Neural Network-Based Climate Prediction for the 21st Century Using the Finnish Multi-Millennial Tree-Ring Chronology

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Abstract: The sun’s activity role in climate change has become a topic of debate. According to data from the IPCC, the global average temperature has shown an increasing trend since 1850, with an average increase of 0.06 °C/decade. Our analysis of summer temperature records from five weather stations in northern Fennoscandia (65°–70.4° N) revealed an increasing trend, with a range of 0.09 °C/decade to 0.15 °C/decade. However, due to the short duration of instrumental records, it is not possible to accurately assess and predict climate changes on centennial and millennial timescales. In this study, we used the Finnish super-long (~7600 years) tree-ring chronology to create a climate prediction for the 21st century. We applied a method that combines a long short-term memory (LSTM) neural network with the continuous wavelet transform and wavelet filtering in order to make climate change predictions. This approach revealed a significant decrease in tree-ring growth over the near term (2063–2073). The predicted decrease in tree-ring growth (and regional temperature) is thought to be a result of a new grand solar minimum, which may lead to Little Ice Age-like climatic conditions. This result is significant for understanding current climate processes and assessing potential environmental and socio-economic risks on a global and regional level, including in the area of the Arctic shipping routes.

Keywords: climate change; climate prediction; super-long tree-ring chronology; neural networks; LSTM; Arctic

1. Introduction

The nature of modern and future climate change is currently a hot topic of discussion. According to the 6th Intergovernmental Panel on Climate Change (IPCC) Report [1], the global surface temperature over the past two decades has been 0.99 °C higher than it was between 1850 and 1900, mainly due to human activities that cause greenhouse gas emissions. However, greenhouse gas emissions are not the only cause of modern climate change. Indeed, according to some estimates [2,3], the contribution of solar activity to global warming in the past century was at least 50%. In addition, a strong correlation between solar activity and global surface temperature has been found during the instrumental period [4,5]. Furthermore, it is certain that glacial and interglacial periods coincide with changes in the geometry of Earth’s orbit, as predicted by the Milankovitch theory [6,7]. Proxy records have revealed sun–climate connections also on sub-Milankovitch timescales of hundreds to thousands of years [7–14]. The main solar cycles, such as the Suess (or de Vries) cycle (~200 years), the unnamed cycle (350–400 years), and the Eddy cycle (~900 years) were identified in the Finnish super-long (~7600 years) tree-ring chronology (FLTR) [7,8]. These cycles were also found in lake sediments in Alaska [9] and in records of Asian summer monsoons [13]. Bond et al. [14] identified a millennial-scale solar cycle in the North Atlantic drift-ice abundance. Zharkova [15] suggested that this cycle, with a duration of 350–400 years, manifests itself as a grand solar minimum of the Maunder minimum (1645–1715 AD) type. During this period, there were practically
no sunspots, and the total solar irradiance (TSI) decreased by about 3 W/m$^2$ [16]. This led to a decrease in the temperature of the northern hemisphere by 1.5 °C [17,18]. This period coincided with a period of more severe winters and frozen rivers (the Thames and Danube) in the United Kingdom and Europe [17,18]. Moreover, Zharkova [15] also demonstrated that the sun has entered a modern grand solar minimum (2020–2053) of Maunder minimum type with Little Ice Age climatic conditions.

These cycles differ from changes in the orbital forcing of the climate and are associated with other solar factors and mechanisms. Currently, variations in solar radiation at different wavelengths and galactic cosmic rays (GCR) are considered to be the main solar factors affecting the atmosphere and climate [16,19–22]. Variations in TSI cause direct heating of the Earth’s atmosphere [16], while solar ultraviolet radiation (UV) affects atmospheric chemistry, ozone abundance, and the thermal structure [19]. Additionally, the GCR, modulated by the solar magnetic field, affect the cloud cover in the low atmosphere, thereby changing the radiation balance [20,21] and the atmospheric circulation pattern [22]. In addition, cosmic dust fluxes of interplanetary and interstellar origins, modulated by magnetic and gravitational fields, can act as condensation centers in the Earth’s atmosphere and therefore affect the aerosol content and cloud cover [23,24].

Increasing global warming will lead to more intense climate-related risks and hazards [1]. Climate change can indeed become a security issue for certain countries and communities [1,25]. For instance, climate change and the associated sea-level rise may lead to population movements from islands and coastal areas [1,25,26]. Furthermore, for Arctic indigenous communities, climate change may restrict their traditional ways of life (hunting and fishing) [1,25,27]. For northern territories, climate change presents both risks and opportunities. The melting of icebergs increases the environmental risks, but at the same time, it provides the possibility of extracting natural resources and opens up the potential for Arctic shipping routes [28,29]. The estimation and prediction of shipping route transformation based on sea ice data has become a significant topic in modelling of climate change [28,29]. Most of these models indicate a declining trend in sea ice concentration and thickness [29]. Indeed, the Arctic sea ice extent in April 2024 was approximately 200,000 square kilometers below the 1991–2000 average. At the same time, it has shown an increasing trend since 2019 [30]. The decline of the sea ice extent will create new trade opportunities, especially for the Northern Sea Route along the Russian coasts [27,28,31].

According to the IPCC, the global surface temperature may rise by 1.4 °C to 4.4 °C due to greenhouse gas emissions in the 21st century [1]. These estimates are based on instrumental temperature records. However, these records are not extensive enough to accurately predict future climate change. The development and expansion of urban heat islands, or urbanization bias, has led to another issue with temperature trend estimates based on weather stations [4]. The proxy series, in particular the FLTR chronology, can extend the climatic record back over the past centuries and millennia [32]. This chronology is based on time series from Scots pine (Pinus sylvestris L.), composed of both modern and subfossil wood samples from northern Finnish Lapland (68°–70° N, 20°–30° E) [32].

Recently, artificial neural networks (ANN) have been used more and more for climate prediction and reconstruction [33–43]. For example, ANNs have been used to reconstruct summer temperatures in Europe [33]. Kalugin et al. [34] used ANNs in the reconstruction of temperature and precipitation using sediment proxies. The ANN approach has also been used to predict the temperature rise over Iran [35]. The recurrent neural network (RNN) is a type of ANN that is particularly useful for analyzing time series [36]. Additionally, the LSTM network has been developed, which is an improved version of the RNN [36,37]. Additionally, it has been found that ANN models, including more recent versions such as LSTM networks, are very suitable for analyzing the nonlinear relationship between climate and tree rings [38–42]. Khaleghi [38] has used an ANN model to evaluate climate change based on the correlation between tree rings, temperature, and precipitation. Molina et al. [39] also used LSTM modelling to investigate tree-ring-based precipitation reconstruction in Europe. Helama et al. [40] compared linear and ANN-based reconstructions.
of summer temperatures in northern Fennoscandia using the FLTR chronology. Other studies have also compared the performance of ANN models with linear models used in tree-ring-based climate reconstructions [41–44]. All these studies have confirmed that ANN models show better results than linear models, especially for the nonlinear climate–tree rings relationship [39–44]. In any case, the performance of different (linear and nonlinear) models for paleoclimate reconstructions can vary depending on various factors, such as the region, the nature of the data, and the timescales used [39–42].

To correctly interpret and model climate change for the 21st century, it is essential to take into account natural climate variability over timescales ranging from centuries to millennia [45]. In previous studies, the FLTR chronology has revealed a significant (but highly nonlinear) sun–climate relationship on sub-Milankovitch timescales from hundreds to thousands of years [7,8]. In light of the above context, this study aims to predict climate change for the 21st century based on the FLTR chronology using a new LSTM model coupled with the wavelet transform and filtering. The wavelet transform and wavelet filtering have been used to reveal a solar cycle of 350–400 years in the tree-ring record. This solar cycle may be responsible for the emergence of a new grand solar minimum of the Maunder minimum type in the 21st century [15].

2. Materials and Methods

2.1. Data Sets

To develop and train the ANN model, we used the Finnish super-long Scots pine (Pinus sylvestris Linnaeus) tree-ring chronology, covering the period from 5634 BC to 2004 AD [32]. This chronology includes tree-ring-width series from living and megafossil trees from the area of subarctic timberline in northern Fennoscandia (68°–70° N, 20°–30° E) (Figure 1). All tree-ring samples were processed using dendrochronological techniques and dated to calendar years using standard procedures. For more details, see [32,40,46]. The dendroclimatic potential of the FLTR chronology has been statistically confirmed [32,46]. The high level of the expressed population signal (EPS) of the chronology (EPS > 0.85) indicates its reliability and usefulness for paleoclimate reconstruction [47]. FLTR-based reconstructions of mid-summer temperatures for the region were created using linear [46] and ANN-based [40] models. A comparison of these different models revealed that ANN-based temperature reconstructions performed better [40].

Figure 1. Map showing sample collection sites with subfossil pines [32] (triangles) and weather stations (black circles): 1—Vardo, 2—Teriberka, 3—Murmansk, 4—Sodankyla, 5—Kem. The blue dashed line indicates the Arctic circle.
The summer (JJA) temperature data from five meteorological stations in the GISTEMP database [48,49] were used to assess recent temperature changes on a regional scale. These stations are located throughout Northern Fennoscandia covering areas from northern Karelia (Kem, 65° N, 34.8° E) and Finnish Lapland (Sodankyla, 67.4° N, 26.6° E) to the Kola Peninsula (Murmansk, 69° N, 33.1° E; Teriberka, 69.2° N, 35.1° E) and northern Norway (Vardo, 70.4° N, 31.1° E) (Figure 1 and Table 1).

**Table 1.** Coordinates and summer temperature trends of five stations in northern Fennoscandia.

<table>
<thead>
<tr>
<th>Station (Coordinates)</th>
<th>Period (Years)</th>
<th>Rate (°C/Decade) (^1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vardo (70.4° N, 31.1° E)</td>
<td>1870–2023</td>
<td>0.12 [0.085 0.158] (^2)</td>
</tr>
<tr>
<td>Teriberka (69.2° N, 35.1° E)</td>
<td>1893–2023</td>
<td>0.09 [0.034 0.15]</td>
</tr>
<tr>
<td>Murmansk (69° N, 33.1° E)</td>
<td>1919–2023</td>
<td>0.1 [0.027 0.176]</td>
</tr>
<tr>
<td>Sodankyla (67.4° N, 26.6° E)</td>
<td>1908–2023</td>
<td>0.15 [0.088 0.202]</td>
</tr>
<tr>
<td>Kem (65° N, 34.8° E)</td>
<td>1891–2023</td>
<td>0.13 [0.077 0.175]</td>
</tr>
</tbody>
</table>

\(^1\) Increasing rate was calculated according to the Kendall–Theil robust line regression method [50]. All trends are significant (Mann–Kendall test \([51]; p<0.01\). \(^2\) The 95% confidence interval of each increasing rate is given in square brackets.

**2.2. Statistical and Wavelet Analysis**

To assess the regional temperature trends, we used the Kendall–Theil robust line (KTRL) regression method. The KTRL, also known as the Sen’s slope estimator, is based on the KTRLine software [50] and is a nonparametric regression method that calculates medians instead of means [50]. Therefore, it is not necessary for the data to be normally distributed, and it is robust to outliers. The statistical significance of the trend was assessed using a nonparametric Mann–Kendall test [51] with the XLSTAT 2022 statistical software.

The wavelet filtering of tree-ring data was used to assess fluctuations in power within a frequency range from \(S_1\) to \(S_2\) [52]:

\[
\overline{W}^2 = \frac{\delta t D}{S_i} \sum_{i=1}^{S_i} \frac{|W(S_i)|^2}{S_i},
\]

where \(W\) denotes the continuous wavelet transform of tree-ring time series, \(\overline{W}\) is the scale-averaged wavelet power, \(\delta t\) is the sampling interval, \(\delta t\) denotes the factor for scale averaging, and the parameter \(D\) is a constant for each mother wavelet function \((D = 0.776\) for the Morlet wavelet with \(w_0 = 6\)) [52]. The Morlet function is defined as a plane wave modulated by a Gaussian function [52]:

\[
\phi(t) = \pi^{-1/4} e^{i w_0 t / S} e^{-t^2 / (2S)^2},
\]

where \(S\) denotes the wavelet scale and \(w_0\) is the non-dimensional frequency, here taken to be 6 to provide a good balance between time and frequency localization [52]. This value of \(w_0\) makes the wavelet scale almost identical to the corresponding Fourier period [52].

Tree-ring data were resampled to a 5-year time resolution and standardized (zero mean, unit standard deviation) before wavelet filtering. All statistical parameters and wavelet filtering were computed through the MATLAB R2022a software.

**2.3. Development and Training of the LSTM Network**

The basic RNN architecture consists of an input layer, a hidden layer, and an output layer. The hidden layer consists of hidden units, or neurons, which update their weights. Data inputs are first passed through the input layer and then transferred to the hidden layers before being sent to the output layer. Each layer of a neural network contains neurons that are connected to neurons in the next layer through weighted links. The training process involves adjusting the weights of these connections to minimize the error between the predicted output and the desired output. [53]. This process is known as backpropagation and is used to optimize the network’s performance. The LSTM model is an advanced version of an RNN with a more
complex structure. It contains additional cells, or memory blocks, with several gates that can be activated or deactivated depending on the error value [53]. The hyperbolic tangent (tanh) function and the sigmoid function were used as the activation functions for the state and gate, respectively, as shown in Equations (3) and (4):

\[ \text{tanh}(y) = \frac{2}{1 + e^{-2y}} - 1, \]  

\[ \sigma(y) = \frac{1}{1 + e^{-y}}. \]  

In this study, an LSTM network was developed and trained using a Levenberg–Marquardt algorithm [53]. Future values of an output series were predicted based on past values of the same series:

\[ y(t) = f(y(t-1), y(t-2), \ldots, y(t-d)), \]  

The mean square error (MSE) was used as a loss function:

\[ \text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (T_i - Y_i)^2, \]  

where \( Y_i \) represents the \( i \)th observation, \( T_i \) is the \( i \)th prediction, and \( N \) is the number of samples.

2.4. Evaluation of the LSTM Performance

The quality of the model was evaluated using three metrics: mean absolute error (MAE), root-mean square error (RMSE), and determination coefficient (\( R^2 \)):

\[ \text{MAE} = \frac{1}{N} \sum_{i=1}^{N} |T_i - Y_i|, \]  

\[ \text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (T_i - Y_i)^2}{N}}, \]  

\[ R^2 = \frac{\left( \sum_{i=1}^{N} (T_i - T)(Y_i - Y) \right)^2}{\sum_{i=1}^{N} (Y_i - Y)^2 \sum_{i=1}^{N} (T_i - T)^2}, \]  

where \( Y \) is the average of the observations.

The LSTM model was developed using the Neural Network Toolbox of MATLAB R2022a.

3. Results

3.1. Temperature Trends in Northern Fennoscandia during the Instrumental Period

Considering the entire instrumental period, the summer temperatures at all five sites have increased at a significant level (\( p < 0.01, \) MK test) (Figure 2 and Table 1). The summer temperature showed an increasing trend at a rate of 0.09 °C/decade for Teriberka, 0.1 °C/decade for Murmansk, 0.12 °C/decade for Vardo, 0.13 °C/decade for Kem, and 0.15 °C/decade for Sodankyla (Table 1). Interestingly, the warming trends in the coastal areas (Murmansk, Teriberka, and Vardo) were lower than in the continental ones (Kem and Sodankyla).
3.2. LSTM Network Development and Time Series Prediction

A method using the LSTM network, coupled with a wavelet transform and wavelet filtering, was applied to predict tree-ring growth. The wavelet transform and wavelet filtering were used to highlight the 350–400-year solar cycle in the tree-ring record. The proposed model consists of two phases (Figure 3). First, a continuous wavelet transform (CWT) was applied to the tree-ring time series. This revealed a statistically significant (or nearly significant) high power in a band (300–400 years) (Figure 4b). The signal is weak (below the 95% confidence level) around 1800–1000 B.C. and 200–1000 A.D. (Figure 5b). Additionally, the CWT analysis reveals other periodicities associated with the main solar cycles at ~200 years (Suess or de Vries) and ~900 years (Eddy). Further, the input tree-ring-width data were filtered using a wavelet filter in a frequency band (300–400 years). Then, the filtered FLTR was used to train an LSTM model. The LSTM model consists of five layers: (1) the first layer is an input layer, which receives the wavelet-filtered tree-ring chronology; (2) the second layer is the LSTM layer with 128 neurons; (3) the third layer is a dropout layer with a probability of 0.5; (4) the fourth layer is a fully connected layer; and (5) the fifth and the final layer is the output layer, which produces the predicted time series.
A fully connected layer is used to multiply the input by a weight matrix [53]. In our model, we used a fully connected layer with an input dimension of 128 (the default) and an output dimension of 1. To avoid overfitting, we also added a dropout layer [54]. In the present model, the hidden layer consisted of 128 neurons, and a dropout of 50% was applied. Every iteration, 64 of these neurons were randomly eliminated. Therefore, the configuration of the LSTM network was 1-128-1-1-1 (number of input parameters (neurons) in the first layer—number of neurons in the hidden layer—dropout layer with probability of 0.5—fully connected layer—number of output parameters in the third layer) (Table 2).

Figure 3. A block diagram of the developed LSTM network for climate change prediction.

Figure 4. (a) Finnish super-long tree-ring chronology (FLTR) [32], (b) corresponding continuous wavelet transform (CWT), and (c) wavelet-filtered chronology over the 300–400-year band (blue) with predicted values using the LSTM (red). The 95% confidence level against red noise is shown as a black contour.
4. Discussion

In this study, the FLTR, filtered using a wavelet in the range of 300–400 years, was used to predict climate change in the current century. The use of this chronology for reconstructing paleotemperatures has already been shown [7,32,40]. FLTR-based mid-summer temperature reconstructions were created using both linear and ANN models [32,40]. A comparison of these models revealed that the ANN-based temperature reconstructions performed better [40]. The temperature sensitivity of the FLTR chronology is higher on multidecadal timescales. The FLTR-based temperature reconstruction explains more than 90% of the variability on these timescales during the instrumental period [7,40]. Addi-

Table 2. Parameters and performance validation (testing period) of the LSTM model.

<table>
<thead>
<tr>
<th>LSTM Parameters</th>
<th></th>
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</thead>
<tbody>
<tr>
<td>Number of LSTM layers</td>
<td>1 (128)</td>
</tr>
<tr>
<td>Number of fully connected layers</td>
<td>1</td>
</tr>
<tr>
<td>Number of dropout layers</td>
<td>1 (0.5)</td>
</tr>
<tr>
<td>Types of activation function</td>
<td>tanh (state); σ (gate)</td>
</tr>
<tr>
<td>Optimizer</td>
<td>Adam</td>
</tr>
<tr>
<td>Learning rate</td>
<td>0.005</td>
</tr>
<tr>
<td>Loss function</td>
<td>mean square error (MSE)</td>
</tr>
<tr>
<td>Number of epochs</td>
<td>700</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Performance validation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$</td>
</tr>
<tr>
<td>MAE</td>
</tr>
<tr>
<td>RMSE</td>
</tr>
</tbody>
</table>

In this study, we trained an LSTM network using the first 92% of a sequence and tested the model on the remaining 8%. We used the adaptive moment estimator (Adam) with a learning rate of 0.005 during training. After training and testing, the model demonstrated low error, a high degree of accuracy, and good performance (Table 2 and Figure 5). Therefore, this LSTM model can be used to predict climate change in the near future, at least for the 21st century.

Figure 4c shows the tree-ring sequence with predicted values using the developed LSTM model for the period 2005–3005 A.D. The curve shows a significant decrease in tree-ring growth in the near future (2063–2073 A.D.). Interestingly, there was a similar decrease (1705–1715 A.D.) that coincides with the Maunder minimum of solar activity (1645–1715).

4. Discussion

In this study, the FLTR, filtered using a wavelet in the range of 300–400 years, was used to predict climate change in the current century. The use of this chronology for reconstructing paleotemperatures has already been shown [7,32,40]. FLTR-based mid-summer temperature reconstructions were created using both linear and ANN models [32,40]. A comparison of these models revealed that the ANN-based temperature reconstructions performed better [40]. The temperature sensitivity of the FLTR chronology is higher on multidecadal timescales. The FLTR-based temperature reconstruction explains more than 90% of the variability on these timescales during the instrumental period [7,40]. Addi-
tionally, the FLTR chronology showed a significant correlation with another regional *P. sylvestris* tree-ring chronology from the Kola Peninsula in northwestern Russia (68.6° N, 33.3° E) during the period of 1445–2005 A.D. in response to powerful (volcanic explosivity index, VEI > 5) volcanic eruptions [55]. All the above facts indicate a high dendroclimatic potential for this chronology and its usefulness for temperature reconstructions. Climate predictions were made using an LSTM neural network, coupled with a wavelet transform and wavelet filtering. This model showed good performance with low errors and high fitting accuracy (Table 2 and Figure 5), and, therefore, it can be used to predict climate change in the near future, at least in the 21st century. The wavelet analysis of the FLTR chronology revealed significant (above or close to 95% confidence level) periodicities that coincide with well-known solar cycles, such as the Suess (or de Vries) cycle (~200 years), an unnamed cycle (350–400 years), and the Eddy cycle (~900 years) (Figure 5b). Previously, all these periodicities were identified in solar–FLTR connections [8]. Zharkova [15] suggested that the 350–400-year solar cycle manifests itself in the form of a grand solar minima of Maunder minimum (A.D. 1645–1715) type. After applying a wavelet filter, we found a significant periodicity above the 95% confidence level in the 300–400-year range. This periodicity was not regular in time, suggesting a nonlinear nature of the signal. Given the nonlinearity of this periodicity, an LSTM model was used, based on a nonlinear approach. This approach revealed the presence of a significant decrease in tree-ring width in the near future (2063–2073). Therefore, considering the close relationship between tree growth and summer temperatures, a temperature minimum is expected in the near future (2063–2073). This is a consequence of the upcoming new GSM of Maunder minimum type with Little Ice Age climatic conditions [15]. Interestingly, a similar minimum (1705–1715), revealed in the FLTR, coincides with the Maunder minimum of solar activity.

At first glance, this result may seem to be in contradiction with regional temperature trends. In this study, we found that the summer (JJA) temperatures at five stations in northern Fennoscandia (between 65° and 70.4° N) increased during the instrumental period, at a rate ranging from 0.09 °C/decade to 0.15 °C/decade (Figure 2). This is consistent with the IPCC’s data, which show an increasing trend at an average rate of 0.06 °C/decade since 1850 [1]. According to the IPCC, the global surface temperature may rise by 1.4 °C to 4.4 °C due to human-induced greenhouse gas emissions in the 21st century [1]. These estimates were based on instrumental temperature data [1]. However, according to some studies, the contribution of solar activity to 20th century global warming may be similar to that of the anthropogenic component [2–5]. Our results and other studies [3,45] have shown that natural climate variability on decadal and millennial timescales is particularly significant for accurately predicting climate change in the 21st century.

Our findings approximately agree with and explain the results of Zharkova’s suggestion that a new grand solar minimum (GSM) of the Maunder minimum type may occur in the near future (2020–2053) [15]. In addition, there are other indications of the approaching new GSM with Little Ice Age-like climatic conditions (or global cooling) [56–60]. According to the Solar Radiation and Climate Experiment (SORCE) satellite observations, during the early 2000s the fluxes of solar spectral radiation (SSR) in the visible and near-infrared ranges increased, while the solar activity level (sunspot number) and TSI fluxes decreased [58,59]. It was hypothesized that the unusual behavior of SSR may be related to the upcoming new GSM [58–60]. Moreover, the solar activity–tree rings connections were most clearly evident during and around the GSM, including the Maunder minimum, when sunspots were practically absent [60].

The potential reduction in global temperature in the near future (2063–2073) due to the upcoming GSM could have significant implications for the environment and socio-economic development in the region, including Arctic shipping routes.

5. Conclusions

An LSTM neural network-based climate prediction for the 21st century was created using the Finnish super-long (~7600 years) tree-ring chronology. The chronology had
been previously wavelet-filtered in the range of 300–400 years. This approach revealed a significant decrease in tree-ring growth in the near future (2063–2073). The predicted decrease in tree ring growth (and regional temperature) seems to be a result of the possible onset of a new grand solar minimum, which could lead to climatic conditions similar to those of the Little Ice Age.

Our findings have shown that natural climate variability on decadal and millennial timescales is particularly significant for accurately predicting climate change in the 21st century. Therefore, this research contributes to the understanding of current climatic processes and the assessment of potential environmental and socio-economic risks at a global and regional level, including in the area of Arctic shipping routes.


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