Call for collaboration:

Benchmark datasets for landslide susceptibility zonation

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(Dated: November 17, 2022)

This is a non–peer reviewed preprint.

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Abstract

Landslide susceptibility, the spatial likelihood of occurrence of landslides in a specific geographical area, is the subject of countless scientific publications. Different authors use heterogeneous data, and apply many different methods, mostly falling under the definition of statistical and/or machine learning approaches, with the common feature of considering many input variables and a single target output, denoting landslide presence. It is a classification problem: given N input variables assuming different values, each combination associated with a 0/1 possible outcome, a model should be trained with some dataset, tested to reproduce the target outcome, and eventually applied to unseen data possibly of practical application.

At variance with many fields of science, no reference data exist to comparatively assess the performance of a given method for landslide susceptibility classification and mapping. We propose a benchmark dataset in Italy, extracted from a larger dataset covering the whole country and based on slope units as basic mapping units. The selected 7,732 slope units encompass an area of about 4,100 km^2 in Central Italy. The attribute table contains 26 columns, corresponding to predictors, and a binary column containing the landslide presence/absence flag.

We release the dataset, along with a "call for collaboration", aimed at collecting a number of different calculations performed with common input data, and establish a benchmark for landslide susceptibility models. Contributions to this collaboration will be presented at the 2023 European Geosciences Assembly, and collected in a journal publication authored by all of the contributors.

I. INTRODUCTION

Landslide susceptibility assessment with statistical/machine learning methods, in a given geographical area, requires a substantial amount of topographic, geomorphological and environmental data to train and test a specific model. The combination of input data and the method of choice are the ingredients to prepare a classification of the study area on the basis of specific mapping units - *i.e.*, elementary portions of the area. A simple square grid may represent mapping units, but slope units works substantially better in representing small portions of topography with uniform likelihood of landslides to occur and, thus, they are the preferred choice for landslide susceptibility mapping (Alvioli et al. 2016, Carrara et al. 1991).

A well–known review of landslide susceptibility journal publications and classification methods was published by Reichenbach et al. (2018). Not only a huge number of publications exist on the subject, but several reviews about landslide susceptibility and landslide susceptibility methods appear every year (see, *e.g.*, (Das et al. 2022, Dias et al. 2021, Lee 2019, Liu et al. 2022, Pourghasemi et al. 2018, Shano et al. 2020, Yong et al. 2022)).

Relevant input data (usually referred to either as "predictors", "factors", "independent variables") is usually a mixed set of morphometric and a variety of thematic data. A landslide inventory is also needed, representing the dependent variable to be reproduced by the model. Different landslide inventories may lead to different susceptibility maps (Bordoni et al. 2020, Pokharel et al. 2021), implying that a given inventory must be selected for the benchmark we aim at. Choice of a specific method/model depends on software availability, personal background, and existence of relevant literature for the area of interest. New methods are proposed regularly and very often it is difficult to judge their relative performance with respect to existing methods.

A meaningful comparison of many different methods would require a common dataset representing a benchmark to train and test each of them in a systematic way. This is a standard procedure in machine learning science and practice: benchmark datasets exist for medical sciences, image recognition, linguistics, and in general any field in which a classification algorithm can be applied. The "Iris dataset" is a famous example of a benchmark in classification of numerical data into three different variants of the flower Iris (Fisher 1936). The user community of machine learning software is ever–growing; for example, TensorFlow (Abadi et al. 2015) has been used in machine learning applications in dozens of fields of science. Versatile software like TensorFlow (and many others) requires calibration/test datasets, for each application field. One example of open datasets for this purpose, listed in alphabetical order, is available on github (Multi-author 2022).

Here, we aim at (1) introducing a benchmark dataset to compare the outcome of different methods for landslide susceptibility assessment in a meaningful way, (2) collecting expressions of interest of researchers active in the field of landslide susceptibility to use such dataset with their method of choice, and (3) proposing the first systematic comparison of the largest possible collection of methods, with a common input dataset.

II. A BENCHMARK DATASET FOR LANDSLIDE SUSCEPTIBILITY ASSESSMENT

We selected a dataset as a candidate reference dataset for a benchmark in landslide susceptibility zonation, as follows.

In first place, as anticipated, we believe that landslide susceptibility maps should be devised on the basis of slope units, as they have a meaningful correspondence with topography, at variance with square grid cells. Thus, we decided to adopt the dataset used by Loche et al. (2022a) for landslide susceptibility maps in Italy. Since the slope unit map adopted in that work is rather large, we decided to select a subset of the entire dataset – which was already available on the web, with some modification.

Out of the entire slope unit map of Italy (Alvioli et al. 2020), containing about 330,000 polygons, we selected a subset of 7,732 slope units encompassing an area of 4,095 km^2 in Central Italy, entirely contained in Umbria Region. Moreover, out of the eight different presence/absence flags in the original map, we selected the flag denoting presence/absence of translational landslides, originally obtained from the Italian National landslide database prepared by different Institutions and collated into a single inventory by the Italian Geological Survey (ISPRA; Trigila et al. (2010)).

We decided to flag landslide presence with two different attribute fields, called 'presence1' and 'presence2'. As the original landslide data was available to us as point information, each point denoting one landslides, we had a choice of how many points would denote landslide presence.

For the field 'presence1', we selected slope units labeled as "without landslide" (presence1 flag 0) where a slope unit contained no points at all, in 3,924 cases (1,443.1 km^2), and as "with landslides" (presence1 flag 1) in the remaining 3,808 cases (2,652.1 km^2).

For the field 'presence2', we selected slope units labeled as "without landslides" (presence2 flag 0) where a slope unit contained up to one point, in 5,309 cases (2,087.1 km^2), and as "with landslides" (presence2 flag 1) in the remaining 2,423 cases (2,008.2 km^2).

Note that using 'presence1' as landslide presence, one would have an approximately balanced dataset with respect to number of zeros/ones; using 'presence2', instead, one would have an approximately balanced dataset with respect to the total surface area covered by the slope units labeled either with zero, or one. Figure 2 shows the spatial distribution of

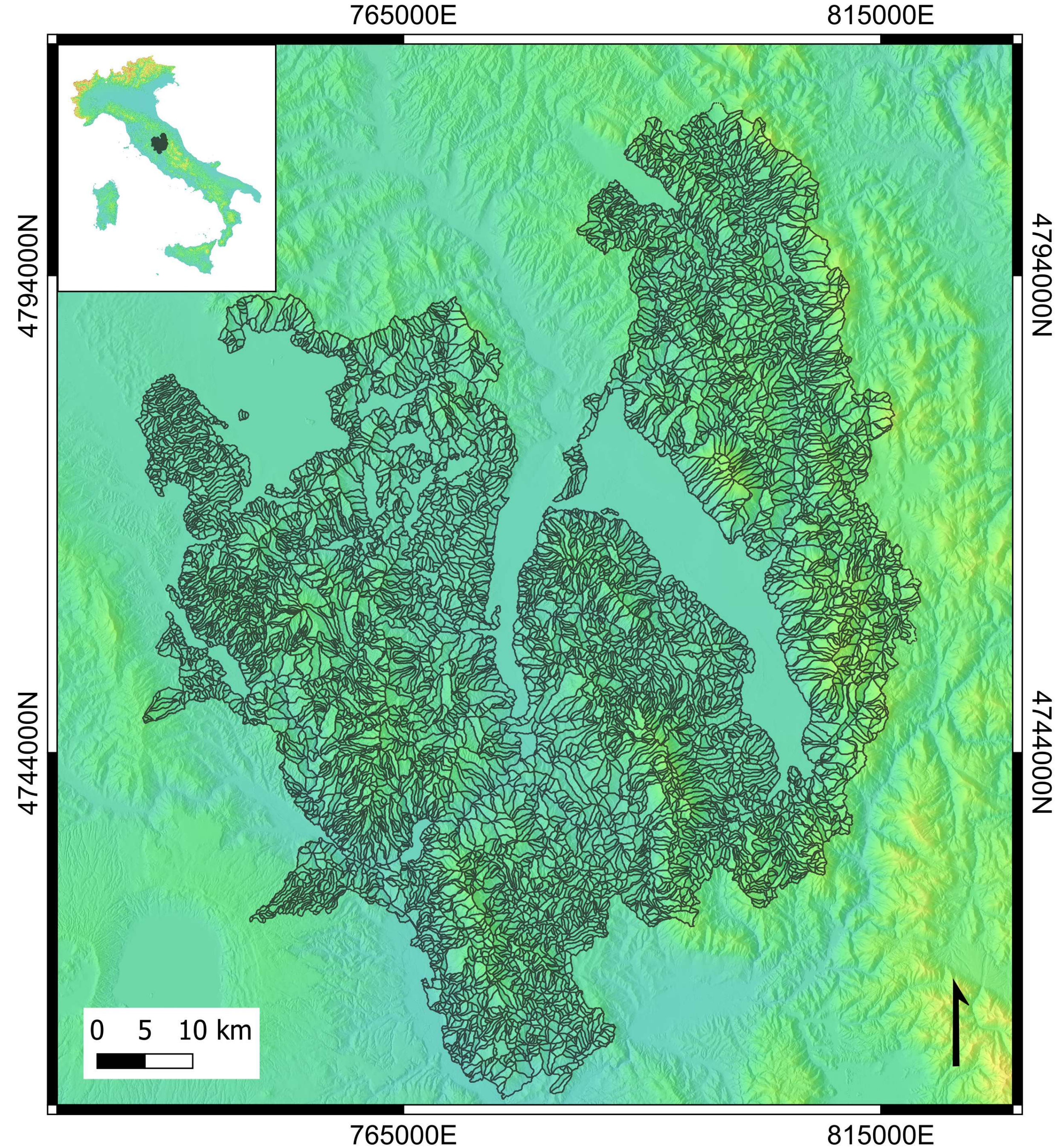

FIG. 1. Geographical location (inset) of the area covered by the slope unit set (main figure) selected in this work as a benchmark dataset for landslide susceptibility zonation. The dataset is a subset of the slope unit map obtained by Alvioli et al. (2020), and used by Loche et al. (2022a) for landslide susceptibility zonation all over Italy, for different kinds of landslides. In the dataset proposed here, we selected point locations of translational landslides from the Italian national inventory known as 'IFFI' (Trigila et al. 2010).

slope units labeled as positive/negative in the two cases.

We invite those who intend to contribute to this call for collaboration to consider both landslide presence flags (independently, of course), to produce two different landslide susceptibility maps for the benchmark study area. Moreover, we invite contributors to use their best strategy, or the strategy that best fit their model of choice, to produce a result for a landslide susceptibility index – a real number ranging form zero to unity – and an uncertainty associated to that, where possible. For example, one could choose to split the proposed dataset into calibration–validation subsets, and to do so multiple times, in order to provide an error bar corresponding to the variability of results around the average value, in each slope unit. A few existing models could have an intrinsic way of providing an error bar, which would be very welcome.

The slope units benchmark dataset is distributed in vector format (see Section IV), with an attribute table containing a number of different morphometric and thematic variables. The morphometric variables were calculated using the EUDEM digital elevation model from the Copernicus Land Monitoring Service, with 25 m resolution. A few variables were obtained from the SoildGrid global dataset (Hengl et al. 2017). The full set of variables is listed in Table I. We did not include lithological data, as the highest resolution map available to us in the area of interest (Bucci et al. 2022) would only contain four different classes with non–negligible presence.

In the simplest approaches for landslide susceptibility classification, slope units are treated as spatially independent from each other. In this case, the necessary information is limited to the relevant part of the attribute table: a matrix with 27 columns (26 independent variables, listed in Table I, and one dependent variable represented by either of the two binary flags denoting landslide presence) - excluding the columns ID and Area. In more sophisticated approaches, the spatial relationship among individual slope units is relevant, and the information contained in the attribute table must be complemented with the slope unit vector map.

For illustrative purposes, we fitted the benchmark dataset with a simple generalized additive model (GAM; (Goetz et al. 2015, 2011, Loche et al. 2022b)). This results, in the present form, is only intended to provide a graphical result – we did not attempt a calibration/validation attempt, no randomization of the input data, and we did not calculate performance metrics. Thus, they will not be part of the final benchmark calculations.

Figure 3 shows the resulting landslide susceptibility maps, corresponding to the target flag 'presence1' (as in Fig. 2(a)) and to the target flag 'presence2' (as in Fig. 2(b)).

Column name	**Variable**	**Short name**
id	Unique slope unit identifier	ID
slope_aver	Mean Slope Steepness [deg]	Mean Slope
slope_stdd	SD of Slope within SU [deg]	SD of Slope
pcurv_aver	Mean Planar Curvature	Plan Curv
pcurv_stdd	SD of Planar Curvature	SD of Plan Curv
tcurv_aver	Mean Profile Curvature	Prof Curv
tcurv_stdd	SD of Profile Curvature	SD of Prof Curv
nthns_aver	Mean Northness	Northness
nthns_stdd	SD of Northness	SD of Northness
easns_aver	Mean Eastness	Easthness
easns_stdd	SD of Easthness	SD of Easthness
elev_avera	Mean Elevation [m]	Elevation
elev_stddd	SD of Elevation [m]	SD of Elevation
twi_averag	Mean Topographic Wetness Index	TWI
twi_stddev	SD of Topographic Wetness Index	SD of TWI
BDRICM_ave	Mean Depth to bedrock (<2.4 m) [m]	Mean BDRICM
BDRICM_std	SD of Depth to bedrock [m]	SD of BDRICM
BLDFIE_ave	Mean Bulk density [kg/m^3]	Mean BLDFIE
BLDFIE_std	SD of Bulk density [kg/m^3]	SD of BLDFIE
CLYPPT_ave	Mean Weight % of clay particles	Mean CLYPPT
CLYPPT_std	SD of Weight % of clay particles	SD of CLYPPT
SNDPPT_ave	Mean Weight % of sand particles	Mean SNDPPT
SNDPPT_std	SD of Weight % of sand particles	SD of SNDPPT
SLTPPT_ave	Mean Weight % of silt particles	Mean SLTPPT
SLTPPT_std	SD of Weight % of silt particles	SD of SLTPPT
Max_Distan	Maximum Distance within SU [m]	MD
D_sqrt_A	Maximum Distance/$\sqrt{SU Area}$	MD/$\sqrt{Area}$
presence1	Binary landslide presence flag	LDS presence 1
presence2	Binary landslide presence flag	LDS presence 2
area	Area [km^2]	Area

TABLE I. Variables contained in the attribute table of the proposed dataset. In the table, SD stands for standard deviation. Depth to bedrock, bulk density, percentage weight of clay, sand and silt particles are from Hengl et al. (2017).

III. CALL FOR COLLABORATION: CONFERENCE VENUE

The venue for discussing and comparing different approaches, all of them using the dataset proposed in this work and, possibly, other datasets should that be necessary, is the 2023 European Geosciences Union General Assembly, to be held in Vienna, & online, 23–28 April 2023. We proposed a session called *Benchmark datasets for landslide susceptibility zonation*, available at the URL: https://meetingorganizer.copernicus.org/EGU23/session/47046. The only way to participate in this call for collaboration is to submit an abstract to the mentioned EGU 2023 session, and present the paper at the conference venue (either in Vienna or online). **Abstract submission was open November, 1st and at the time of writing the deadline is 10 January 2023, 13:00 CET.**

The session aims at establishing one or more benchmark datasets that could be helpful in landslide susceptibility research, to compare the plethora of existing methods and new methods to come. We proposed an interactive session: we expect abstract proposals to describe the method(s) they intend to apply, the type of data it requires, and an independent case study for which the method proved successful. Ideally, participants should be ready to disclose minimal computer code (in any major programming language) to run their method, to apply the code to the benchmark dataset prior to the conference, and present their results. We aim at submitting the results in a high-rank journal publication, including datasets, benchmark and (possibly) computer codes in collaboration with the participants who complied to the guidelines given here and any updates that may follow, at the session description link: https://meetingorganizer.copernicus.org/EGU23/session/47046.

IV. DATA AVAILABILITY

The dataset singled out for this benchmark calculation is a subset of the slope unit map of Alvioli et al. (2020), used by Loche et al. (2022a) to prepare landslide susceptibility maps all over Italy. Figure 1 shows the spatial location of the area of interest, and Table I lists the variables contained in the attribute table of the vector map.

The benchmark dataset is available for download at the main slope unit project page, at: https://geomorphology.irpi.cnr.it/tools/slope-units, under the section `Data` → `Benchmark Dataset`. We provide the dataset

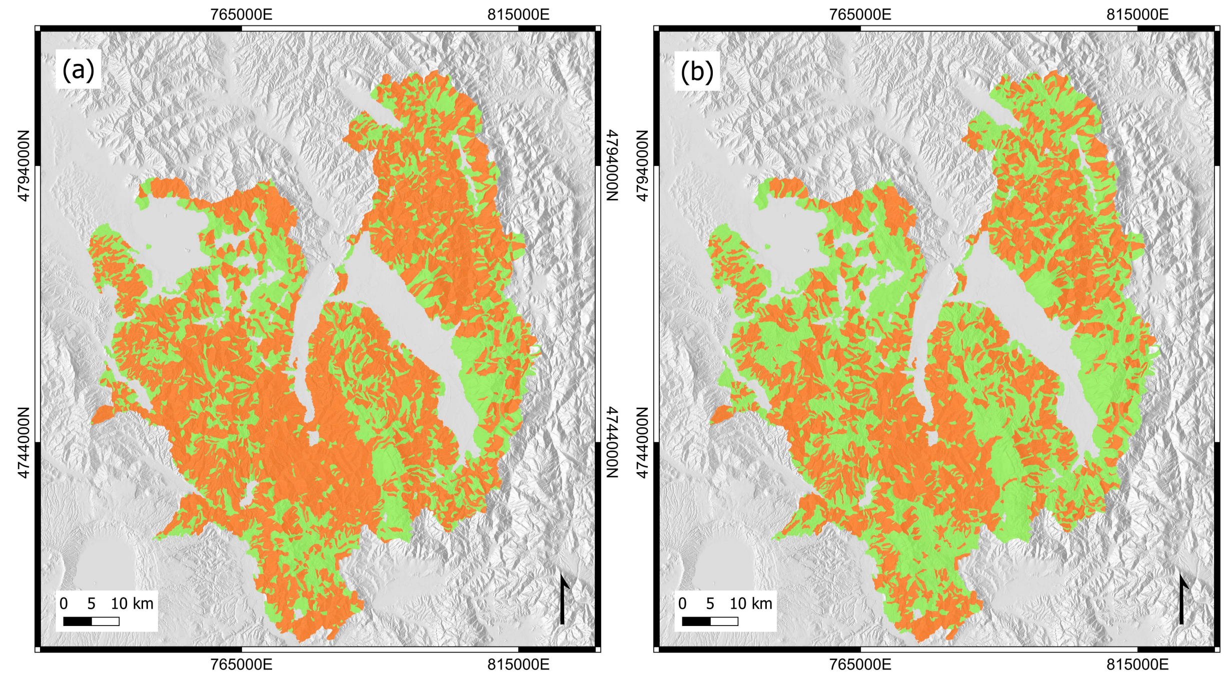

FIG. 2. Spatial distribution of positive (with landslides; orange) and negative (without landslides; green) slope units, in the dataset proposed in this work (*cf.* Fig. 1). Landslide presence is either from the field 'presence1' (a) or 'presence2' (b) in the attribute table (*cf.* Section II and Table I).

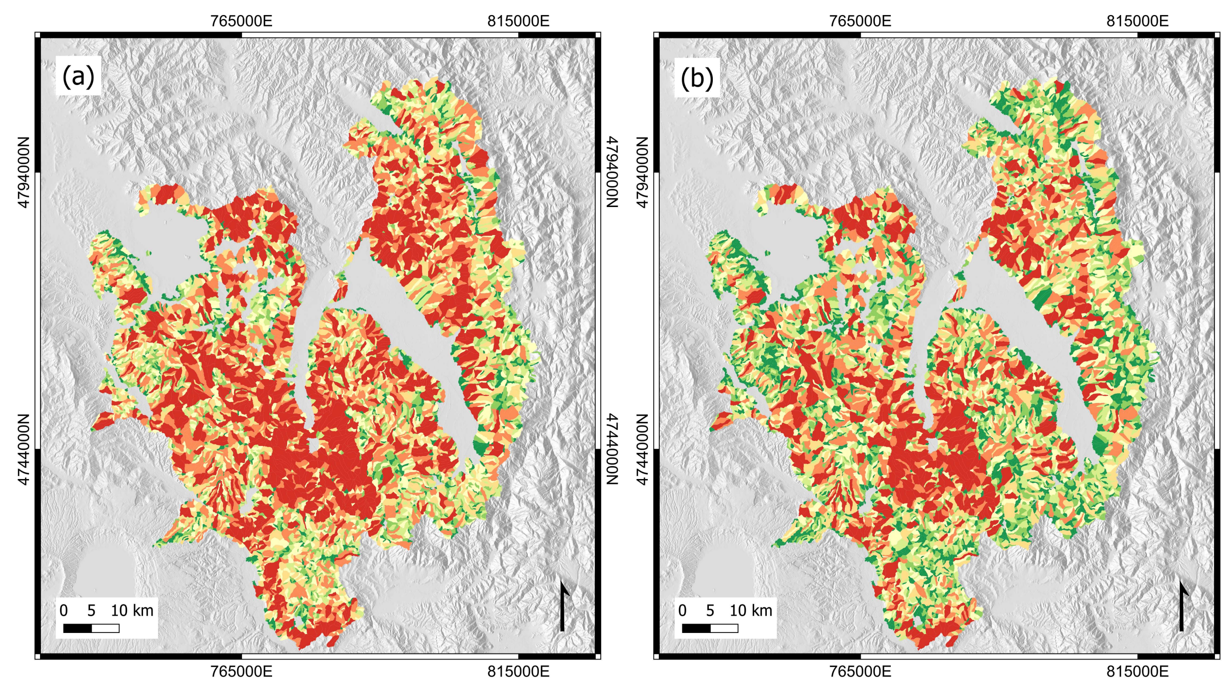

FIG. 3. Sample susceptibility maps, obtained as a simple fit (no calibration/validation, no multiple random selections) of the 'presence1' (a) and 'presence2' (b) landslide presence flags, using the input variables listed in Table I, using a GAM model. *For illustrative purposes only.*

in vector format, both in OGC GeoPackage format (GeoPackage is an open, standards-based, platform–independent, portable, self–describing, compact format for transferring geospatial information) and in ESRI Shapefile format. The two vector maps are identical, both of them contain the same attribute table, and they are provided in EPSG:32632 - WGS 84 / UTM zone 32N projected reference system.

The full slope unit map of Italy, and the results on the national susceptibility maps, are also available at the same web page: please note that they are NOT necessary for this call for collaboration, neither the results for landslide susceptibility obtained from the benchmark dataset should be compared with the results obtained at national scale. In fact, the input data is so different that no specific degree of match is expected between results at the national scale and on the small subset selected for this benchmark.

V. ACKNOWLEDGMENTS

C.H. Grohmann is funded by FAPESP (grant # 2019/26568-0) and CNPq (grant # 311209/2021-1).

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