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Title: Development of new metrics to assess and quantify climatic drivers of extreme event driven Arctic browning.

List of authors:

Rachael Treharne[1], Jarle W. Bjerke[2], Hans Tømmervik[2], Gareth K. Phoenix[1].

[1]Department of Animal and Plant Sciences, The University of Sheffield, Western Bank, Sheffield, S10 2TN, UK

[2]Norwegian Institute for Nature Research, FRAM – High North Research Centre for Climate and the Environment, NO-9296 Tromsø, Norway

Corresponding author:

Rachael Treharne[1]

[1]Department of Animal and Plant Sciences, The University of Sheffield, Western Bank, Sheffield, S10 2TN, UK

rtreharne1@sheffield.ac.uk

+44(0)7788765609

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Abstract

Rapid climate change in Arctic regions is resulting in more frequent extreme climatic events. These can cause large-scale vegetation damage, and are therefore among key drivers of declines in biomass and productivity (or "browning") observed across Arctic regions in recent years.

Extreme events which cause browning are driven by multiple interacting climatic variables, and are defined by their ecological impact – most commonly plant mortality. Quantifying the climatic causes of these multivariate, ecologically defined events is challenging, and so existing work has typically determined the climatic causes of browning events on a case-by-case basis in a descriptive, unsystematic manner. While this has allowed development of important qualitative understanding of the mechanisms underlying extreme event driven browning, it cannot definitively link browning to specific climatic variables, or predict how changes in these variables will influence browning severity. It is therefore not yet possible to determine how extreme events will influence ecosystem responses to climate change across Arctic regions.

To address this, novel, process-based climate metrics that can be used to quantify the conditions and interactions that drive the ecological responses defining common extreme events were developed using publically available snow depth and air temperature data (two of the main climate variables implicated in browning). These process-based metrics explained up to 63% of variation in plot-level Normalised Difference Vegetation Index (NDVI) at sites within areas affected by extreme events across boreal and sub-Arctic Norway. This demonstrates potential to use simple metrics to assess the contribution of extreme events to changes in Arctic biomass and productivity at regional scales. In addition, scaling up these metrics across the Norwegian Arctic region resulted in significant correlations with remotely-sensed NDVI, and provided much-needed insights into how climatic variables interact to determine the severity of browning across Arctic regions.

1 Introduction

An increase in frequency of climatic extreme events is among the most marked consequences of climate change (IPCC, 2017). In the Arctic, climate change is progressing faster than almost anywhere else in the world, especially during winter (AMAP, 2017), and increases in extreme events - particularly those associated with winter climate - are therefore being observed (Vikhamar-Schuler et al., 2016, Graham et al., 2017). Although traditionally, climate change research has focussed on changes in mean conditions, it is now recognised that extreme events can have major impacts on ecosystems (Zscheischler et al., 2014, Solow, 2017). In Arctic regions, these impacts include considerable changes in vegetation biomass, productivity and phenology (Bokhorst et al., 2008, Jepsen et al., 2013, Reichstein et al., 2013). However, proper quantitative understanding of the climatic drivers that cause these extreme event impacts is currently lacking, since research has so far focussed on an 'impact orientated' approach, where ecological consequences are studied in detail, while climatic drivers are generally defined in qualitative, descriptive terms.

This is of concern since extreme events linked to winter climate change are already causing major disturbance in the form of sudden mortality and extreme stress in widespread Arctic and sub-Arctic vegetation, with the potential to cause large scale and magnitude impacts, such as the record low productivity of the Nordic Arctic Region (NAR) observed in 2012 (Bokhorst et al., 2009, Bjerke et al., 2014, 2017). Such events include, for example, transient periods of extreme winter warmth, leading to premature dehardening and frost damage (extreme winter warming), or exposure to cold, wind and irradiance following loss of snow cover, leading to severe desiccation damage (frost drought). These are important drivers of 'Arctic browning', a decline in biomass and productivity observed across Arctic regions in recent years (Epstein *et* *al.,* 2015, 2016, Phoenix & Bjerke, 2016). However, although remotely sensed Normalised Difference Vegetation Index (NDVI) has been used to assess the extent and impacts of extreme events identified during field studies (Bokhorst et al., 2009), detecting events using this approach is challenging (Treharne et al., 2018). Methods to quantitatively define climatic drivers of extreme event driven browning are therefore needed before the contribution of extreme events to remotely-sensed vegetation change across Arctic regions can be fully determined.

Extreme events are typically defined using climatological thresholds or using an impact-orientated definition (van de Pol et al., 2017). The latter approach may define an extreme event as one where the ability of an organism to acclimate is substantially exceeded (Gutschick & BassiriRad, 2003) or as a climatologically rare event that alters ecosystem structure or function outside the bounds of normal variability (Smith et al., 2011). Impact orientated definitions are commonly used for 'compound events'; events driven by combinations of interacting variables which separately may not trigger an extreme response, but, together, cross ecological thresholds to trigger an extreme response (van de Pol et al., 2017). Extreme climatic events which drive Arctic browning, such as frost drought and extreme winter warming, are examples of compound events. These events have therefore so far been defined by their biological impacts; most clearly vegetation mortality (Bokhorst et al., 2011) or a marked visible stress response indicated by persistent anthocyanin pigmentation (Bjerke et al., 2017).

Events such as these which are defined by an ecological impact and driven by a combination of multiple climatic variables are especially complex to quantify, compare or predict (Easterling et al., 2000). This complexity is compounded when the physiological thresholds beyond which an extreme response is triggered are likely to differ with event timing, preceding conditions and the occurrence of successive events (Knapp et al., 2015, Sippel et al, 2016, Wolf et al, 2016, Ummenhofer & Meehl 2017). This is particularly relevant in Arctic regions, where the depth and extent of insulating snow cover determines whether vegetation is exposed to ambient conditions such as air temperature (Williams et al., 2014; Bokhorst et al., 2016), where event timing may drastically change the conditions to which vegetation is exposed, such as light intensity, and where susceptibility to an extreme response may be heavily dependent on preconditioning, such as the duration of chilling prior to an extreme winter warming event, which could determine susceptibility to premature loss of winter freeze tolerance (dehardening).

In common with much extreme event literature (Bailey & van de Pol, 2015, Altwegg et al., 2017), assessment of the multivariate climatic drivers in studies of extreme event driven Arctic browning is therefore typically descriptive and unsystematic, dealing with a single event or a few, often differing, events. Nonetheless, these studies have provided critical insights into these events, including a qualitative understanding of event drivers and quantification of major impacts on vegetation growth, phenology and productivity, and on ecosystem CO_2 fluxes (Bokhorst et al., 2008, 2009, 2011; Bjerke et al., 2014, 2017; Parmentier et al., 2018). However, their ability to attribute these measured responses definitively to specific hypothesised climatic drivers is limited. In addition, this approach cannot determine where response thresholds lie, or therefore predict how the severity of the browning response could scale with different climate variables, or when specific conditions might be expected to result in vegetation damage.

This is of concern given the scale of observed browning impacts, which include substantial loss of biomass at landscape or greater scales (Bjerke et al., 2014, 2017) and large changes in ecosystem CO_2 fluxes with significant implications for landscape-level carbon balance. Furthermore, as the frequency of many types of extreme climatic event is predicted to increase in Arctic regions as climate change progresses, the scale and extent of these impacts are likely to increase (Vikhamar-Schuler et al., 2016, Graham et al., 2017). To fully understand how these events will influence the responses of Arctic ecosystems to climate change, a more systematic approach is needed; correlating measured response to specific, process-based climatic variables. As a first step, a framework to quantify the drivers of extreme event-driven Arctic browning, and the interactions between them, is required to understand how variation in these drivers influences the severity of response in vegetation communities, and ultimately drives browning. This quantitative understanding is critical to identify the contribution of extreme events to Arctic browning trends at regional scales, and to fully understand how winter climate change will impact Arctic plant communities.

Therefore, the aims of this work were to apply established ecological understanding about the drivers of specific instances of extreme event driven browning to (a) identify simple, process-based, quantitative climate metrics that can be used to quantify extreme winter conditions in a systematic, comparable way and (b) assess the relationship between these metrics and changes in satellite NDVI at regional scales. The development of climate metrics initially utilised a dataset of plot-level measurements of NDVI and visible vegetation damage across 19 sites known to have been affected by extreme winter climatic events (primarily frost drought and extreme winter warming experienced during the 2013/14 winter) and subsequent browning. Following this, national meteorological and modelled snow cover datasets were used to compare climate metrics with remotely sensed NDVI across the Norwegian Arctic region. It was hypothesised that (a) simple climate metrics will be identified that correlate with NDVI in areas known to have been affected by browning, (b) these metrics will reflect ecological understanding about the mechanisms underlying extreme climatic event driven browning, and (c) these metrics will correlate with NDVI change at regional scales.

2 Methods

2.1 Developing climate metrics using plot-scale analysis

2.1.1 Plot-level NDVI

Widespread browning of evergreen shrubs across boreal and sub-Arctic regions of Norway was observed following the 2013/14 winter, attributed to extreme winter weather conditions (Meisingset et al., 2015; Bjerke et al. 2017). For this plot-scale analysis, observations of browning recorded in the growing seasons following these extreme winter conditions (2014 or 2015) were collated from 19 sites (Fig. 1) in boreal and sub-Arctic Norway. The number of plots at each site ranged from 1 to 143 (with a mean of 19), with each plot measuring 1 x 1m. Replicate plots were located at least 2 m apart and were chosen to reflect the full range of observed browning, including green, healthy vegetation apparently unaffected by extreme events (control plots). Browning at the majority of these sites was driven by the extreme conditions during the 2013/14 winter, with remaining sites browned during previous winters (2011/12 at the earliest; Bjerke et al., 2014). Observations consisted of plot-level NDVI measurements and/or visual assessments of plant damage (mortality; observed as browning). NDVI measurements were taken using either digital NDVI cameras (passive NDVI sensors), in which the usual light sensor is replaced with an infrared sensor, enabling the camera to record visible light in the blue channel and near infrared in the red channel (Llewellyn Data Processing, New Jersey), or an active NDVI sensor (Greenseeker; Trimble, California). The Greenseeker NDVI sensor emits red and infrared light and measures the reflectance of each wavelength in terms of the normalized difference vegetation index (NDVI) and is mainly used in precision agriculture (Bourgeon et al., 2017) and in phenological monitoring; including of browning trends and events in the Arctic (Anderson et al. 2016; Bokhorst et al., 2018). The visual assessments of browning were recorded either as percentage cover of browned vegetation (mortality), or the proportion of the dominant species affected by browning (own data and data provided by J. Bjerke). NDVI and observed browning (plot survey) were significantly correlated. This correlation was calculated separately across plots within each of the three Norwegian counties of Troms, Nordland and Nord-Trøndelag to allow for some regional variation while minimising the loss of statistical power ($p < 0.05$ in all cases). The correlation was then used to predict plot-level NDVI at plots where observed browning alone, and not NDVI, was recorded.

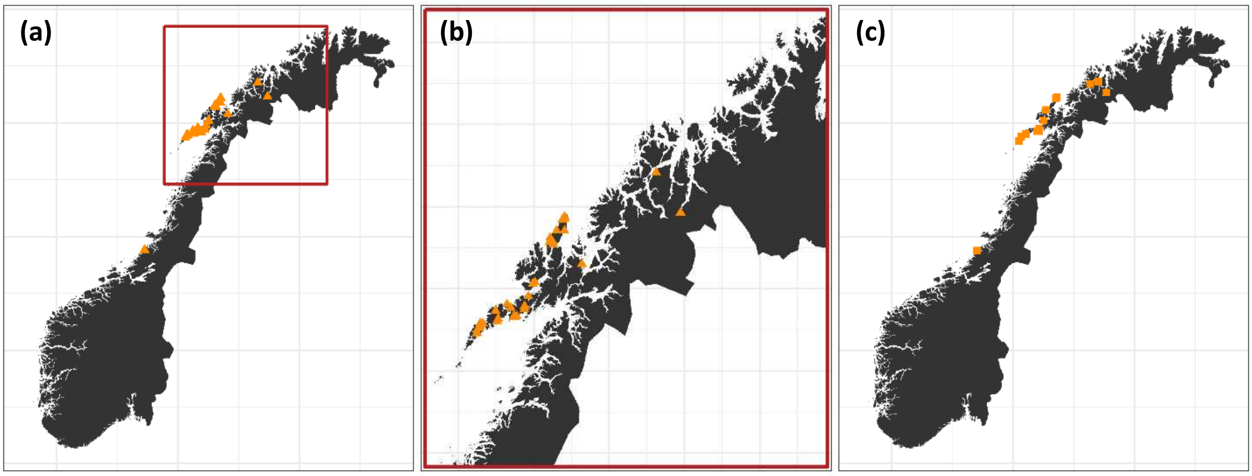

Figure 1: (a) Map of Norway showing locations of 19 sites (orange triangles) where extreme event-driven browning was observed and plot-level NDVI was measured. The Norwegian Arctic Region, the area used for regional level analysis, is outlined in red. This area is shown separately and enlarged in (b). The locations of the weather stations from which climatic data was analysed are shown in (c).

In addition, a ‘pre-browning’ NDVI value was estimated for each site. This ‘pre-browning’ value was assigned to the growing season preceding the winter during which browning occurred (i.e. 2013 for the majority of sites). To estimate these pre-browning values, linear regressions of NDVI and observed browning were calculated separately for each county ($p < 0.05$) and used to predict NDVI in vegetation with no observed browning. This approach produced ecologically sensible estimates for healthy dwarf-shrub heathland NDVI of between 0.67 and 0.75 (Street et al., 2007). At two sites, 5-6 NDVI values in undamaged vegetation adjacent to observed browning plots were recorded; in these cases recorded NDVI values in undamaged vegetation were averaged to estimate pre-browning values for those sites.

2.1.2 *Climate data*

Snow depth maps of Norway with a daily temporal and 1 x 1 km spatial resolution were obtained from The Norwegian Water Resources and Energy Directorate (NVE). This publically available data is produced using the SeNorge snow model (http://www.senorge.no), which is forced by daily observations of temperature and precipitation and performs well in Norway (Saloranta, 2012).

From SeNorge snow maps, daily snow depth values were extracted from each pixel which contained plot-level browning observations in the dataset described above. This data was extracted for each winter between 2011 and 2015. Daily snow depth values for each site were then obtained by taking a simple average across the pixels containing plot-level browning observations for each site.

Daily mean, minimum and maximum air temperature was obtained from the Norwegian Meteorological Institute via the publically available eklima.no web portal. Data for 2011 – 2015 was downloaded from the weather stations closest to each site (maximum distance < 25km) at an elevation of < 200m (as sites were located in relatively low-lying areas). Based on the quality and availability of air temperature data from these stations, data from 14 stations was subsequently analysed. See Fig. 1c for weather station locations.

2.1.3 *Development of metrics*

Snow and air temperature data was combined into a single dataset. Only data from the winter period was used to develop climate metrics, to avoid any confounding effect of occasional late spring or summer snowfall. To identify an appropriate window for this winter period during which snow cover and cold temperatures could reasonably be expected, and therefore during which warmth and exposure may have ecological consequences, first winter snow fall and final spring snow melt for each winter (2011/12 – 2014/15) were identified. This was done by selecting all periods of absent snow cover (0 mm snow depth) throughout the year; first winter snowfall and final spring melt were recorded as the dates following and preceding the long summer exposure period in consecutive years. Winter was thus defined from Day of Year 305 (Day of Winter 1) to Day of Year 120 (Day of Winter 181 or 182). A consistent winter period was used rather than defining when winter began and finished each year separately (based on climate data). This was because the latter approach might exclude periods of unseasonable warmth or absent snow cover in early or late winter, since these periods would not be classed as winter.

Within each winter a set of approaches were used to extract 'events' which may have influenced NDVI. These were 'exposure events' based on absent snow cover (0 mm snow depth) or 'warming events' based on warm winter temperatures (> 2 ˚C). A 2 ˚C threshold for warming events was chosen based on assessment by eye of plotted temperature data during warming events known to have resulted in browning, with this temperature found to ensure the full duration of any warming event was captured. Furthermore, differentiation between short, relatively mild warming events and prolonged periods of high temperatures was subsequently facilitated by an 'intensity' metric (below and Table 1). Periods of exposure or warming occurring before initial winter snowfall or cold temperatures were excluded. The variables recorded for each event type were chosen based on the mechanism of damage particularly associated with either winter warming (i.e. premature dehardening and initiation of spring-like bud burst, followed by frost damage on the return of cold temperatures) or frost drought (loss of snow cover and subsequent exposure, leading to gradual desiccation as transpiration exceeds uptake from frozen or near-frozen soils) (Table 1). These two processes account for the majority of reported extreme climatic event-driven browning in mainland Norway (e.g. Hørbye, 1882; Printz, 1933; Bokhorst et al., 2009, 2012; Bjerke et al. 2014, 2017). Thus, for exposure events (most likely to be associated with frost), event duration, start date and mean air temperature were recorded. For warming events (most likely to be associated with extreme winter warming), a wider range of variables were recorded (Table 1). These include the intensity metric, calculated as air temperature*duration. Weighting air temperature in this way reflects the process through which extreme winter warming drives browning; exposure to temperatures of sufficient warmth and duration to (a) melt snow and expose vegetation, and then (b) subsequently initiate bud burst and premature loss of freeze tolerance.

Using this approach, several events were extracted for each year. To select those most likely to influence growing season NDVI, up to 4 events were selected for each year. These were (a) 'Maximum intensity warming events'; the warming event with the highest 'Intensity' (air temperature*duration; Table 5.1), (b) 'Temperature drop warming events'; the warming event with the greatest 24-h temperature drop following the final day of the event, (c) 'Maximum duration exposure events'; the maximum duration exposure event (i.e. no snow cover) (d) 'Maximum warmth exposure events'; the warmest exposure (no snow cover) event.

Table 1: Variables (climate metrics) recorded for each event type (either warming events based on consecutive daily air temperatures of > 2˚C, or exposure events based on consecutive days of absent (0mm) snow cover) as extracted from snow depth and air temperature data.

Variable	**Meaning**	**Event type**
Count	Event duration (days).	Warming; Exposure
Start date	Date (Day Of Winter) of the first day of the event.	Warming; Exposure
Intensity	Cumulative mean daily air temperature (˚C) linearly weighted by duration throughout the event. E.G. for a 3 day event with daily mean air temperatures of 4˚C, 6˚C and 3˚C, Value = (4*1) + (6*2) + (3*3) = 25.	Warming
Mean snow depth	Mean snow depth (mm) during the event.	Warming
Mean air temperature	Mean air temperature (˚C) during the event.	Exposure
End minimum temperature	Minimum temperature 24 hours following the final day of the event (˚C).	Warming
24 hour temperature drop	Difference between mean daily air temperature on the last day of the event and minimum air temperature 24 hours later (˚C).	Warming
5 day temperature mean	Mean daily air temperature over the 5 days following the event (˚C).	Warming

2.1.4 Satellite NDVI

Remotely sensed NDVI data were extracted from the publically available MOD13Q1 version 6 dataset. MOD13Q1 provides level 3 16-day composites of vegetation indices at 250 m resolution in a sinusoidal projection. Tiles were downloaded for DOY 193 in 2015, the nearest date to when plot-level measurements were recorded, using USGS Earth Explorer. These tiles were re-projected to the UTM Zone 33 projection using the NASA HDF-EOS To GeoTIFF Conversion Tool (HEG) and mosaicked to encompass the full extent of plot-level data. At the plot-scale analysis stage, remotely sensed NDVI values were used only to test for an overall correlation between plot-scale and remotely sensed NDVI values (supporting information).

2.1.5 Statistical analysis

Correlations between metrics representing selected events and subsequent growing season NDVI were assessed by multiple regression. Selection of metrics with high explanatory power for use in multiple regression was initially guided by tree-based regression analysis, following which interactions included in multiple regression of each event type (a – d) against NDVI were based on *a priori* knowledge and predictions relating to the mechanisms through which each event may cause browning (Bokhorst et al., 2008; Bjerke et al., 2017). Terms and interactions without a significant correlation with NDVI change were removed step wise. A maximum of three terms was included in each multiple regression. Plot-level and MODIS NDVI were compared by linear regression.

2.2 Applying climate metrics at regional scales

The Norwegian Arctic region (Fig. 2) was selected for upscaling as a clearly definable region encompassing the majority of sites used for plot-level analysis. This area extends southwards to the Arctic Circle (66˚ 33' N) and eastwards to the longitude of Magerøya, Finnmark (25˚ 40' E); the most northerly point of the Nordic Arctic Region (NAR, Bjerke et al., 2014).

2.2.1 Satellite NDVI

Both time integrated NDVI (TI-NDVI) and peak/maximum NDVI have been widely used in Arctic vegetation studies (Stow et al., 2004). The TI-NDVI is considered as a robust proxy for total growing-season productivity (Stow et al., 2004; Epstein et al., 2017). Remotely sensed NDVI data were extracted from the publically available MOD13Q1 version 6 dataset described above from the beginning of May (DOY 129) to the end of August (DOY 241). Tiles were extracted for this period in 2014, as the most marked and widespread browning observed at plot-level occurred during the 2013/2014 winter, and from 2005 to 2010 (inclusive) to create a baseline period for comparison. Tiles were re-projected and mosaicked as described above. Unvegetated areas (NDVI < 0.12) were masked out. Images were aggregated (by mean) to a 1 km resolution to facilitate comparison with climate data.

From this May-August NDVI dataset, time-integrated NDVI (TI-NDVI; the sum of NDVI values during this period) was calculated for 2014 and the 2005-2010 baseline period. Change detection was then carried out between 2014 and the 2005-2010 baseline period, producing TI-NDVI change. This process was also carried out for mean July (approximately peak biomass) NDVI.

2.2.2 Climate data

Data was obtained from The Norwegian Water Resources and Energy Directorate (NVE) and the Norwegian Meteorological Institute as described above. To provide air temperature data continuously across the Norwegian Arctic region, data was downloaded from every Norwegian Meteorological Institute weather station with an elevation of < 200m in the counties of Nordland, Troms and Finnmark; a total of 77 stations. The 200m cut-off was used since above this, weather stations tended to be on mountainsides, where data may be less representative of the broader surrounding landscape and so be less suitable for interpolation (the majority of the heathland vegetation typically affected by browning is in low lying regions). Mean daily air temperature from each station was interpolated across these three counties using Inverse Distance Weighted interpolation, before the resulting air temperature map was cropped to the Norwegian Arctic region. Climate data (both air temperature maps and SeNorge snow maps) were resampled using nearest neighbour assignment resampling to correspond to each other and to MODIS data.

2.2.3 Climate metrics

Maximum intensity warming events and maximum duration exposure events were chosen to investigate further in this analysis due to their high explanatory power in the plot-level analysis. Extreme event metrics for these two event types were calculated as described above for the 2013/2014 winter within each 1 km pixel.

2.2.4 Statistical analysis

Multiple regressions of the parameters for each event type were carried out using Generalised Least Squares against TI-NDVI change. This was also done for July NDVI change (change in mid-season NDVI). All regressions were carried out at a 4 km resolution by aggregating raster data to reduce computational intensity. As the Moran's *I* test indicated significant spatial autocorrelation in model residuals, this was accounted for by using correlated error structures (exponential, Gaussian, linear, spherical and rational quadratic) and selecting the appropriate model error structure (rational quadratic for TI-NDVI and exponential for July NDVI) according to the AIC criterion (Burnham & Anderson, 2002).

3 Results

3.1 Climate metrics in plot-scale analyses

Climatic events described by simple metrics were well correlated with plot-level NDVI. 'Maximum intensity warming events' were calculated as the greatest value within a pixel of sum of daily mean air temperature multiplied by event duration (i.e. intensity) in periods of consistently warm (> 2˚C) winter air temperatures. The start day in winter, mean snow cover and intensity of these events explained more than 60 % of variation in plot-level NDVI in multiple regression (Fig. 2a; F = 14.26, D.F. = 4, 27, p < 0.001, R^2 = 0.63; see supporting information for multiple regression formulae), with high intensity, later start day and lower mean snow cover corresponding to lower NDVI values. 'Temperature drop warming events' were calculated as the periods of consistently warm air temperature (> 2 °C) with the greatest drop in temperature during the 24 hours following the final day of the event. The start day and intensity of these events explained almost 50% of variation in NDVI in multiple regression (Fig. 2b; F = 10.81, D.F. = 3, 33, p < 0.001, R^2 = 0.45). Again, high intensity and later start day were associated with lower NDVI. For both warming event types (maximum intensity warming events and temperature drop warming events) there was a significant interaction between intensity and start day (p < 0.05), meaning that the effect of intensity upon NDVI was weaker later in the winter. Tree-based regression analysis (supporting information) of metrics calculated for warming events also highlighted the 24-h temperature drop following an event as a metric with high explanatory power for variation in NDVI; mean NDVI in plots which had experienced a maximum intensity warming event with a 24-h temperature drop of more than 5.7 °C was 0.2 (NDVI) lower than in those which had not. While the importance of the 24-h temperature drop is of interest and provides some insight into mechanisms underlying plant damage following warming events, its computational complexity (in particular its use of minimum as well as mean air temperature datasets) meant that it was unsuitable for further analysis within this work and was therefore not included in multiple regression analyses.

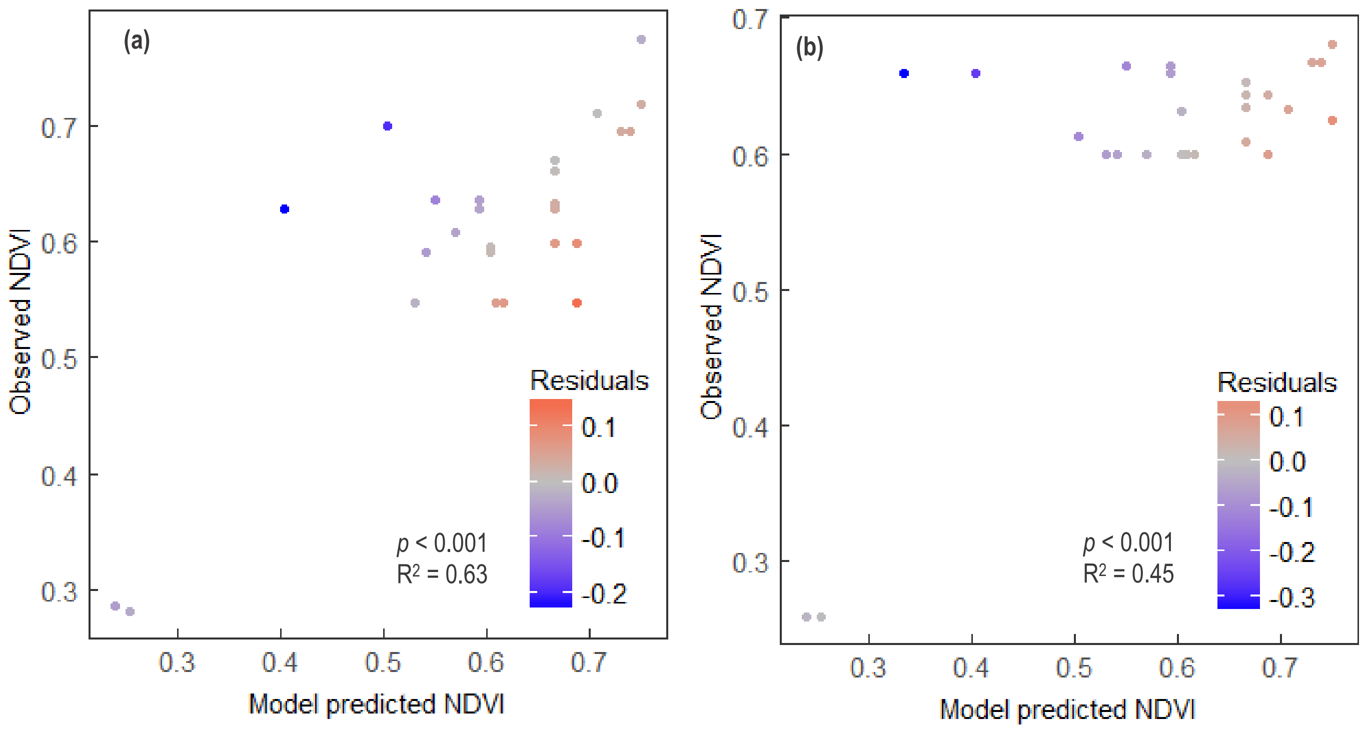

Figure 2: Correlations between plot-level NDVI as predicted by multiple regression models and plot-level NDVI observed in the field. Correlations are shown for (a) 'Maximum intensity warming events' and (b) 'Temperature drop warming events'. Points are coloured according to the value of residuals; warm colouring indicates that multiple regression predicted higher NDVI values than were observed in the field, while cold colouring indicates that multiple regression predicted lower NDVI values than observed. See supporting information for explanation of number of visible data points.

'Maximum duration exposure events' were calculated as the periods of consistently absent snow cover (0 mm snow depth) with the longest duration in days during winter. The start day of and mean temperature during these events were highly correlated with NDVI in multiple regression (Fig. 3a; $R^2 = 0.61$, $F = 17.87$, D.F. = 3, 29, $p < 0.001$). 'Maximum warmth exposure events' are the periods of consistently absent snow cover with the highest mean temperature. The start day and duration of these events were also significantly correlated with NDVI in multiple regression, albeit with a weaker R^2 (Fig. 3b; $F = 3.802$, D.F. = 3, 29, $p < 0.05$, $R^2 = 0.21$). In both cases there was a significant interaction between the two model predictors (start day and mean temperature), meaning that the effect of start day on NDVI was weaker for longer events.

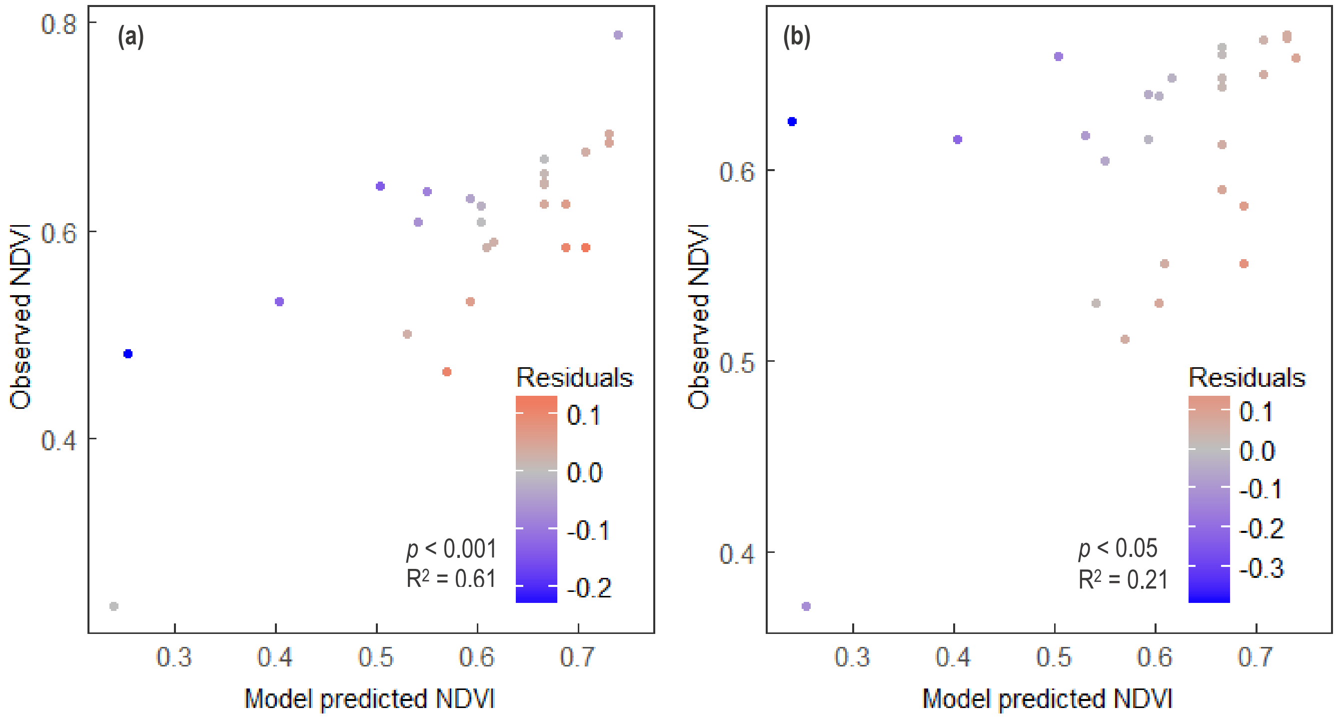

Figure 3: Correlations between plot-level NDVI as predicted by multiple regression models and plot-level NDVI observed in the field. Correlations are shown for (a) 'Maximum duration exposure events' and (b) 'Maximum warmth exposure events'. Points are coloured according to the value of residuals; warm colouring indicates that multiple regression predicted higher NDVI values than were observed in the field, while cold colouring indicates that multiple regression predicted lower NDVI values than observed.

3.2 Climate metrics in regional scale analyses

Climate metrics calculated and mapped across the Norwegian Arctic implicate the processes underlying frost drought and extreme winter warming in MODIS NDVI change between the 2005-2010 baseline period and 2014. They also highlight interesting characteristics of winter climate and the conditions which lead to extreme climatic event-driven browning.

3.2.1 Event characteristics

Maximum intensity warming event metrics (intensity, start day and mean snow cover) show that prolonged periods of warmth during winter were rare across the Norwegian Arctic region in the 2013/14 winter (indicated by low maximum intensity across much of the region; Fig 4a). Such rare occurrence is consistent with climatic conditions which can produce an ecologically extreme response (i.e. extreme events). The median value of intensity in the 2013/14 winter was 61 across the entire Norwegian Arctic region, compared to a median of 328 specifically in observed browning sites. The wide variation inherent in this variable (with a range of 3 to 2440) across the Norwegian Arctic region means that when mapped, areas where events of especially high intensity took place – reflecting prolonged, unseasonable warmth – are clearly distinguishable by eye (Fig 4a). Visual assessment suggests that high intensity events, when they do occur, are most often found in coastal areas. Furthermore, while most warming events across the region occurred in the first half of the winter period, with 60% occurring in January alone, events with the highest maximum intensity typically began later in the season (Fig 4; best model: R.S.E = 187.24, D.F = 5265; start day: $t = 9.56$, S.E. = 0.07, $p < 0.001$). There was no significant correlation between event intensity and mean snow cover during the event.

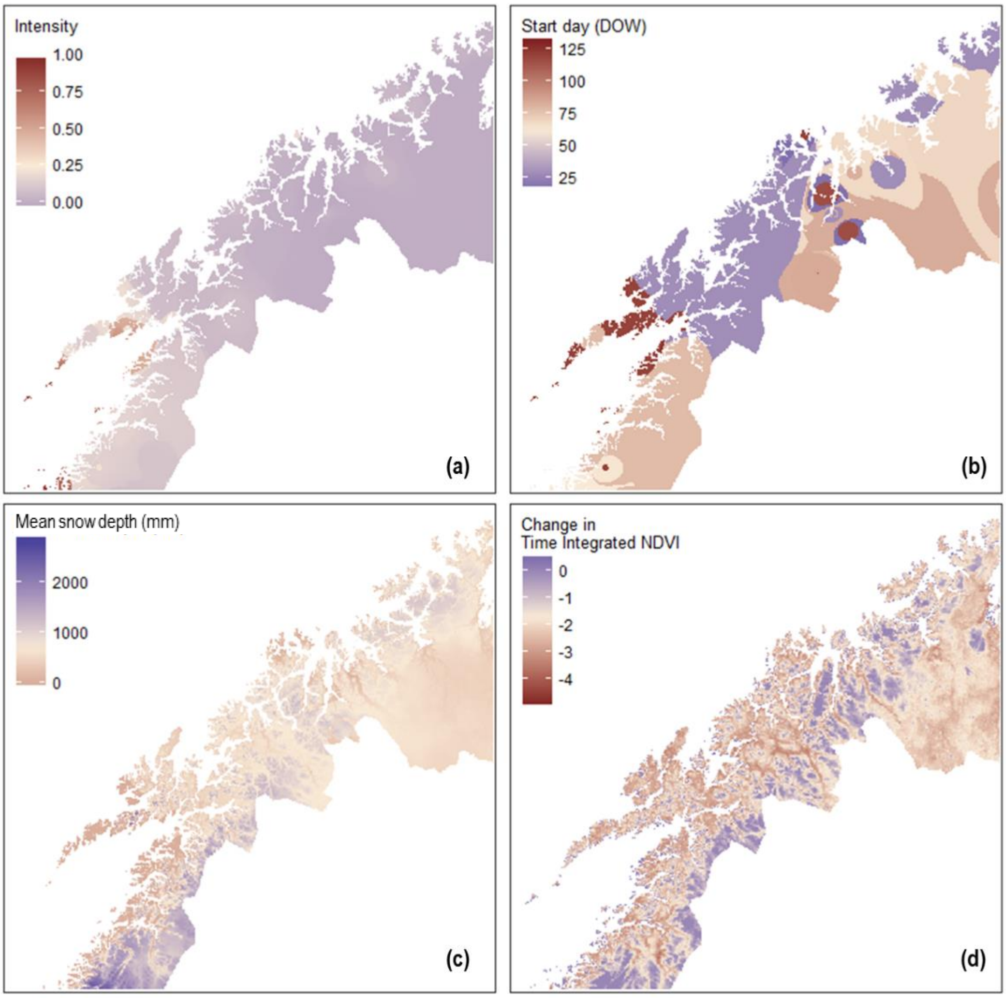

Figure 4: Climate metrics calculated for the warmth event with the highest intensity in each 1 km^2 pixel. Climate metrics shown are (a) intensity; cumulative warmth weighted linearly by event duration, here rescaled to a range of 0-1 for easier interpretation, (b) the start day of the event (Day of Winter 1 equivalent to Day of Year 305) and (c) mean snow depth (mm) during the event. The change in time integrated NDVI between the baseline 2005-2010 period and 2014 is shown (d) for comparison with the potential climatic drivers (a) – (c).

Similarly, exposure event metrics show that exposure (snow depth = 0) during winter was relatively rare across the Norwegian Arctic in the 2013/14 winter (Fig. 5a) and was limited primarily to coastal areas. Where exposure events did take place further inland, visual comparison suggests they typically began later in the winter compared to those taking place close to the coastline (Fig. 5b). All winter 2013/14 exposure events across observed browning sites plus the majority (59 %) of exposure events across the Norwegian Arctic region were associated with a mean air temperature of more than 0 °C during the event. However, 21 % of Norwegian Arctic-region exposure events were relatively cold, with mean air temperature below or equal to −2 °C. Visual comparison suggests these cold exposure events may be more common further inland. Timing of the longest exposure events across the region was relatively evenly spread throughout the majority of the winter period, although with a higher proportion (32 %) of events occurring in April.

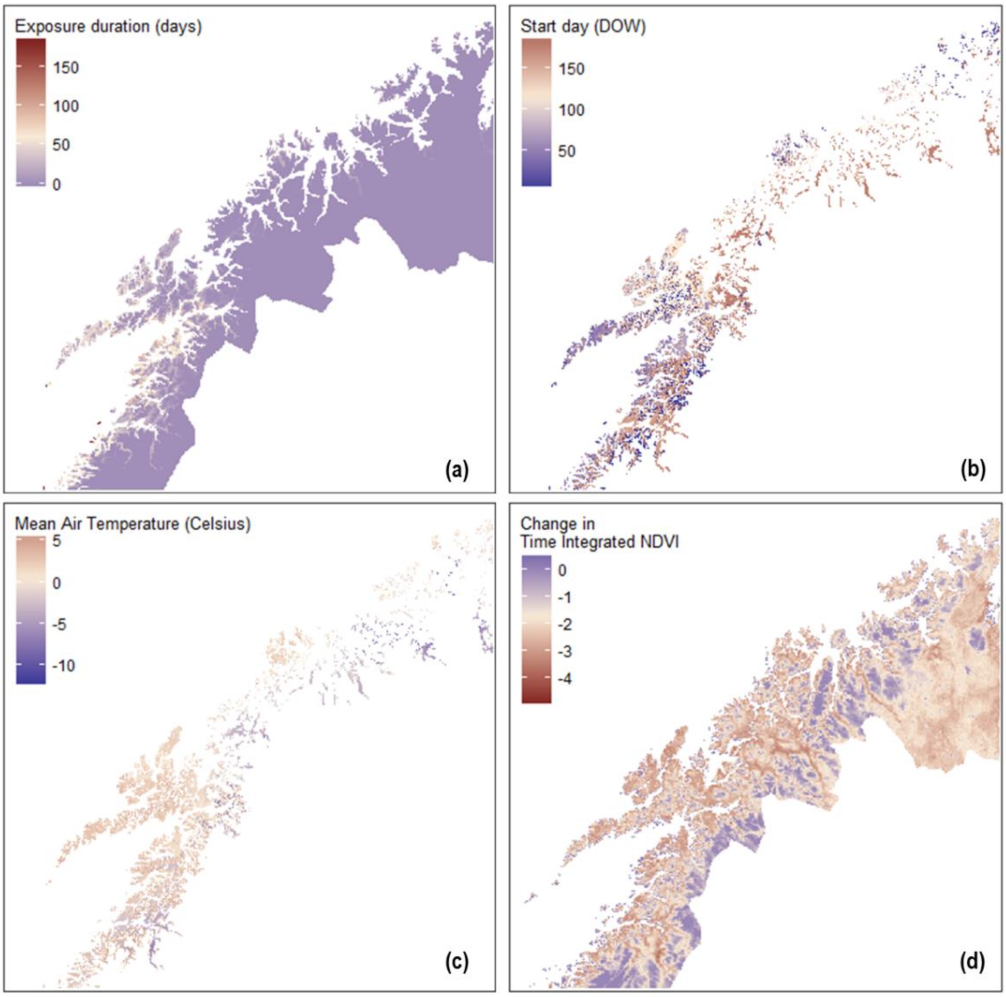

Figure 5: Climate metrics calculated for the exposure event with the longest duration in each 1 km^2 pixel. Climate metrics shown are (a) event duration (b) the start day of the event (Day of Winter 1 equivalent to Day of Year 305) and (c) mean air temperature (˚C) during the event. The change in time integrated NDVI between the baseline 2005-2010 period and 2014 is shown (d) for comparison with the potential climatic drivers (a) – (c).

3.2.2 Correlation with MODIS NDVI

Maximum intensity warm events: both the intensity of the event (Fig. 4a), and the mean snow cover during the event (Fig. 4c) were significantly positively correlated with change in time integrated NDVI (TI-NDVI), i.e. cooler and shorter warming events with shallower snow resulted in greater negative change in TI-NDVI. (Fig. 4d; best model: R.S.E. = 0.54, D.F. = 5259; intensity: t = 2.1, S.E. < 0.001, p < 0.05; mean snow cover: t = 13.9, S.E. < 0.001, p < 0.001). There was also a significant negative interaction between intensity and mean snow cover (t = -5.19, S.E. <0.001, p < 0.001) and, while the start day of the event did not have a significant main effect, there was a significant positive three-way interaction between intensity, mean snow depth and start day (Fig. 6, t = 2.56, S.E. < 0.001, p < 0.05). Overall, these terms and interactions show that increasing event intensity (greater air temperature * duration) at the shallowest snow depths results in smaller TI-NDVI reductions (Fig. 6, 25 cm line), while at the deepest snow depths increasing event intensity results in greater TI-NDVI reductions (Fig. 6, 100 cm line). As winter progresses (moving left to right on Fig. 6), the slope of the relationship between TI-NDVI change and event intensity becomes more positive at any given snow depth; meaning that the threshold of snow depth above which this slope is negative increases.

There was no correlation between change in peak-season (July) NDVI and any maximum intensity warm event metric.

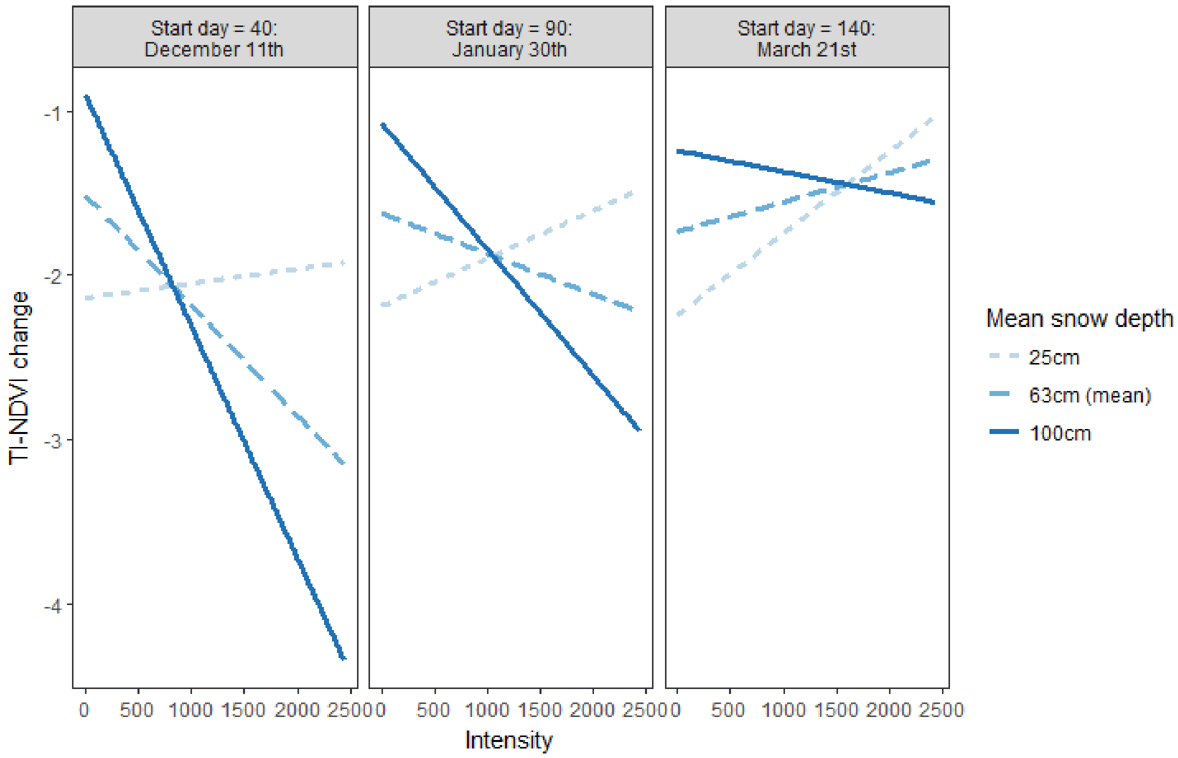

Figure 6: Three-way interaction between intensity (the sum of air temperature multiplied by duration for each day of the event), start day, and mean snow depth in multiple regression of maximum intensity warmth events (the warming event within each pixel with the greatest intensity) with TI-NDVI change. Lines illustrate relationships between event intensity and TI-NDVI change at snow depths of 25cm (short dashed line), the mean value across the Norwegian Arctic Region of 63cm (long dashed line) and 100cm (solid line). Panels show these relationships at different time points during winter.

Maximum duration exposure events: Start day of the longest exposure event (Fig. 5b) was negatively correlated with change in TI-NDVI, i.e. later longest exposure events resulted in greater negative NDVI change (best model: R.S.E. = 0.57, D.F. = 2331; start day: $t = -3.91$, S.E. < 0.001, $p < 0.001$). The mean temperature of the event (Fig. 5c) was positively correlated with change in TI-NDVI (greater negative TI-NDVI change with cooler events; $t = 3.29$, S.E. = 0.015, $p < 0.001$), while event duration (Fig. 5a) showed no correlation ($p > 0.05$). There was an interaction between start day and mean temperature, showing that the slope of the positive relationship between TI-NDVI change and mean temperature became shallower, and eventually became negative, as the winter progressed (Fig. 7 $t = -3.5$, S.E. < 0.001, $p < 0.001$).

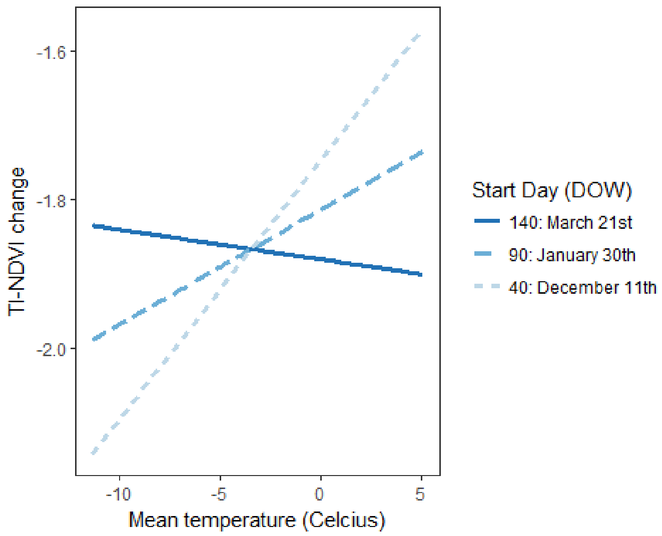

Figure 7: Two-way interaction between the start day and mean air temperature of maximum duration exposure events (periods of consistently absent snow cover with the longest duration in each pixel). Lines illustrate relationships between mean temperature and TI-NDVI change on Day of Winter (DOW) 40 (December 11th; short dashed line), DOW 90 (January 30th; long dashed line) and DOW 140 (March 21st; solid line).

There were no correlations between any exposure event metric and change in July NDVI ($p > 0.05$).

4 Discussion

We demonstrate that simple climate metrics can explain variation in NDVI (vegetation greenness) in areas known to have been affected by extreme event-driven Arctic browning. These process-based metrics (i) provide quantitative assessment of the climatic conditions that drive browning, reinforcing previous descriptive and qualitative assessments of these climatic drivers by showing that periods of unusual warmth and low snow cover during winter are associated with loss of vegetation greenness (Hancock, 2008; Bjerke et al., 2014, 2017; Bokhorst et al., 2009; Meisingset et al., 2015), and (ii) provide much-needed insight into how variation in these climatic drivers influences the severity of the browning observed. This work also suggests that with further work such metrics, easily calculated from mean daily air temperature and snow depth, could be used to assess the contribution of winter climatic extreme events to Arctic browning at regional scales, and ultimately to improve predictions of how changing Arctic winters will affect the biomass and productivity of vegetation communities.

4.1 Plot-level analysis

Metrics representing both maximum intensity warming events (the period of consistently warm, > 2 °C, air temperature with the highest intensity in the plot's pixel, where intensity is the sum of daily mean air temperature multiplied by event duration) and maximum duration exposure events (the period of consistently absent snow cover, 0 mm snow depth, with the longest duration in days in the plot's pixel) explained a substantial proportion of variation in plot-level NDVI across observed browning sites. In analysis of maximum intensity warm events, high intensity, late start date and shallow snow depth were associated with low NDVI. This is consistent with NDVI and biomass reductions driven by extreme winter warming or frost drought events (Bokhorst et al., 2009, Bjerke et al., 2014; Meisingset et al., 2015). In extreme winter warming, unusual winter warmth causes premature dehardening and initiation of spring-like bud-burst following snow melt and exposure of vegetation to warmth, after which the rapid return of sub-zero temperatures causes frost damage (Phoenix & Lee, 2004; Bokhorst et al., 2008). It is likely that vegetation could be more prone to extreme winter warming damage later in winter, after a substantial cold period has already been experienced and when light levels are increasing, meaning any subsequent warm period is more likely to trigger premature de-hardening and bud-burst (Körner, 2016; Parmentier et al., 2018). Alternatively, frost drought occurs when vegetation is exposed and soils are frozen, which reduces the availability of free water and promotes winter desiccation (Tranquillini 1982; Sakai & Larcher, 2012). In late winter, soils are most likely to be closer to their coldest year-round temperature. Exposure events with a higher mean air temperature at this time may therefore encourage plant transpiration and water loss, but may not be sufficiently warm to initiate soil thaw and an increase in the availability of free water (Larcher & Siegwolf, 1987). Desiccation is likely to be further accelerated in late winter due to higher solar irradiance, which promotes physiological activity including transpiration and increasing water loss (Hadley & Smith, 1986, 1989). However, since there is a high explanatory power of the 24-h drop in temperature following the end of the warm period, it appears likely that the browning observed at these sites is driven largely by extreme winter warming rather than frost drought.

In analysis of maximum duration exposure events, a late start day and comparatively warm mean air temperature (1.7˚C) was associated with lower plot-level NDVI, with the negative correlation between mean air temperature and NDVI steepening throughout the winter. Similarly to the above, this could either indicate frost drought or extreme winter warming. Regardless, it would appear that periods of warmth associated with snowmelt or shallow snow depth, particularly in late winter, are strong drivers of the NDVI reductions observed at these sites. This is also consistent with observations that reductions in *Vaccinium myrtillus* biomass in the 2014 growing season in coastal Norway were associated primarily with winter warmth (Meisingset et al., 2015). These results represent a first attempt to disentangle these complex climatic variables and physiological responses. Further work is required to build upon and refine this approach and so develop models with higher explanatory power, as well as models applicable to wider or different Arctic regions.

4.2 Regional-scale analysis

Climate metrics calculated for both event types – maximum duration exposure events and maximum intensity warming events – show that both prolonged, warm periods during winter and periods of winter exposure are rare across the Norwegian Arctic region; the majority of the region experienced low maximum intensity of warmth events and no periods of exposure during the 2013/14 winter. This is consistent with ecological theory that states that extreme events should be rare enough that organisms are not (or poorly) adapted to them, such that when these events do occur, an extreme ecological response is produced (Smith 2011). As might be expected, the highest magnitudes of both event types occurred primarily along the coastline, where temperatures are warmer and the climate more variable. As both mean temperatures and temperature variability are expected to increase as climate change progresses (AMAP, 2017), this suggests that coastal areas may act as indicators of conditions likely to become more common as colder, inland areas warm, and supports predictions that the magnitude and frequency of these events will increase across Arctic regions as climate change progresses (Vikhamar-Schuler et al., 2016, Graham et al., 2017).

Climate metrics for both event types correlated with change in TI-NDVI. For maximum duration exposure events the strongest predictor of change in TI-NDVI was mean temperature during the exposure event. However, this relationship changes throughout the winter; the negative correlation between start day and change in NDVI (with later events associated with greater TI-NDVI reductions) is steeper where mean temperature is high. This means that early in the winter, cold exposure events are associated with greater TI-NDVI reductions, but in late winter, from around March, it is warmer events that cause larger TI-NDVI reductions. It is these late winter, relatively warm events which contribute to the largest reductions in TI-NDVI overall. Similarly to the plot-level analysis, this could suggest that in late winter, when vegetation has already experienced cold winter temperatures and light availability is increasing, warm conditions may be more likely to initiate premature dehardening, driving extreme winter warming damage (Bokhorst et al., 2010). However, there is also evidence that the impact of exposure events on change in TI-NDVI may be driven to some extent by frost drought. As described above, mild temperatures and high light levels in late winter could accelerate desiccation by encouraging transpiration and water loss before soils begin to thaw (Parmentier et al., 2018). The contrasting link between TI-NDVI reduction and colder temperatures in early winter suggest greater possibility of frost drought as the driving mechanisms of damage: in early winter when normal air temperatures are higher and soils have had little time to chill, cold exposure events may accelerate or exacerbate soil freezing (Hancock, 2008; Zhao et al., 2017), promoting vegetation desiccation.

For maximum intensity warmth events the strongest predictor of change in TI-NDVI was mean snow depth during the event. Although, overall, maximum intensity warmth events with shallower snow depths were associated with greater TI-NDVI reductions, the relationship between the severity of these events and change in TI-NDVI was determined by interactions between mean snow depth, start day and the intensity of the event. In early winter, increasing event intensity was associated with greater reductions in TI-NDVI when the mean snow depth during those events was deeper. Also, as winter progresses, the relationship between intensity and TI-NDVI becomes shallower, and by late winter increasing event intensity is associated with greater loss of TI-NDVI only at relatively deep snow depths. Overall, this shows that at low temperatures, shallow snow depth and exposure were consistently associated with greater reductions in TI-NDVI. However, these relationships may also reflect smaller impacts of increasingly severe warm spells in vegetation communities which typically experience shallow snow cover or periods of exposure during winter (for example coastal vegetation communities), compared to those where snow cover is typically deep and persistent (Bokhorst et al., 2016). This would arise where vegetation in areas with normally low snow depth may be more adapted and resilient to fluctuations in winter temperature because they typically are (more likely to be) exposed above the snow (Kudo & Hirao, 2006, Bienau et al., 2014). Increasing warming event intensity in these vegetation communities may therefore have little effect. In contrast, areas with greater snow depth may be much more sensitive to extreme temperature fluctuations and higher rates of water loss associated with exposure since here vegetation is typically covered by deep snow throughout winter, and hence is less well adapted to exposure. Further work should determine whether amount of snowmelt (i.e. initial snow depth – final snow depth) during a warming event may be a more ecologically relevant metric than mean snow depth.

It is not clear why the relationship between change in TI-NDVI and event intensity is positive in late winter, even at mean snow depth (i.e. less negative TI-NDVI change with greater intensity). This may be related to the alleviation of water stress from snow melt-water, or to the impact of increased soil moisture following snowmelt on phenology (Vaganov et al., 1999; Barichivich et al., 2014). Alternatively, it may suggest that late in the winter, when mean air temperatures are beginning to increase, warming events are less likely to be followed by the rapid drop in temperature which was highlighted by plot-level analysis as an important driver of NDVI decline. Without this temperature drop, warming in later winter may simply encourage earlier spring snowmelt and accelerate phenology, without damaging effects (Meisingset et al., 2015). However, this appears to conflict with the association between large NDVI reductions and warm exposure events during late winter, but the reason for these apparently conflicting associations is not clear.

The regional-scale findings arise from analyses of change in TI-NDVI, yet regional-scale climate metrics did not correlate with change in July NDVI (approximately peak biomass, or peak NDVI). The peak season value of NDVI reflects the seasonal trajectory of photosynthetic activity and can therefore help with interpretation of TI-NDVI (Park et al., 2016). However, it is likely that the influence of altitudinal, latitudinal and coast-inland variability on the timing of peak NDVI, combined with detection of this from just two MODIS images within a single month, means that the genuine peak NDVI may not be well reflected in the methods used here. TI-NDVI may make for better comparison of greenness among sites that have contrasting phenology and timing of peak biomass. In addition, while winter extreme climatic events can drive extensive vegetation mortality, and therefore biomass loss, they also frequently cause severe stress and delayed phenology (Bjerke et al., 2017). Subsequent recovery from stress and catch-up in phenology and/or growth (Koller, 2011; Treharne et al., 2018), would reduce detection from peak season NDVI (Anderson et al., 2016), while the initial stress and phenology impacts would be incorporated in (and likely detected in) TI-NDVI, which correlates with total growing season productivity (Epstein et al., 2017).

4.3 Plot-level compared with regional analyses

Analyses at plot-level and regional scales, combined with correlation between plot-level and remotely sensed NDVI (supporting information), indicated similar processes underlying the greatest reductions in NDVI, in particular periods of unusual warmth and exposure during winter, and especially during late winter. However, regional-scale analysis showed more complexity compared to plot-level analysis; for example with colder temperatures during exposure periods associated with greater TI-NDVI reductions in early winter. This illustrates that, while the plot-level analysis focussed on the drivers of pre- and post-damage NDVI in observed browning sites, when these drivers are scaled up to regional analysis, a wider range of processes are involved in NDVI change. As TI-NDVI reflects cumulative productivity across the May – August growing season, reductions in this indicator could reflect altered phenology, and lower productivity in otherwise 'undamaged' vegetation, as well as the more extreme ecological responses associated with extreme event-driven browning, such as mortality and visible stress responses (Treharne et al., 2018). Assessing this greater range of conditions driving TI-NDVI change is necessary to investigate the drivers of reductions in greenness observed at landscape to pan-Arctic scales in recent years (Epstein et al., 2015, 2016; Phoenix & Bjerke, 2016; Park et al., 2016). Nonetheless, this work shows that a small number of climate metrics can explain a substantial proportion of variation in NDVI across a region affected by browning in the 2014 growing season. While further work will be required to apply these or similar metrics at a broader scale this demonstrates potential for such simplified approaches requiring a limited range of climate datasets to attribute drivers of browning and be used in models to predict browning in the future.

5 Conclusion

This analysis has demonstrated that the severity of NDVI reductions, both across sites where browning has been observed and at a regional scale, can be related to simple, process-based climate metrics. These metrics reinforce ecological theory about the drivers underlying winter climatic extreme event-driven browning, showing that prolonged periods of unusual warmth and vegetation exposure during winter have negative consequences for NDVI. They also provide novel and much-needed insight into how different climatological variables and timing interact to produce greater or less severe browning. Looking forward, with further development utilizing satellite data with medium to high spatial resolution, simple climate metrics could be used to assess the impact of winter extreme climatic event driven-browning on productivity at regional scales and improve predictions of changes in browning frequency in the future.

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Co-author contributions

Project conceived and designed by RT, GKP, JWB and HT.

Field data collected by RT, JWB and HT. Data analysis carried out by RT with support from all co-authors.

Manuscript preparation led by RT, with support (substantial critical feedback, revisions and additions to text) from all co-authors.

Final version of the manuscript read and approved by all co-authors.

Highlights

- New metrics quantified climatic drivers of extreme event-driven Arctic browning.
- These metrics explained up to 63% of variation in greenness at affected sites.
- Prolonged warmth or vegetation exposure in winter are associated with browning.
- Event metrics correlated with satellite greenness across Arctic Norway.

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