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ETHOS.TISED: A python package for temporal downscaling of solar irradiance

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ABSTRACT

High temporal-resolution solar irradiance data are essential for a wide range of energy and climate applications. However, most climate models and reanalysis datasets are only available at hourly resolution. ETHOS.TISED is an open-source Python package which facilitates the temporal downscaling of global horizontal irradiance from hourly to minute-scale resolution, using daily variability indicators for all climates and locations. The synthetically generated minute-scale resolution data show close agreement with measured observations as demonstrated by the normalized root mean squared error and the Kolmogorov-Smirnov integral test, which quantify the point-to-point and distributional divergence between measured and synthesized time series, respectively. By enabling the reproducible generation of high-frequency irradiance time series, the software improves the robustness and reliability of research and applied studies in energy system modeling.

Metadata

Nr	Code metadata description	*Metadata*
C1	Current code version	*V1.1.0*
C2	Permanent link to code/repository used for this code version	https://github.com/FZJ-IEK3-VSA/ETHOS.TISED
C3	Permanent link to reproducible capsule	https://github.com/FZJ-IEK3-VSA/ETHOS.TISED
C4	Legal code license	*MIT License*
C5	Code versioning system used	*GIT*
C6	Software code languages, tools and services used	*Python ≥ 3.13.0, Pandas, NumPy, pvlib, sklearn, SciPy, timezonefinder, kgcpy*
C7	Compilation requirements, operating environments and dependencies	*Windows*
C8	If available, link to developer documentation/manual	https://github.com/FZJ-IEK3-VSA/ETHOS.TISED/blob/main/README.md
C9	Support email for questions	o.omoyele@fz-juelich.de

1. Motivation and significance

The intermittent nature of solar energy and its significance in contributing to the energy system scenarios for greenhouse gas neutrality have prompted a higher level of detail in its modeling [1]. Conventional solar irradiance data are frequently generated at hourly or even coarser resolutions through most climate models and meteorological reanalysis [2–6]. These coarse resolutions fail to capture the intra-hour variabilities that are inherent in solar irradiance data [7]. This, in turn, often leads to inaccuracies in system modeling. Since irradiation can vary significantly within minutes, higher temporal resolution data is essential for a more accurate modeling, particularly for small-scale offgrid systems [8–10]. These high-resolution solar irradiance data are a critical input for many areas of climate and energy research, including energy scenario modeling, photovoltaic power modeling and reliability, short-term variability analysis, grid stability studies, and the assessment of ramping events [11–14]. Critical parameters such as, optimal cost of operation [15–17], inverter sizing and clipping [18–20], levelized cost of electricity [16,20], and grid stability [11] are particularly sensitive to high resolution irradiance variability

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and are therefore inadequately captured using hourly data. Several studies have, therefore, developed methods to increase the temporal resolution of solar irradiance [14]. These methods are classified into five approaches, namely: Deterministic, Markov, Stochastic, Machine learning, and Non-dimensional [14]. Many of the approaches lack accuracy, are too complex, require large datasets, lack reproducibility, or lack global applicability (see Table 3). The non-dimensional approach is comprehensive, computationally cheap, adaptable to arbitrary locations, and produces good accuracy [21]. Of the previous methods, only Frimane et al. [22,23], Ruiz-Arias [24], Munkhammar [25], Larrañeta et al. [26], DAYSIM[1] [27,28], and the Copernicus Atmosphere Monitoring Service (CAMS) Radiation Service and associated tools [29–31] made their works reproducible, through publicly available codes, to the best of the authors' knowledge. Table 1 gives the authors' names, type of irradiance data, temporal resolution, downscaling approach, and the programming language used. While the non-dimensional approach currently produces the best validation measures, it has so far been applied only to datasets comprising both direct normal irradiance (DNI) and global horizontal irradiance (GHI), or to DNI data alone [32]. Until now, there has been a lack of standalone software for GHI downscaling using the non-dimensional approach. Other software, as shown in Table 1, lacks good accuracy, is complex, or is not globally applicable (site's localized data is required).

This paper introduces the open-source software ETHOS.TISED (TIme SEries Downscaler), which implements the non-dimensional downscaling methodology originally presented by Omoyele et al. [21] within the ETHOS (Energy Transformation Pathway Optimization Suite) Model suite [33].[2] The downscaling is reproducible and maintains observed statistical properties, including variability, distributional shape, and temporal structure, while preserving the daily energy output. Users provide hourly resolution irradiance data, the geographic location (latitude and longitude), and the year of interest. This software package supports researchers and modelers in the accurate and reproducible modeling and design of photovoltaic systems for energy system applications.

2. Software description

2.1. Software methodology

The downscaling procedure implemented in ETHOS.TISED is based on the non-dimensional approach using non-dimensional irradiance profiles [34–36]. In Fig. 1(a), an example of GHI time series is shown. Fig. 1(b) shows the corresponding normalized non-dimensional profile. The created profile is stored in a database as non-dimensional minute-resolution profiles. The transformation from hourly to minute-level resolution is performed as follows:

- Normalization of irradiance and time: The hourly GHI is converted into a non-dimensional form by normalizing GHI by extraterrestrial irradiance and time between sunrise and sunset (Fig. 1). This removes site- and season-specific effects and enables comparison across days.
- Computation of daily indicators: From the normalized hourly data, five daily indicators (see Fig. 1 and Table 4) are calculated (clearness index, variability index, normalized variability index, distribution, and integrated complementary cumulative distribution function). These indicators summarize the statistical and atmospheric characteristics of each day.
- Similarity matching using k-nearest neighbors: The computed indicators are used to identify similar days in a pre-constructed daily indicators database representing high-resolution (minute-level) non-dimensional irradiance profiles. A k-nearest neighbor algorithm is applied to select the most similar days.
- Retrieval of high-resolution profiles: The corresponding non-dimensional minute-resolution profiles from the selected nearest neighbors are retrieved from the database.
- Conversion to physical irradiance: The selected profiles are converted back to physical units by converting time to the actual sunrise–sunset duration, and multiplying by extraterrestrial irradiance. This produces the final one-minute GHI time series.

An exposition of the methodology of ETHOS.TISED can be found in Omoyele et al. [21].

2.2. Software architecture

The Python package provides a single user-facing entry-point class, *SolarModel*, which users directly instantiate to configure and run the model. It downscales an hourly GHI time series data to a minute-scale time series data based on the location and the year provided by the user (see Fig. 2). The downscaling method is implemented in six interdependent sub-methods:

(1) **Detecting Climate Class:** Irradiances from different locations, but the same weather class have similar variabilities [37]. Therefore, the database is separated into different weather classes based on the Köppen-Geiger weather classification [38]. To match the database climate type, an automatic climate detection of the climate type is required. This uses the kgcpy package [39], through latitude and longitude (WGS 84, EPSG:4326), to obtain the Köppen-Geiger climate of the location to be downscaled. Due to the scarcity of high-resolution data, some climates are not represented in the database. To accommodate all Köppen-Geiger climate types in ETHOS.TISED, a mapped climate zone, is created based on climate similarity (the mapped climates are exposited in Ref. [21]).

(2) **Setting Time Zone:** The software package requires a downscaling year as input. This is further processed by the Pandas package [40] into the start and the end time in both hourly and minute-scale resolutions for the entire downscaling year. The start and the end times require the time zone of the location. The class utilizes the timezonefinder[3] package through the latitude and longitude to obtain the location's time zone.

(3) **Getting the Extraterrestrial Irradiance:** The extraterrestrial irradiance is the amount of irradiance in the uppermost layer of the Earth [36]. It is a parameter required in the variability indicators of clearness and variability indices. It is obtained at both

Table 1
Open-source downscaling methods in the literature.

Authors	Renewable	Temporal resolution	Downscaling approach	Code language
Frimane et al. [22,23]	GHI	1 h – 1 min	Stochastic	R
Ruiz-Arias [24]	GHI	1 h – 1 min	Deterministic	Python
Munkhammar and Widén [25]	GHI	1 h – 1 min	Markov	Matlab
Larrañeta et al. [26]	GHI+DNI or DNI only	1 h – 1 min	Non-dimensional	Matlab
DAYSIM [27,28]	GHI and DNI	1 h – 1 min	Stochastic	C/C++
CAMS [29–31]	GHI and DNI	Up to 1 min	Deterministic	Python

[1] Walkenhorst et al. [27] improved the stochastic approoach of Skartveit and Olseth [28] to downscale one hour data to one minute. This is included in the DAYSIM code (https://github.com/MITSustainableDesignLab/Daysim).

[2] https://go.fzj.de/ethos_suite

[3] https://github.com/jannikmi/timezonefinder

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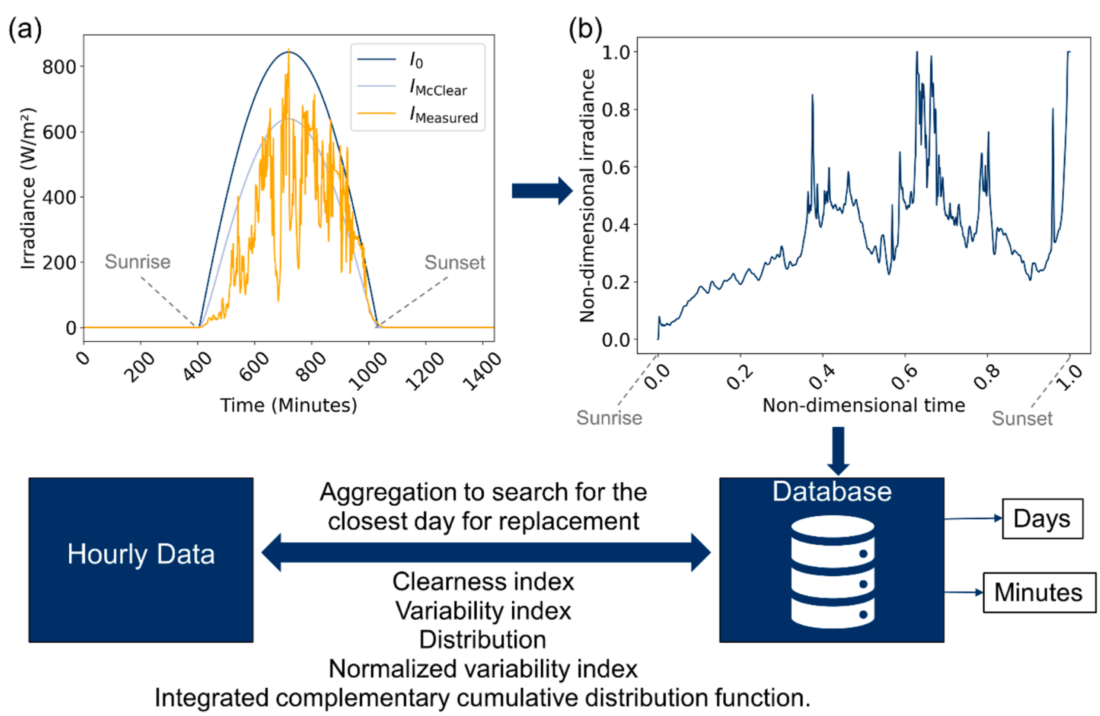

Fig. 1. Non-dimensional Approach for Downscaling Solar Irradiance. $I_{Measured}$ is the measured irradiance, $I_{McClear}$ represents the clear sky irradiance, and I_0 is the extraterrestrial irradiance.

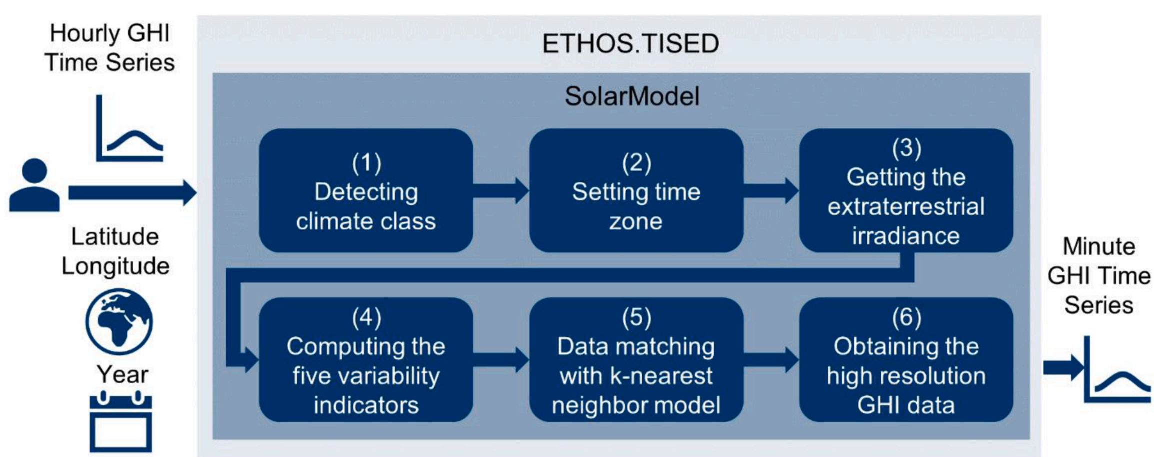

Fig. 2. Architecture diagram, use case and the required input data of ETHOS.TISED. The GHI is the global horizontal irradiance.

hourly and minute-based resolutions utilizing pvlib's [31] McClear clear sky API through Copernicus Atmosphere Monitoring Service [30], using latitude, longitude, elevation, start, and end time.

(4) **Computing the Variability Indicators:** The five variability indicators in Table 4 are computed using NumPy [41], Pandas [40], and pvlib [31] (with pvlib applying to clearness index, variability index, and distribution). Beyond the extraterrestrial irradiance, pvlib is also used for obtaining the solar angles, which are essential for computing the distribution variability indicator.

(5) **Matching the Variability Indicators:** The daily variability indicators computed from the hourly resolution are matched with the ones in the database of similar climate types. This matching is done with the k-nearest neighbor of the scikit-learn Python package [42]. Based on the match, similar days are predicted from the data.

(6) **Obtaining the High-Resolution Irradiance Data:** The predicted similar days, which are non-dimensional profiles, are converted back to one-minute resolution GHI data. This means that the daily sunrise and sunset, as well as one minute of extraterrestrial irradiance, are required. All of which are calculated using pvlib. Then the output is optimized for the daily cumulative sum between the synthetic and the measured data using SciPy [43]. The output is a one-minute resolution synthetic GHI data with consistent variability, distribution, and daily cumulative as the original one-hour resolution data.

2.3. *Software functionalities*

ETHOS.TISED is designed for simple use through the *SolarModel* class, which requires hourly GHI data (single column array), latitude, longitude, and year as inputs (Fig. 3). The model automatically performs the downscaling and generates a one-minute resolution GHI time series,

```python
import pandas as pd
from ethos_tised import SolarModel

hourly_data = pd.read_csv('data_hour.csv')

synthetic = SolarModel(
       Lat=52.455778,
       Lon=13.523917,
       date=2018,
       data=hourly_data
       )
```

Fig. 3. Implementation of the ETHOS.TISED Python package for Berlin, Germany.

which can be exported as a .csv or .xlsx. If gaps are detected in the user's input hourly data, the *SolarModel* class automatically imputes them using k-nearest neighbors, provided the hourly data follows the formatting illustrated in *hourly_data_missing.csv* included in the ETHOS. TISED *data directory*. In terms of computational performance, downscaling one full year of hourly GHI data to minute resolution typically requires approximately 20–45 s on a standard desktop computer (Intel i7 processor, 16 GB RAM). Since each day is processed independently, computational cost scales linearly with the number of years, while memory usage remains moderate as only one year of data and the relevant climate subset are loaded at a time. A code snippet for this workflow is shown in Fig. 3, for example, to downscale hourly resolution data of Hochschule für Technik und Wirtschaft (HTW) Berlin weather data of 2018 [44].

Additionally, statistical parameters and some metadata about the input and output time series and the downscaling process are calculated and shown by the *SolarModel* class. This is presented in the example in the next section (Fig. 5).

3. Illustrative examples

To showcase the application of ETHOS.TISED, a GHI time series from the HTW Berlin [44] (as detailed in Section 2.3) is used. It is measured in hourly resolution and one-minute resolution and is thus used as one of the validation cases for ETHOS.TISED in Ref. [21]. While only hourly data is required for the model, the one-minute measurements are included here to illustrate the agreement between synthesized and measured high-resolution data. Fig. 4 compares the hourly input, synthesized one minute resolution data, and measured one-minute resolution data for three random days in 2018. As expected, the measured data shows higher variability and sharper peaks than the hourly input, while the synthesized data closely follows its overall behavior.

To demonstrate the correct implementation and numerical consistency of the software, selected statistical properties of both the measured and synthesized data are compared in Table 2. The hourly normalized

Table 2
Statistical description of the measured and the synthetic global horizontal irradiance (GHI). quartiles (25 %, 50 %, and 75 %) represent the empirical distribution of GHI values.

Parameter	Measured GHI	Synthetic GHI
Mean	137.461	137.461
Standard deviation	226.918	229.225
Min.	0.000	0.000
25 %	0.000	0.000
50 %	3.000	0.000
75 %	190.000	185.036
Max.	1218.000	1218.567

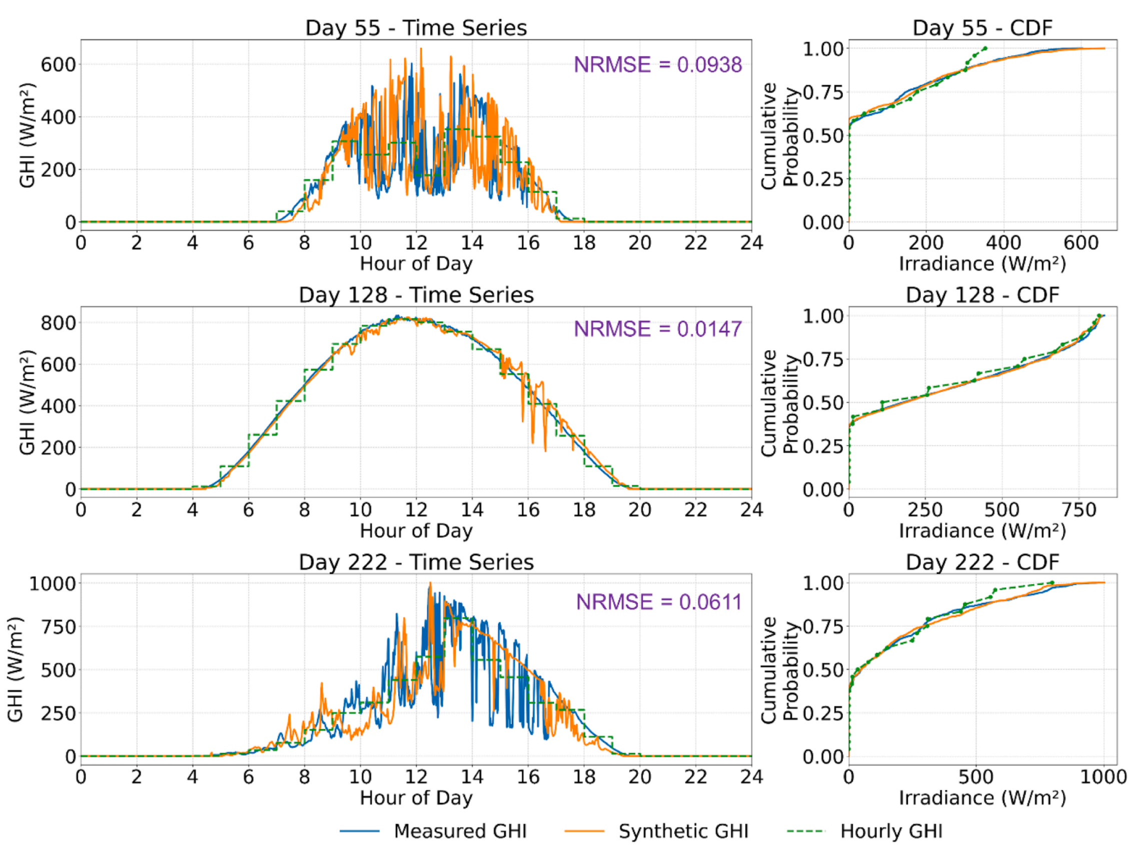

Fig. 4. Comparison of measured and synthetic global horizontal irradiance (GHI) for three random days in Berlin, Germany. NRMSE and CDF are the normalized root mean squared error and the cumulative distribution function of the measured and synthetic GHI values over each day, respectively.

```
Timezone: Europe/Berlin
Start: 2018-01-01 00:00:00+01:00
End: 2018-12-31 23:59:00+01:00
Detected Köppen-Geiger Zone: Cfb
Mapped Climate Zone: Cfb

                     day      synthetic_ghi
count      525600.000000      525600.000000
mean          183.000000         137.460745
std           105.366129        229.2251564
min             1.000000           0.000000
25%            92.000000           0.000000
50%           183.000000           0.000000
75%           274.000000         185.035931
max           365.000000        1218.566709
```

Fig. 5. Output of the SolarModel function from the ETHOS.TISED Python package. Additional output may be printed if the model class performs data imputations.

root mean squared error for each day produces an annual value of 6.8 % and the Kolmogorov-Smirnov integral is 0.1 %. These results are consistent with previously reported validation results in Ref. [14] and confirm the correct behavior of the software implementation.

While Fig. 4 presents profiles with close agreement, some individual days may deviate due to measurement errors or limited representation in the database. However, since each day is separately optimized, the daily cumulative irradiance remains almost the same. This ensures high overall accuracy and mitigates underestimation effects associated with hourly data in energy system models [7,21]. The database can also be extended to include additional climate types, improving representation of diverse irradiance patterns. Further examples and all steps required to reproduce the example, including data preprocessing and model configuration, are provided as scripts in the *Examples* folder of the repository, enabling reproducibility or adaptation to new locations and datasets with minimal effort.

Fig. 5 summarizes the key outputs of the model, including selected internal metadata processes and statistical indicators. Notably, the Köppen-Geiger climate zone of the location is reported. If the exact climate type is unavailable in the database, a similar mapped type is assigned automatically, based on the work of Ref. [21]. Since only the downscaling year is supplied as an input, the start and end times are also printed in the snippet, before statistical properties of the data, including the mean, standard deviation, minimum, range, and maximum values. Further documentation is provided in the GitHub repository to guide users through installation and common use cases.

4. Impact and discussion

The ETHOS.TISED model constructs sub-hourly variability from hourly solar irradiance data at any location, addressing a key limitation in high-resolution energy system modeling: data scarcity. By bridging the temporal resolution gap between the commonly available meteorological datasets, usually in hours, and the accurate and reliable energy system models relying on minute resolution, the tool significantly expands the usability of existing data sources without the need for costly high-frequency measurements.

For energy system researchers and modelers, ETHOS.TISED supports more accurate representation of solar generation variability, improving analyses of operational costs, components sizing, control strategies, ramping behavior, and grid stability. The synthetic minute resolution data improve the representation of intra-hour fluctuations that are otherwise lost in hourly datasets, leading to more reliable assessments of system flexibility requirements and operational constraints. Mantuano et al. [45] applied ETHOS.TISED in their work on data imputation, converting hourly resolution data to one minute in locations bereft of sub-hourly resolution data. Hourly resolution data underestimates costs and components' capacities (such as inverter) up to 1.7 % and 50 % respectively, as compared to minute-scale resolution [7,10]. The use of ETHOS.TISED to increase the hourly resolution GHI to one minute significantly reduces the cost and components' capacity underestimations, indicating the effective application of the software in energy system modeling [21].

In applied contexts, the tool benefits planners, utilities, and policy makers by enabling high-resolution solar assessments in regions where only coarse temporal data are available. This is particularly valuable for scenario analyses, long-term planning studies, and climate-impact assessments, where measurement-based minute-resolution data are scarce or non-existent. In addition, the availability of synthetic minute-resolution irradiance data is highly relevant for the design and analysis of self-sufficient and off-grid energy systems, such as those in rural or remote areas, as well as for applications with high reliability requirements, including critical infrastructure and healthcare facilities. By providing an open-source, reproducible, and computationally efficient downscaling approach, ETHOS.TISED promotes transparency and consistency in solar data preprocessing workflows.

5. Conclusions

This paper presents ETHOS.TISED, an open-source Python package for temporal downscaling of solar irradiance data from hourly to minute-scale resolution. The software implements a daily indicator matching framework that introduces sub-hourly variability while conserving the daily energy output and mean values. Its efficiency and global applicability are showcased by the validations and applications across multiple locations, different years, and various climate types, with good statistical scores in normalized root mean squared error and the Kolmogorov-Smirnov integral test. By formalizing this approach in a reusable software implementation, ETHOS.TISED bridges the gap between the methodological development in temporal downscaling and its practical applications in high-resolution energy system modeling.

While one of the major limitations of high-resolution modeling is data scarcity, ETHOS.TISED addresses this by providing highly resolved time series data. This, in turn, improves the level of detail in energy system modeling, improving cost, capacity estimation, variability analysis, grid integration studies, and scenario modeling. The modular architecture and reliance on the standard Python library facilitate integration into existing data workflows and support reproducible research practices.

The current version of ETHOS.TISED has some limitations. First, downscaling is restricted to data from 2004 onwards, as this is currently the earliest year supported by the extraterrestrial irradiance API provided by Copernicus. Second, the current implementation only supports the downscaling of annual datasets and does not yet allow for the processing of shorter or non-annual time periods. Third, the output resolution is presently limited to minute-scale data, and extensions to other sub-hourly resolutions have not yet been implemented. Addressing these limitations constitutes a natural direction for future development and will further enhance the applicability of the framework. With this, ETHOS.TISED is expected to serve as a robust and extensible tool for generating high-temporal-resolution solar irradiance time series across a wide range of scientific and applied energy research contexts.

CRediT authorship contribution statement

Olalekan Omoyele: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Julian Belina:** Writing – review & editing, Writing – original draft, Software. **Noor Titan Putri Hartono:** Writing – review & editing, Validation, Supervision. **Maximilian Hoffmann:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Jann Michael Weinand:** Writing – review & editing, Supervision, Resources, Methodology, Formal analysis, Conceptualization. **Miguel Larrañeta:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jochen Linßen:** Writing – review & editing, Supervision, Funding acquisition. **Detlef Stolten:** Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table 3
Methods of downscaling solar irradiance.

Approach	Principle	Representation of sub-hourly variability	Data dependency	Computational demand	Typical limitations
Deterministic	Uses mathematical rules to interpolate between hourly values	Very limited, smooth transitions only	No reference data required	Very low	Very low accuracy, cannot produce consistently reliable profile
Stochastic	Introduces random variabilities constrained by statistical properties	High, captures variability and intermittency	Requires statistical calibration data	High	Risk of unrealistic sequences if poorly constrained
Markov-based	Models transitions between discreet irradiance states	High state dependent variability	Requires state transition probabilities	High	Increasing complexity with the number of states
Machine learning	Learns temporal patterns from historical high-frequency data	Potentially very high, data driven	Large, labelled datasets required	Very high	Limited generalization beyond training data
Non-dimensional	Matches solar irradiance variability indicators	High, physically consistent variability	Requires representative profile database	Low to moderate	Performance depends on reference profile coverage

Table 4
Five daily variability indicators.

Indicators	Definitions	Math expression
Clearness index [46]	The ratio of measured irradiance, H, to extraterrestrial irradiance, H_o	$k_d = \frac{H}{H_o}$
Variability index [47]	Quantifies the temporal variability of measured solar irradiance, H_k, relative to a reference extraterrestrial irradiance, H_0. Δt is the time interval and n is the number of intervals in a day.	$VI = \frac{\sum_{k=2}^{n}\sqrt{(H_k - H_{k-1})^2 + \Delta t^2}}{\sum_{k=2}^{n}\sqrt{(H_{o,k} - H_{o,k-1})^2 + \Delta t^2}}$
Normalized variability index [48]	Scales the variability index of the measured irradiance, H_k, by the variability of the maximum extraterrestrial irradiance, H_{max}. Δt is the time interval and n is the number of intervals in a day.	$NVI = \frac{\sum_{k=2}^{n}\sqrt{(H_k - H_{k-1})^2 + \Delta t^2}}{\sum_{k=2}^{n}\sqrt{(H_{max,k} - H_{max,k-1})^2 + \Delta t^2}}$
Distribution [37]	The ratio of the sum of irradiation over the morning period, H_{mn}, to the sum of irradiation over the entire day, H_T.	$F_m = \frac{H_{mn}}{H_T}$
Integrated complementary cumulative distribution function [49]	Quantifies the overall picture of the irradiance variability. The CCDF is the complementary cumulative distribution function. H_{min} and H_{max} are the minimum and maximum daily irradiance values, respectively.	$ICCDF = \int_{H_{min}}^{H_{max}} CCDF(H)\, dH$

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