($p < .0001$). These three variables were tasseled cap wetness (TCW, $r = 0.60$, $p < .001$), elevation ($r = 0.58$, $p < .001$), and mean annual air temperature (MAAT, $r = 0.38$, $p < .001$), which accounted for 38.8%, 31.2%, and 29.9% of the overall variance in vegetation greenness, respectively.

Among these variables, elevation, which reflects the spatial heterogeneity of vegetation, has an important influence on the growth status of vegetation in and around the drainage lake area. In our study area, elevation gradually increased from coastal to inland regions, and vegetation type gradually transitioned from wet meadow tundra to shrub tundra. For Arctic tundra, soil temperature, moisture, and elevation were important influencing factors, which is consistent with the findings of previous studies (Berner et al., 2020; Lara et al., 2018). TCW is a strong predictor of peripheral vegetation greenness but is excluded from the regression model of vegetation greenness in the drainage lake area. This is because TCW reflects the overall moisture content (Frazier et al., 2015) and is highly correlated with soil moisture, texture, and vegetation water content (Crist, 1985; Zanchetta et al., 2016). Changes in TCW are dominated by soil moisture when there is no significant change in vegetation status (Lamqadem et al., 2018). For vegetation growing in the drainage lake area, YSLD was the most important predictor variable as vegetation greenness increased with time. Among climate variables, moisture, represented by TAP and MASW, was more important than temperature (MAAT).

DISCUSSION

In this study, we found that the Arctic tundra vegetation grew rapidly in the thermokarst lake drainage area and exhibited a higher level of greenness than the surrounding vegetation after a few years. We hypothesize that this may be because the relatively warm, moist, and nutrient-rich sediments on the lake bottom are conducive to the development of highly productive plant communities. In addition, we found that vegetation in the floodplain drained lake basin grew more slowly and less luxuriantly. This may be due to the lower productivity of the vegetation communities in the floodplain and the micro-topography of the drained lake basin, which makes it more susceptible to flooding. Over time, vegetation growing in the drainage lake area in the floodplain may continue to flourish and grow more luxuriantly than the peripheral vegetation. However, verifying this will require studies on a longer timescale.

After lake drainage, the pioneer plants are generally sedges and graminoids that dominate in wet areas (Magnússon et al., 2020; Zona et al., 2010). The expansion of pioneer plants may expedite nitrogen turnover by increasing nitrogen uptake (DeMarco et al., 2014), as well as the amount of plant litter that allows year-round microbial decomposition (DeMarco et al., 2011; McLaren et al., 2017). With the modification of edaphic conditions by biogeochemical and

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**FIGURE 5** Multivariate regression models for vegetation greenness represented by NDVI in and around the drainage lake area. The mean linear regression trend line (red) is bounded by 95% confidence interval (light green). The inserted pie charts show the relative contribution of each variable retained in the model to overall variance. All variables are positively correlated with vegetation greenness. MAAT, mean annual air temperature (K); MAST, mean annual soil temperature (K); MASW, mean annual soil water (m$^3$ · m$^{-3}$); NDVI, normalized difference vegetation index; TAP, total annual precipitation (m); TCW, tasseled cap wetness; YSLD, year since lake drainage.
biophysical processes, plant succession occurs in the drainage lake area, manifesting itself in the proliferation of perennial grasses and shrubs (Vowles & Björk, 2019). The vegetation in the drained lake basins will not evolve into a forest ecosystem and its productivity will gradually slow down as the ecosystem matures and reaches a stable state. In addition, productivity growth is limited also because nutrients are locked up in living plant material and dead organic matter (Zona et al., 2010).

As the Arctic continues to warm, the development of thermokarst landscapes in the permafrost region will intensify (Lara et al., 2016) and the frequency of thermokarst lake drainage events will increase (Anthony et al., 2018). This study found that vegetation in the drainage area of thermokarst lakes grew rapidly and reached a higher level of greenness than the peripheral vegetation. This constitutes a negative feedback process, as the rapid growth of vegetation in the drained lake not only absorbs CO$_2$ but also helps to reduce the thawing of permafrost (Anderson et al., 2019; Blok et al., 2010; Douglas et al., 2020). Vegetation greening reduces surface albedo (Loranty et al., 2011; Pearson et al., 2013), enhances permafrost insulation, and reduces soil temperature for permafrost in summer, thus buffering permafrost degradation from the changing climate (Liljedahl et al., 2016; Nauta et al., 2015). Overall, rising temperatures enhance permafrost thaw and microbial decomposition but also promote vegetation growth and shrub expansion (Natali et al., 2019; Schuur et al., 2015). In addition, thermokarst features such as thaw lakes are important sources of methane emissions (Anthony et al., 2021; Walter et al., 2006, 2007), while refreezing of taliks and colonization of drained basins by plants can result in areal-based carbon fluxes in drained lake basins that are one to three orders of magnitude lower than those from abruptly thawed lakes (Anthony et al., 2018; Zona et al., 2010, 2016). The net climate feedback of these processes is currently fraught with uncertainty, and thermokarst lake drainage events are likely to play an important role, as they have a non-negligible impact on the greening/browning dynamics and carbon balance of the Arctic tundra ecosystems (Magnússon et al., 2020).

In our study area, humidity plays a more important role in plant growth than temperature. This is because northern Alaska is relatively arid and the emerging vegetation in the drained lake basin is vulnerable to water stress, and soil moisture is a major control of ecosystem respiration and net ecosystem exchange (Zona et al., 2010). In addition, a notable decrease in vegetation greenness was observed in all of the thermokarst lake drainage areas after experiencing heavy rains in 2018 while the peripheral vegetation changed only slightly. This could be influenced by the micro-topography of the drained lake basins. On the one hand, runoff and nutrients move downslope from more elevated sites to converge in the thaw lakes (Anthony et al., 2014; Zona et al., 2010) and contribute to vegetation growth after lake drainage. On the other hand, drained lake basins are low-lying and susceptible to flooding and heavy rainfall, and vegetation growth is suppressed when experiencing waterlogging (Nauta et al., 2015). Another interesting finding regarding the micro-topography of drained lake basins is that we can infer how thermokarst lakes drain and locate drainage channels by the greenness of vegetation in the drainage areas (Figure 6). The drainage of thermokarst lakes can be divided into lateral drainage and internal drainage (Hinkel et al., 2007; Jones et al., 2011; Marsh et al., 2009). Lateral lake drainage events are characterized by the formation of drainage channels associated with bank overtopping due to increased precipitation and flooding (Jones & Arp, 2015). The observation and detection of drainage channels require remote sensing images with meter and sub-meter resolutions while the most widely accessible Landsat and Sentinel-2 data have image resolutions of 30 and 10 m, respectively. However, we found that drainage channels could be detected indirectly through changes in vegetation greenness (Figure 6). Based on the results of the LandTrendr algorithm, it can be intuitively found that the drainage channel behaves as a strip

![Figure 6](image-url) (a) A hillshade map derived from the 2-m resolution ArcticDEM product showing the micro-topography of a drained lake basin. The drainage channel in the northeast corner of the lake is faintly visible. (b) Vegetation growth in the drainage lake area detected by the LandTrendr algorithm between 2000 and 2020. The vegetation greenness around the drainage channel shows remarkable changes
arising from the drained lake basin where the greenness changes more rapidly than the surrounding area.

5 | CONCLUSIONS

Rapid thermokarst lake drainage events have been detected in northern Alaska based on continuous satellite imagery over the past 20 years. Quantitative analysis (using NDVI) of the drainage lakes and surrounding areas on a pixel-by-pixel basis indicated that (1) emergent vegetation grew rapidly in the drained lake ecosystem, with greenness increasing at rates up to 10 times the surrounding average; (2) approximately 5 years (25%-75% range: 4–6 years) after the lake drainage event, the drained lake basins reached the greenness level of the peripheral vegetation; and (3) vegetation growing in the drainage lake area is lusher than that in the surrounding area, with differences in greenness of up to 25% over time. Based on these results and the fact that the frequency and magnitude of thermokarst lake drainage events are increasing, we suggest that drained thermokarst lake basins are hotspots of Arctic greening, with profound implications for permafrost stability and greenhouse gas emissions. We expect that additional confidence will be gained in the modeling of vegetation dynamics in future studies that encompass permafrost-thermokarst-vegetation interactions.

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CONFLICT OF INTEREST

The authors declare no competing interests.

AUTHORS’ CONTRIBUTIONS

Yating Chen led all aspects of the study; Yating Chen and Xiao Cheng conceived and designed the experiment. Yating Chen and Aoobo Liu performed the experiments and data analysis. All authors contributed to the discussion and writing of the manuscript.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the following sources: The United States Geologic Survey Landsat 5, 7, and 8 Surface Reflectance data and the ECMWF climate reanalysis data (ERAS-Land) are available from Google Earth Engine (https://developers.google.com/earth-engine/datasets/).

ORCID

Yating Chen https://orcid.org/0000-0001-6710-0434

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