e-Journal of Nondestructive Testing - ISSN 1435-4934 - www.ndt.net

EWSHM 2024
11th European Workshop on Structural Health Monitoring

An innovative predictive method based on supervised teacher-student learning for forecasting limited structural responses of long-span bridges from satellite images

Alireza ENTEZAMI[1], Bahareh BEHKAMAL[1], Carlo DE MICHELE[1], Stefano MARIANI[1]
[1]Department of Civil and Environmental Engineering, Politecnico di Milano, Piazza L. da Vinci 32, 20133 Milano, Italy, alireza.entezami@polimi.it, bahareh.behkamal@polimi.it, carlo.demichele@polimi.it, stefano.mariani@polimi.it

Abstract. Forecasting the responses of large-scale civil structures offers an alternative to field measurement. Recently, spaceborne remote sensing technology has been increasingly adopted to monitor complicated and large structures. This approach involves extracting structural displacements from synthetic aperture radar images. To overcome some important restrictions associated with these images, the best solution is to exploit machine learning-aided prediction of displacement responses. For this purpose, it is necessary to measure key external factors, particularly environmental and operational conditions. In some cases, installing sensors for these factors may not be tractable, in which case some unmeasured and unknown conditions, which can affect structural responses, are not incorporated into the prediction process. To avoid poor performances and inaccurate forecasting outputs, this paper proposes a predictive solution using the idea of supervised teacher-student learning. This method consists of two parts of an elaborate regression model via a long-short-term-memory neural network acting as a teacher and a simple model through a single-hidden-layer feedforward neural network behaving as a student. The effectiveness and success of the proposed method are benchmarked by limited information of a long-span bridge. Results show that this method can adequately forecast limited bridge responses in the presence of the impacts of unmeasured predictors.

Keywords: Forecasting, Machine Learning, Teacher-Student Learning, Supervised Regressor, Limited Data, Long-Span Bridge

1. Introduction

Evaluation of structural behavior of critical and large-scale civil structures is of paramount importance to every society in order to preserve them against catastrophic incidents attributable to external loadings such as earthquakes, strong winds, floods, etc. Structural

Media and Publishing Partner
https://doi.org/10.58286/29848

health monitoring (SHM) presents a practical and promising strategy for structural behavior evaluation, damage diagnosis, structural failure mode anticipation, and remaining useful life. This strategy is based on installing different sensors through either contact [1] or non-contact [2] installation frameworks, measuring important data including structural responses and environmental/operational conditions, extracting engineering features from raw structural responses, analyzing extracted features, and performing SHM tasks [3]. Generally, an SHM program can be implemented by model- and data-driven methods [4-7], so that the former needs finite element modeling and updating, while the latter entirely lies in the paradigms of pattern recognition and machine learning (ML).

Structural behavior evaluation in the model-driven framework is based on modeling the finite element model of the structure under study, updating its initial model, simulating different external loadings and environmental actions, and analyzing the behavior of the structure of interest [8, 9]. In contract, structural behavior evaluation via the data-driven strategy relies on data measurement, feature extraction, and feature analysis under real-world external loadings (i.e., ambient vibration or forced vibration) and environmental variability (e.g., daily and seasonal temperature, humidity, and wind) [9-11]. One of the limitations of the model-based structural behavior assessment is its dependency on a correct finite element model of the real structure. As usual, the numerical and real models have discrepancies, in which case finite element model updating with the aid of sensory data from experimental tests is mandatory [12]. The obstacle is that this process may be challenging for complicated and large-scale civil structures. Accordingly, the structural behavior assessment via the data-driven framework seems more beneficial than the model-driven strategy.

Nevertheless, the direct concentration on measured data from different sensing systems makes limitations. A fact is that civil engineers cannot measure all possible parameters that affect structural behavior and responses. Owners and stakeholders of civil structures may not persuade to pay considerable costs for sensor deployments and next-generation and expensive data acquisition systems with uncertain outputs. Some civil structures are placed in impassable environments so that the installation of sensors and data acquisition systems may be problematic or even dangerous. Moreover, harsh weather conditions and aging may cause sensor malfunction, in which case regular sensor inspection is necessary. All these limitations may lead to incomplete and erroneous data measurements that can affect overall performances of data-driven methods. These limitations underscore the necessity of a more effective and efficient sensing system for monitoring of civil structure. Spaceborne remote sensing can alleviate these limitations by providing new data in terms of synthetic aperture radar (SAR) images from some satellites. Using these images, which can cover a large area on the earth, as well as interferometric techniques, displacement responses are extracted and used as important structural responses. However, this strategy includes some limitations. SAR images are often huge (i.e., in the unit of GB) and limited so that it may not be feasible to provide real-time measurements. Encounter with a small set of displacement samples is the other challenge in the spaceborne remote sensing.

To address the demanding issues regarding structural behavior assessment under the data-driven framework, the most effective and efficient solution is to leverage ML-aided data forecasting. This solution aims to train supervised ML models (i.e., regressors) and then predict unseen response data [13-16]. The success of such models depends strongly on training data that contains predictors (e.g., environmental/operational factors) and responses. As discussed above, the measurement of all potential predictors may not be possible. On the other hand, limited data may degrade ML model performances [17, 18]. This paper intends to overcome these challenges by proposing an innovative ML method based on the idea of supervised teacher-student learning. This method consists of two parts of an elaborate regression model acting as a teacher and a simple model serving as a student. Initially, the measured and available predictor and response data is fed into a teacher model developed from a long-short-term-memory (LSTM) neural network thereby reconstruing the response data. Subsequently, residual data between the measured and reconstructed response data is computed to use as a new predictor. Considering this new predictor along with the original measured response data, a student model developed from a single-hidden-layer feedforward neural network (SLFN) is trained to finally predict unseen response data. The effectiveness and reliability of the proposed predictive method are testified by limited information of long-span bridges. Results show that this method sufficiently succeeds in predicting bridge responses using the only ambient temperature as the main predictor.

2. Proposed method

2.1 Long-Short-Term-Memory (LSTM) Neural Network

The LSTM is a type of recurrent neural network that can learn long-term dependencies in data that allows it to store and manipulate information over long time intervals. This process is carried out by using three gates including an input gate, a forget gate, and an output gate. These gates control what information to keep, discard, or output from the internal memory cell of the LSTM. The cell can store values for any length of time and the three gates control how much information enters or leaves the cell. The input gate decides what new information to add to the cell, while the forget gate adjusts the memory content by keeping or discarding the relevant information based on rules. Finally, the output gate determines when the information is sent out from the cell. The main functions embedded in an LSTM neural network can be derived as follows:

$$\mathbf{r}_t = \sigma(\mathbf{V}_{xr}\mathbf{x}_t + \mathbf{V}_{sr}\mathbf{s}_{t-1} + \mathbf{e}_r) \tag{1}$$

$$\mathbf{a}_t = \sigma(\mathbf{V}_{xi}\mathbf{x}_t + \mathbf{V}_{si}\mathbf{s}_{t-1} + \mathbf{e}_a) \tag{2}$$

$$\mathbf{q}'_t = \tanh\left(\mathbf{V}_{sc}\mathbf{s}_{t-1} + \mathbf{V}_{xq}\mathbf{x}_t + \mathbf{e}_q\right) \tag{3}$$

$$\mathbf{q}_t = \mathbf{r}_t\mathbf{q}_{t-1} + \mathbf{a}_t\mathbf{q}'_t \tag{4}$$

$$\mathbf{p}_t = \sigma\left(\mathbf{V}_{xp}\mathbf{x}_t + \mathbf{V}_{sp}\mathbf{s}_{t-1} + \mathbf{e}_p\right) \tag{5}$$

$$\mathbf{s}_t = \mathbf{p}_t\tanh(\mathbf{q}_t) \tag{6}$$

where $\mathbf{x}_t$ and $\mathbf{s}_{t-1}$ denote the input and hidden states at time steps t and t–1; $\mathbf{a}_t$, $\mathbf{r}_t$, $\mathbf{p}_t$, and $\mathbf{q}_t$ stand for the activations of the input, forget, and output gates and the cell at time step t, respectively; $\mathbf{V}_x$ and $\mathbf{V}_h$ are the weight matrices of the input and hidden states; $\mathbf{e}$ is the bias vector of each gate and state; and σ refers to an activation function.

In order to use the LSTM for the regression-based forecasting problem, one needs to add the predictor and response data to the input and fully connected layers. Finally, a regression layer is considered to predict unseen response data. For simplicity, Fig. 1 shows the general form of the LSTM for regression modeling.

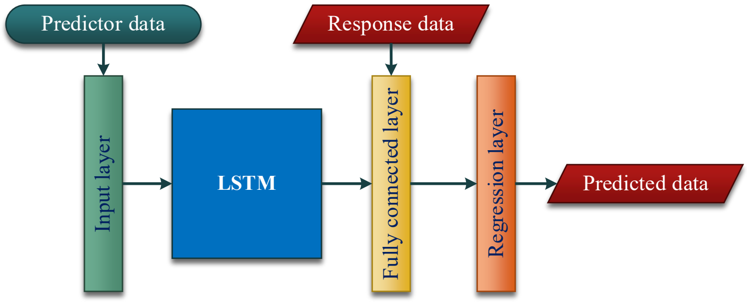

Fig. 1. General form of regression modeling via the LSTM

2.2 *Single-Layer Feedforward Network (SLFN)*

The SLFN is the simplest form of an artificial neural network (ANN) that contains a single hidden layer connecting between the input and output layers. This model also conforms to a feedforward strategy where the information moves only in one direction, from the input layer to the output layer without any cycles or loops. The single hidden layer is most likely a fully connected layer with more than one neuron. In this layer, the inputs are multiplied by weights and biases based on an activation function such as rectified linear unit (ReLU), hyperbolic tangent (tanh), sigmoid, and linear functions. Given the input (predictor) $\mathbf{x}$ and output (response) $\mathbf{y}$, the main function of the SLFN is written as follows:

$$\mathbf{y} = \tau(\mathbf{W}\mathbf{x} + \mathbf{b}) \tag{7}$$

where $\mathbf{W}$ is the weight matrix; $\mathbf{b}$ denotes the bias vector; and τ is the activation function. For the regression problem, the SLFN is compatible with the supervised learning paradigm. In this case, the input layer receives training data including both the predictors and responses. The data is fed into the hidden layer and then SLFN predict the response data at the output layer. To simplify, the general form of the SLFN in the regression problem (i.e., the supervised learning framework) is illustrated in Fig. 2.

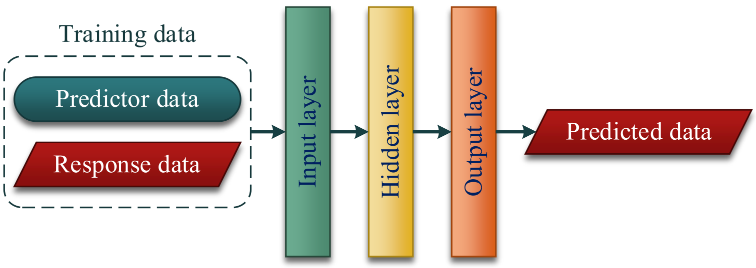

Fig. 2. General form of regression modeling via the SLFN

2.3 *Framework of Supervised Teacher-Student Learning*

The main motive for proposing the supervised teacher-student learning strategy is to address the restrictions of unmeasured predictors and limited information. Although the proposed data forecasting method has a more complicated structure compared to state-of-the-art regressors, it can overcome the mentioned limitations. Generally, this method consists of two main parts including a teacher model, which is a rigorous regressor, and a student model, which is a simpler regressor than the teacher model. According to the previous contents, the LSTM and SLFN act as the teacher and student models, respectively.

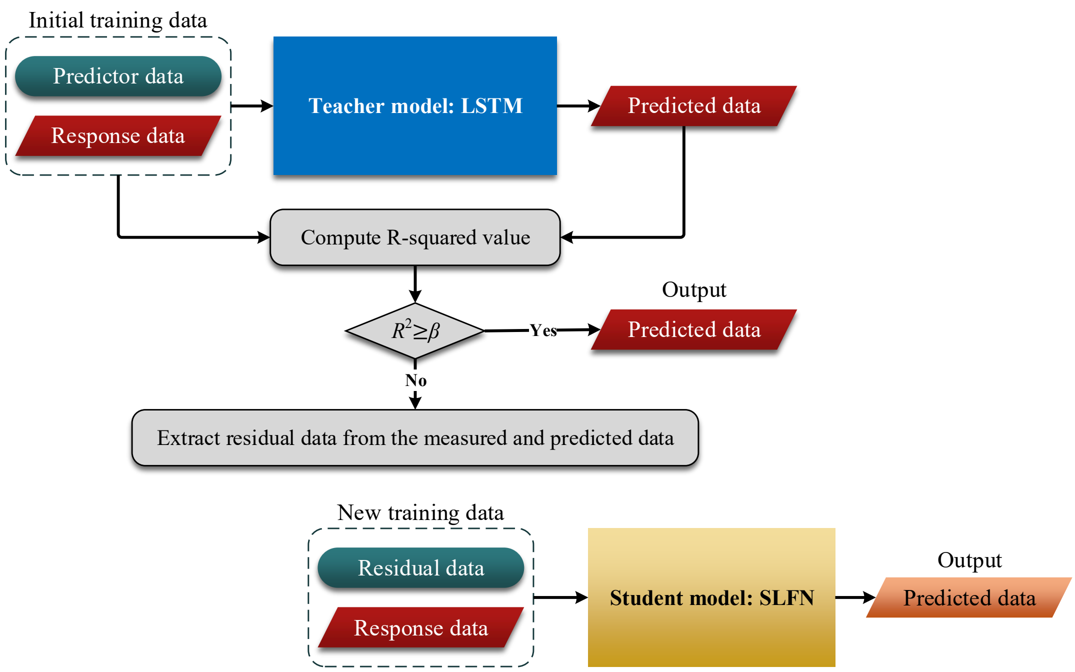

Fig. 3. Workflow of the proposed solution derived from the supervised teacher-student learning

To begin, the proposed method inputs the measured predictor and response data into the LSTM with the aim of forecasting the response data. If the measured predictor is the major factor for variability in the response data, the teacher model operates properly with reliable performance. In statistics, the R-squared (R^2) metric is one of the widely-used measure for checking the performance of a regressor. Good forecasting follows a large value of R^2 equal or close to one and vice versa. In case of the influence of unmeasured predictors, the model cannot predict appropriately. For this issue, the residual between the measured and predicted response data is considerable. The underlying rationale behind this fact is the residual data contains the unmeasured predictors [19]. Hence, one can incorporate the residual data as a new predictor. Using the measured response and also new predictor from the teacher model (i.e., LSTM), a SLFN model is trained to predict the response data based on the concept of student model. For ease of understanding, Fig. 3 depicts the flowchart of the proposed predictive method, where the variable β is a value regarding the goodness-of-fit in regression modeling.

3. Application

3.1 A Steel Arch Bridge with Limited Data

The steel arch bridge constructed within 2000-2003 is located in Shanghai, China. Fig. 4 indicates a side view of this structure along with its main dimension. The total length of the bridge is equal to 750m including a main span of 550m and two side spans of 100m. The bridge girder was fixed by the arch ribs and columns and it was ended with the cross-beam at the side spans. The girder of the main span was constructed from a double steel box-beam model. This girder included 39.5 m width and 2.7m height, where was supported on the arch rib through suspenders and connected to the integral arch and girder segment of the side span by bearings at the two ends.

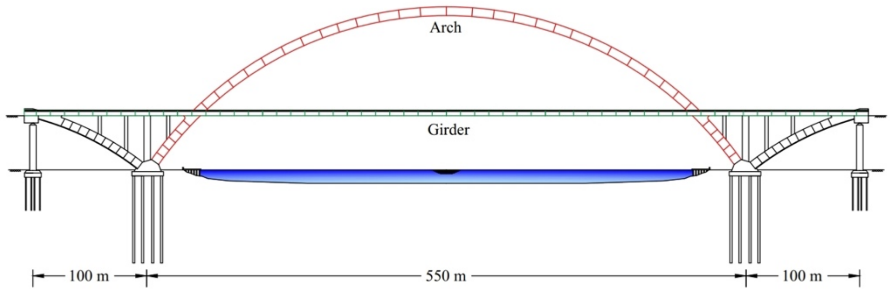

Fig. 4. The steel arch bridge

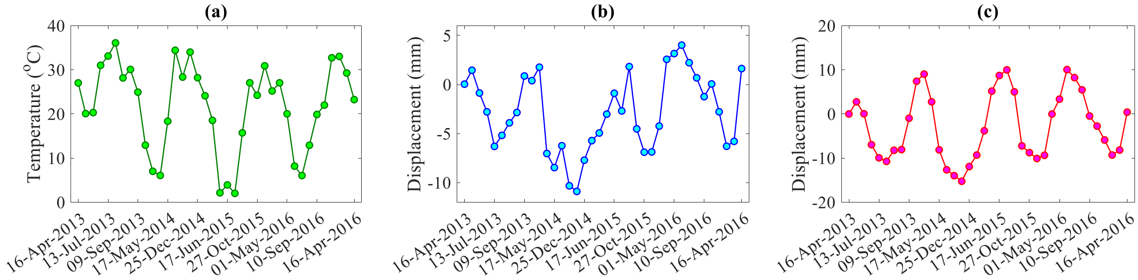

Fig. 5. Limited data of the steel arch bridge: (a) the temperature data, (b) the displacements at the bridge arch, (c) the displacements at the bridge main girder

Due to the geological and environmental characteristics of the zone where steel arch bridge is located, it was decided to study the bridge behavior between 2013-2016. For this reason, 38 SAR images from TerraSAR-X were used to extract displacement responses at the bridge arch and main girder [21]. During the structural behavior evaluation, air temperature was recorded to investigate the effect of this environmental factor on the bridge. Fig. 5 shows the limited temperature and displacement data.

3.2 Data Forecasting

To anticipate the bridge behavior, the recorded temperature data is selected as the main single predictor data, while each of the displacement data at the bridge arch and girder is considered as an individual response. Moreover, in order to model the teacher and student models, the training and testing datasets consist of 80% and 20% of all samples. For developing the teacher models, one needs to train two LSTM models. Hence, it is necessary to determine the model parameters, especially the number of units. The number of epochs is set as 2000 and the Adam optimizer is used as the main optimization technique for learning the LSTM. Under some sample units, the R^2 values of the sample units are computed to choose one of them with the maximum R^2 amount as shown in Fig. 6, where the LSTM models regarding the bridge arch and girder require fourteen optimal units.

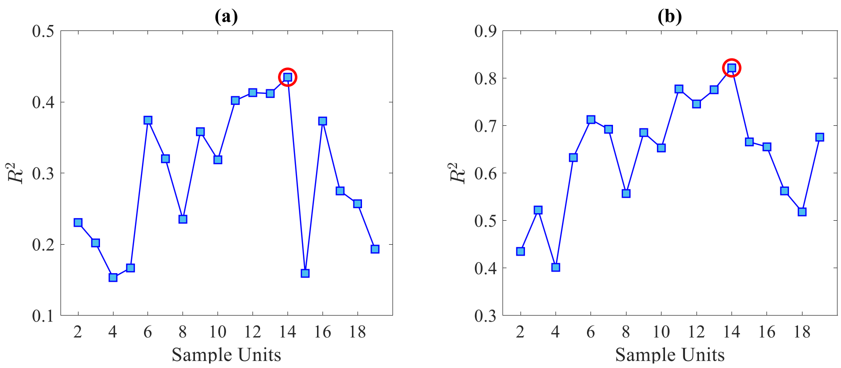

Fig. 6. Determination of the optimal unit numbers for the LSTM: (a) arch, (b) girder

One of the salient observations in Fig. 6 is that the optimal teacher model at the bridge arch, i.e., Fig. 6(a), does not operate properly due to its low R^2 rate. Having considered β=0.8, this means that other unmeasured predictors alongside of the ambient temperature affect the displacement response at the bridge arch; hence, the student model should be trained by extracting the residual between the measured and predicted responses. On the other hand, as Fig. 6(b) appears, the optimal teacher model yields a R^2 value more than β, in which case it is not required to train any student model. Therefore, the predicted response data of the LSTM at the bridge girder is used as the final output.

To train the SLFN of the bridge arch, the residual data between the measured and LSTM-predicted responses is set as a new predictor. Accordingly, new training data is applied to the SLFN to forecast new predicted points. In the SLFN, the only parameter that remains undetermined is the number of neurons in the single hidden layer. Using some sample neurons, the R-squared measure is exploited to find the optimal number as shown in Fig. 7. As can be seen, the optimal neuron number is identical to 4.

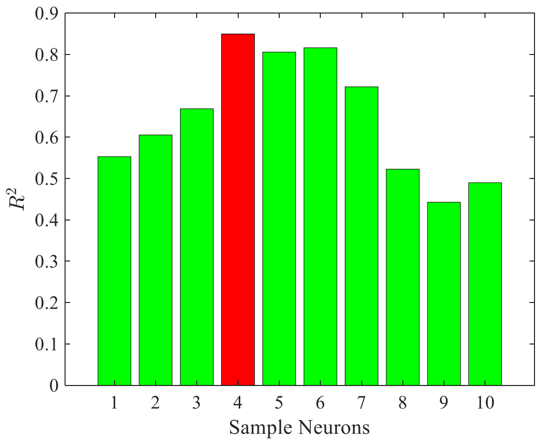

Fig. 7. Determination of the optimal neuron number of the single hidden layer of the SLFN for the bridge arch element

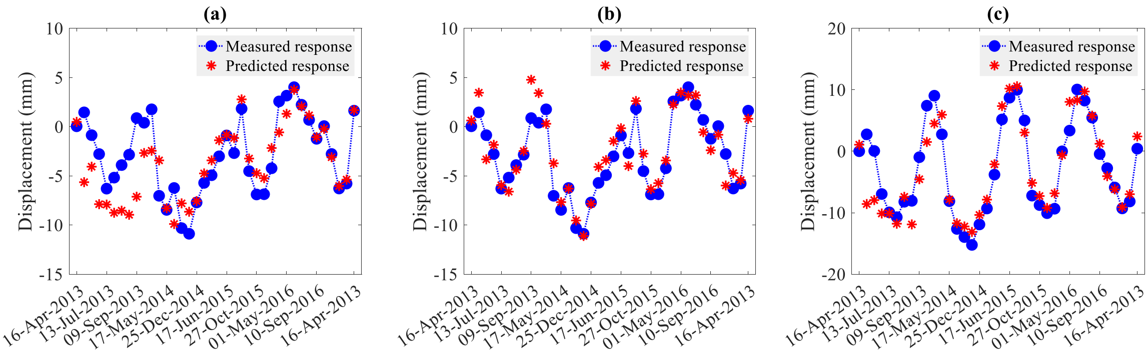

Fig. 8. Displacement forecasting: (a) the bridge arch using the teacher model, (b) the bridge arch using the student model, (c) the bridge girder using the teacher model

Table 1. Correlation coefficients of the temperature and SAR-extracted displacement responses

Bridge component	Teacher model: LSTM	Student model: SLFN
Arch	0.4347	0.8491
Girder	0.8217	–

Fig. 8 and Table 1 present the results of data forecasting concerning the bridge arch and girder. In Fig. 8(a), it compares the measured and LSTM-predicted response samples of the bridge arch. As can be discerned, there are large discrepancies between the samples implying the poor performance of the teacher model (LSTM) for forecasting the displacement of the bridge arch. From Table 1, this model gives R^2=0.4347. In contrast, Fig. 8(b) indicates the predicated response samples from the SLFN. In most cases, the measured and predicted data points are in good agreement. In other words, the use of the student regression modeling improves the performance of data forecasting from R^2=0.4347 to R^2=0.8491, as also presented in Table 1. Eventually, Fig. 8(c) compares the measured and predicted response points at the bridge girder using the teacher model (LSTM). Reliable data forecasting with R^2=0.8217 are observable.

4. Conclusions

This paper has proposed an innovative predictive method based on the paradigm of supervised teacher-student learning for forecasting limited data in the presence of unmeasured predictors. The proposed method has contained two parts of teacher and student regression modeling. For developing a teacher model, the LSTM neural network has been considered. Moreover, the student model with a simpler structure has been based on the SLFN. The unknown parameters of both models have been determined by using the R-squared metric. Limited temperature and displacement data of a steel arch bridge have been used to validate the proposed method.

The results have demonstrated that the proposed method performs suitably when unmeasured predictors affect response data. Moreover, this method presents a flexible strategy for regression modeling so that the teacher model can also yield the final output when it satisfies the criterion of date forecasting. In the case study, it has been observed that other unmeasured environmental/operational factors have impacted on the bridge arch; however, the proposed method could compensate this limitation of field measurement. Furthermore, it has been seen that the recorded temperature has been the main reason for variability in the displacements of the bridge girder so that the teacher model could obtain the final forecasting output.

Funding

This research was partially funded by the European Space Agency (ESA) under ESA Contract No. 4000132658/20/NL/MH/ac.

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