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Localized Actual Meteorological Year File Creator (LAF): A tool for using locally observed weather data in building energy simulations

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ABSTRACT

The Localized Actual Meteorological Year File Creator (LAF) application provides web-based access to real meteorological data and processes it into a weather file suitable for building energy modeling. Building energy consumption is affected by what is inside the building (such as occupants, appliances, HVAC systems, etc.) and by what is outside: the weather conditions the building is exposed to. However, freely available weather data files are limited to a number of specific locations, usually airports, which are often located away from city centers where buildings are concentrated. The authors have developed a new tool that supports the investigation and quantification of micro-climate conditions on building energy consumption. LAF is built on the Python open-source programming language and has a Graphical User Interface (GUI) that allows users to create custom weather data files for building energy simulations. Many sets of actual meteorological year weather data for long time periods are publicly available online (such as the MesoWest database) for thousands of locations in the US. LAF selects weather data according to user specifications and automatically processes it through an API across multiple weather stations and multiple time periods. The user may easily select a specific location, time frame, and time step that best meets their needs. This article presents a useful tool for energy modelers, building designers and operators to assist with building performance analysis and optimization.

Code metadata

Current code version	v1.0
Permanent link to code/repository used for this code version	https://github.com/ElsevierSoftwareX/SOFTX_2018_60
Legal Code License	LGPL
Code versioning system used	Git
Software code languages, tools, and services used	Python
Compilation requirements, operating environments & dependencies	Available pre-compiled for major operating systems
If available Link to developer documentation/manual	https://github.com/SSESLab/laf/blob/master/README.md
Support email for questions	amanda.d.smith@utah.edu

1. Motivation and significance

In 2018, commercial and residential buildings accounted for about 40% of the energy use in the United States [1] and in previous years buildings have accounted for 21% of primary energy consumed in the world [2]. Buildings are also responsible for a substantial share of the emissions in urban environments, contributing to air quality issues and consequent health implications.

Building energy simulations play a crucial role in improving the energy and environmental performance of actual buildings. According to Raftery et al. [3], building energy simulation is considered the best practical approach for performance analysis in the building industry. By taking advantage of ever more powerful

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computational resources and having more exact building models, it is possible to have increasingly precise predictions of building energy loads.

Accurately predicting a given or proposed building's energy load has important economic and environmental consequences for those who will be managing the building's energy use, but increasingly accurate predictions resulting from more highly resolved weather data are also of great interest to the research community as well [4,5], due to their relevance to addressing questions relating to large-scale adaptation to climate change and management of peak electricity demands. We propose here a novel, customizable tool that provides widespread access to the use of actual observed weather data within building simulations.

Building energy modeling (BEM) or building performance simulation consists of using computer software to predict building energy loads. An example of a BEM platform is EnergyPlus [6], a free, open-source software package developed by the U.S. Department of Energy (DOE). It requires two basic inputs to start the simulations: the building model, in Input Data File (.idf) format, and the weather data, in EnergyPlus Weather (.epw) format as illustrated in Fig. 1.

The IDF file contains the information about the building itself (including its geometry, material construction, and type of HVAC system). The DOE, in collaboration with many national laboratories and US colleges, has been financing and developing building models and building energy simulation packages intended to progress toward a more accurate representation of the American building stock [7,8].

The EPW file contains the weather data, including temperature, humidity, solar radiation, wind speed, and rainfall. For U.S locations, the weather data for EnergyPlus simulations are typically taken from Typical Meteorological Year (TMY) files [9]. They provide an annual data set that contains hourly weather values that represent typical conditions for a specific location, considering a more extended time interval, such as 30 years. Although they were created to represent a typical meteorological year, TMY weather data are not site-specific to most U.S. commercial buildings or to a given calendar year. The weather file represents only one location per city, typically an airport weather station, while most commercial buildings are located near densely populated areas that are geographically separated from the airport.

The weather influences building energy consumption on multiple scales. On one hand, macro-climate conditions influence the regional weather. Different urban areas are located in regions with unique geographic features that will affect the weather differently at a regional scale.

On the other hand, microclimate conditions are also important in terms of building energy consumption. A building's energy demand in urban environments is influenced by multiple phenomena, driven by the urban physics in that area. Structures are subjected to: (i) increases in ambient air temperature due to urban heat island effects, (ii) reductions of wind speeds due to wind-sheltering effects, (iii) reduced energy exchanges during night due to reduced sky view factors, (iv) altered solar radiation gains due to shadowing effects and reflections, and (v) altered radiation balances due to interactions with surrounding structures [10–12].

Particularly in cities characterized by warm climates, urban heat islands can drastically alter the overall urban energy consumption and thus affect health and comfort of the citizens [13]. As illustrated by Yavuzturk [14], the temperature of the asphalt on highways increases considerably with respect to other materials within the urban canopy. This effect is augmented due to a lack of vegetation along many major roads. The asphalt present on highways can, as a consequence, re-irradiate surrounding buildings and contribute to urban heat island effects.

Buildings can be affected by a number of other site-specific phenomena, including concentrated air pollution [15,16] or the presence of dense vegetation or other human structures nearby. Each of these can alter the building's surrounding weather conditions, especially the effective ambient temperature and the amount of radiation a given surface on the building receives. Furthermore, if the building is at a different altitude than the location where the weather file being used was created, or if it is located in an urban canyon, it may experience local weather patterns that are not represented by a generic weather file.

Many authors in the literature [11,17–20] researched the impact urban microclimate phenomena may have on renewable energy sources. Additionally, extreme peaks in microclimate-related weather variables that are not captured by TMY files can substantially affect the performance of renewable energy sources such as PV and CSP systems [21,22]. As stated by Pyrgou et al. [23] "experimentally collected weather data taking into account local phenomena should be used in building simulations instead of the traditional weather data-sets, i.e. TMY".

Currently in both the research and industry communities, to account for urban microclimate in building energy modeling and renewable power generation systems modeling, three main practices are commonly used:

(i) The first option consists of buying weather data, possibly already formatted for building energy simulations. The data may just be historical data-sets of weather values in selected locations or they might be interpolations of historical data-sets, aimed to represent "average" weather conditions. Services such as Meteonorm [24] and White Box Technologies [25] sell weather data and there are many examples in the literature of researchers who took advantage of these services [26–30]. When weather data are proprietary, the user is only partially aware of the quality and origin of the purchased data, and the procedures employed to generate the data are usually not shared with the customers.

(ii) A second option consists of transforming TMY3 data to incorporate urban microclimate effects. TMY3 is the most recent version of the TMY data sets [9]. In the literature, multiple studies show the application of algorithms to adapt weather data in Hong Kong [11,31], Perugia (Italy) [23], Thessaloniki (Greece) [32], Melbourne (Australia) [12], and Hangzhou (China) [33]. This option may be more economical, but it relies on the parameterization of urban features or on detailed computational analysis (i.e. CFD) of the same, which requires expert knowledge and analyst time. The methods are mostly tailored to the specific location where they were developed and may not be transferable.

(iii) The third option consists of using actual meteorological year (AMY) weather data, taken from active weather stations [11,12,23,33,34]. Although this practice can be convenient, both economically and in terms of accuracy, it is not always possible to have many weather stations in the same urban area, providing reliable data for multiple years.

The lack of available and reliable data, therefore, limits the possibility to study the impact and the variability of microclimatic effects, as represented by observed weather data.

In prior work, the authors [35] began to address the following questions: how do microclimate conditions vary inside the same urban environment? Does their variability have the same impact on the different building energy loads? What is the relative weight of the discrepancy between weather data taken in different areas of the same city and TMY3 data? What is the error associated with using TMY3 data to predict building energy loads? Site-specific weather data provided by the MesoWest database [36] were employed to compare the weather from two stations in the Salt Lake Valley with the TMY3 file for Salt Lake City, Utah. The previous questions were only partially answered. The main conclusions of this analysis were: (i) weather boundary

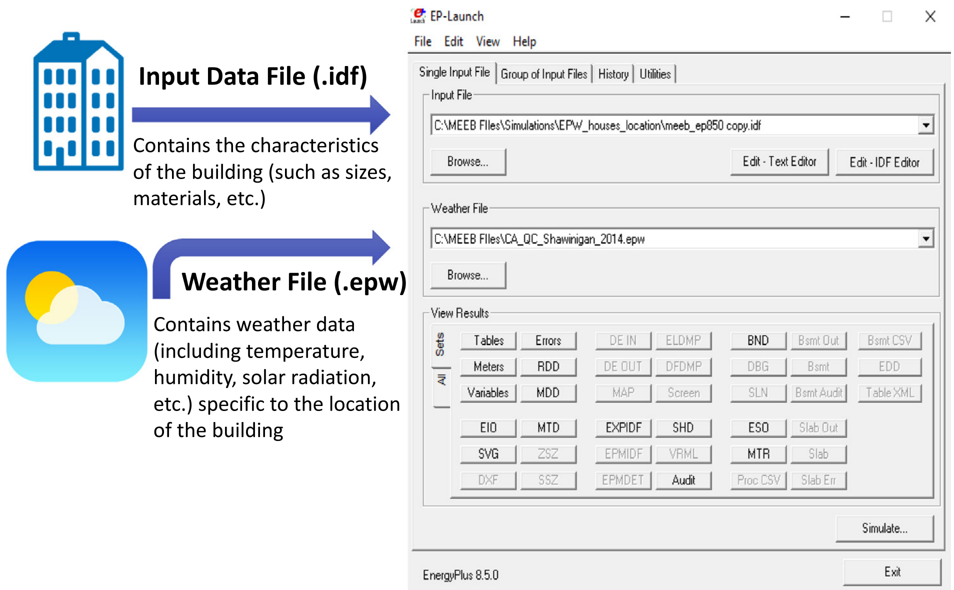


Fig. 1. EnergyPlus main interface.

conditions negligibly affect electric loads (this was verified for four building types); and (ii) heating loads are highly affected, however, the impacts on heating loads are not consistent from year to year.

A larger range of years of data and more weather stations are needed to have a broader picture of the spatial and temporal variability of site-specific weather conditions. However, producing weather files ready to be used for EnergyPlus simulations (EPW files) is a technically challenging task that might prove a barrier to use of weather data outside the standard files provided with EnergyPlus [37], especially to inexperienced users. Additionally, MesoWest data often contain missing data-points and need to be processed before being converted into EPW files.

In order to meet these needs and to fully take advantage of the MesoWest database in the study of the microclimate variability in urban areas, the authors introduce a new tool here. The Localized AMY File (LAF) Creator can convert input custom weather data into EPW files, ready to be used for EnergyPlus simulations. The output file will be created based on the TMY3 source file representative of the closest city. Custom weather variables (such as dry bulb temperature, wind speed and direction or relative humidity), as selected by the user, will be written over the ones taken from TMY3 data.

The app will also pre-process custom weather files, checking their quality performing imputation for missing data points. Finally, the app will give the user the possibility to automatically download weather data from the closest MesoWest weather station as well as the closest available TMY3 file. In contrast with the common practices described above, LAF freely provides available weather data, measured by multiple stations in the same cities and over multiple years, in a format that is easily usable by the building energy modeler.

It represents a useful tool to provide site-specific weather data to building energy system designers and to expand the investigation of the effects of weather variability to many new locations.

2. Software description

The software is written entirely in Python [38] (version 3.6). The Graphical User Interface has been developed taking advantage of the library PyQt5 [39]. Additional libraries were employed to deal with computation and data handling: SciPy [40], Pandas [41], NumPy [42] and Matplotlib [43].

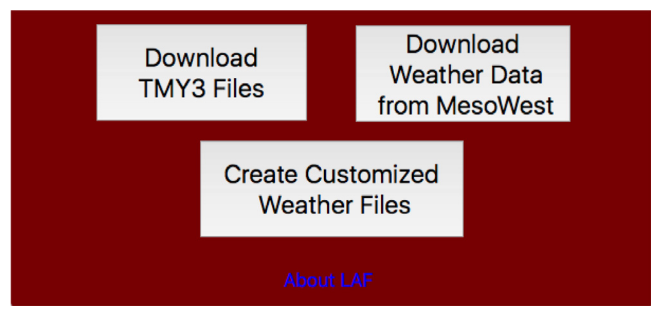


Fig. 2. Screenshot of the main interface.

The source code has been compiled for MacOSX and Windows using py2app [44] and PyInstaller [45] respectively.

It is freely available on *Github.com* (https://github.com/SSESLab/laf).

2.1. Software architecture

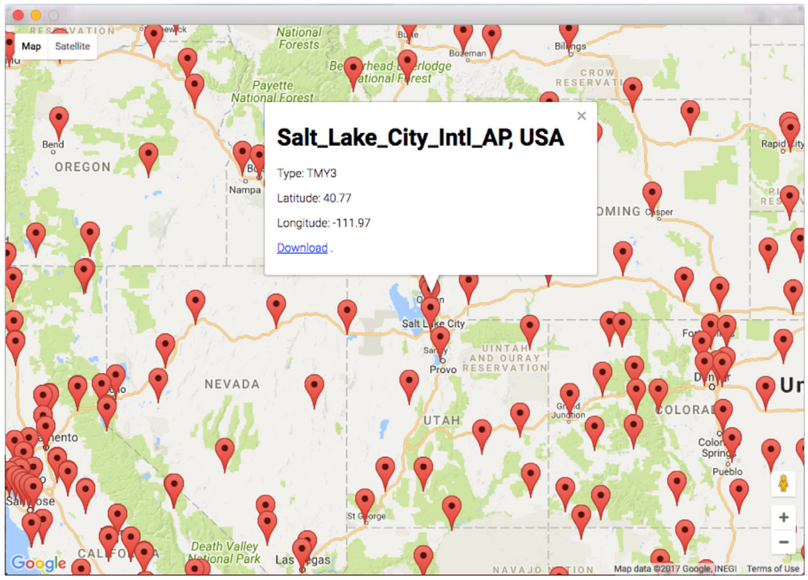
The software is composed of three separate modules: the *TMY3 module*, the *MesoWest module* and the *EPW (weather file creation) module*. Each module is independent and can be used individually, with no dependence on the others (see Fig. 2).

TMY3 module

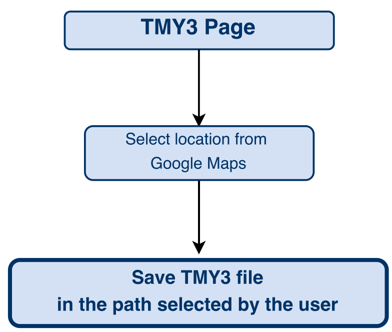
Fig. 3.a shows the screenshot of the Graphical User Interface for the *TMY3 module*. The operations related to each button are shown in the flowchart in Fig. 3.b.

A Google Maps interface shows all the available stations in USA and Canada providing *.epw* files. The user can choose the preferred urban location, click on the closest station and directly download the *.epw* file for that location.

The stations shown come from a list available on http://climate.onebuilding.org [46]. It provides coordinates and a web link to download the TMY3 file for each available location. CWEC files for Canadian urban areas are also included.



(a)



(b)

Fig. 3. Screenshot and flowchart representation of the *TMY3 module*.

MesoWest module

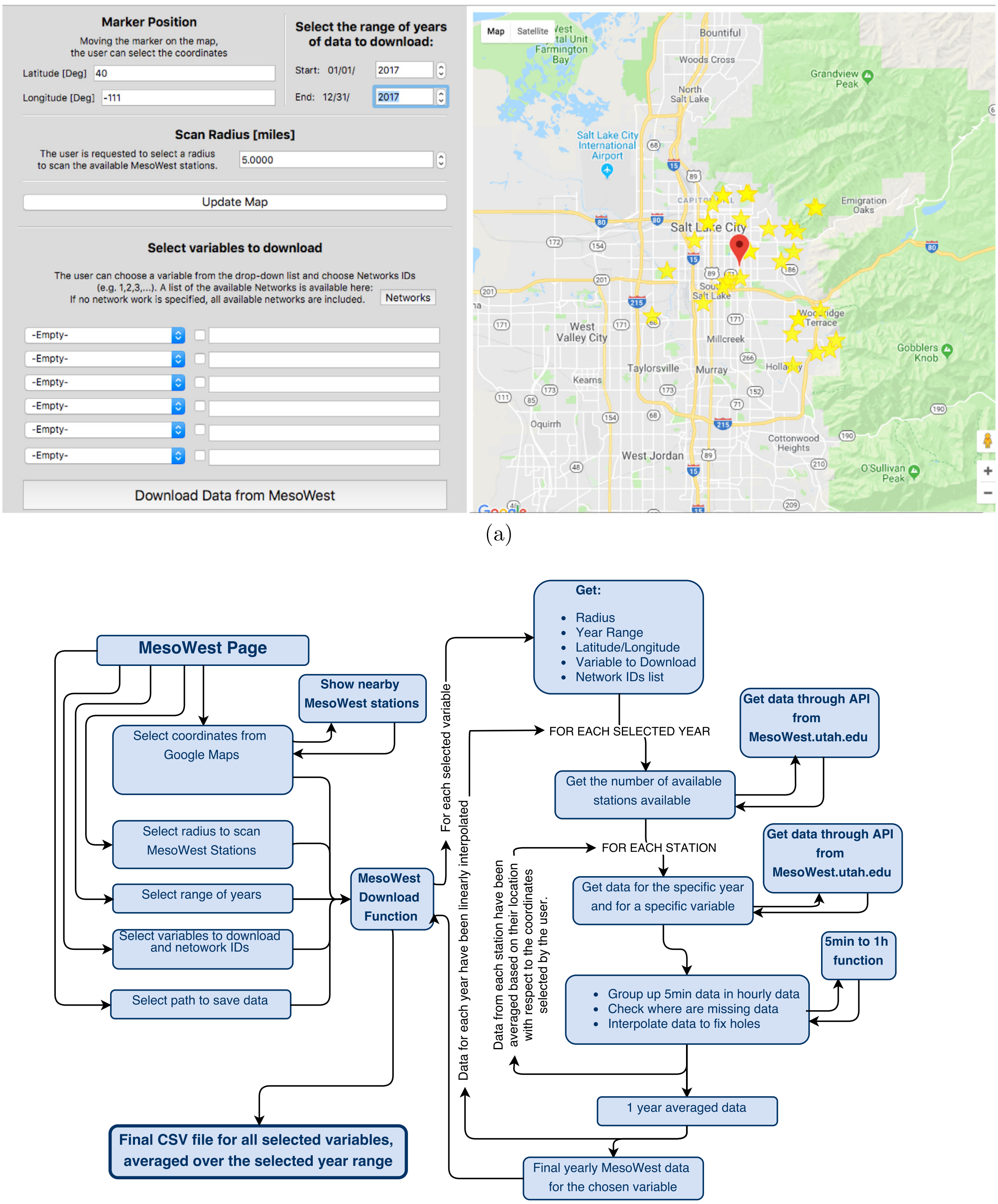
Fig. 4.a shows the screenshot of the Graphical User Interface for the *MesoWest module*. The operations related to each represented button are shown in the flowchart in Fig. 4.b.

Similarly to the previous module, the user will choose the geographic coordinates to download data accordingly. The user can select the desired location by moving the marker on the map. On the map, the active MesoWest stations in the selected radius in the selected year are shown [36]. The user will select a radius (5 miles by default) to scan MesoWest stations, which can be extended up to 30 miles. Clicking on *update map*, after the radius and the marker location are changed, will cause a new group of MesoWest stations to be displayed. Clicking on each station, the user can inspect the name of the station, its coordinates, the corresponding Network ID and the available weather variables and their associated period of record. Multiple meteorological networks are available to download data from. With the MesoWest API it is possible to use a flag to specify the networks to use. Each network has specific features and can capture specific variables, but a station or network might be biased due to its location, sensor accuracy, sensor reliability or sensor drift. As shown by Tyndall et al. [47], some networks are more reliable than others. The NWS (National Weather Service) network "consists of professional grade equipment", while the CWOP (Citizen Weather Observer Program) network "frequently relies on lower-grade sensors sited on residences". On top of that, it is not possible to know the condition of a station located in private houses; the stations' surroundings or any possible bias effects are not known. However, in some cases the quality of the data of CWOP is comparable to NWS data [47].

CWOP stations can be highly unreliable, but they also have the advantage of being the most diffuse network in many urban areas. The current software was created to provide customized micro-climate urban weather data to run building energy simulations. For this reason, the user has the option to choose what networks to include for each selected weather variable. The CWOP network is available, along with the NWS network, RAWS (Remote Automated Weather Stations), the MW (MesoWest) network and other networks listed in the window accessed through the "Network" button. Each network could potentially be more reliable for certain variables rather than others in a given location; the user has the opportunity to select the most appropriate list of networks for a particular weather variable. The user is cautioned to consider the possible biases of the CWOP data, as well as any bias effect of any given network.

Moreover, by moving the marker and the radius, it is possible to check which variables are available in each station, which network provides the variables, and what the corresponding period of record is. The user can select the desired year accordingly. If more than one year is selected, the output file will contain a linear average of the data for each selected year.

It is important to understand the implications when selecting multiple years. The TMY3 data are the most recently released



(a)

(b)

Fig. 4. Screenshot and flowchart representation of the *MesoWest module.*

version of the TMY data, which were constructed taking into account generally 15 to 30 [9] calendar years. For each month, a representative month (among the years considered) was selected that had behavior representing as closely as possible the average weather behavior in the selected month over the years considered [9]. A particular month in a TMY3 file, though, is not a linear average of all the variables over the selected time range. It actually corresponds to a particular set of data from a specific month from a specific weather station for each urban area, typically in the closest airport.

Fig. 5 shows the comparison between the dry bulb temperature from the TMY3 data for Salt Lake City, UT and the linear average of dry bulb temperature between 2004 and 2016 for the Salt Lake City airport. The plot shows daily average data for each day of the year. The average dry bulb temperature from the airport is smoothed out with respect to the TMY3 data. The latter maintains more of the inherent temperature fluctuations since the data employed belong to real historical months. The averaged airport data, because of the arithmetic mean procedure, do not show the fluctuations visible in the TMY3 data. Even

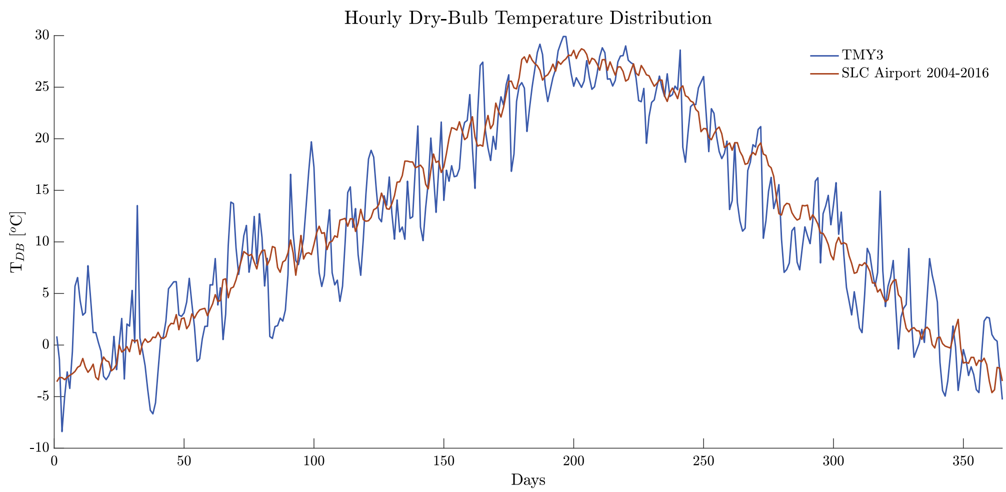


Fig. 5. Comparison between TMY3 data and averaged AMY data for the Salt Lake City, UT airport.

though on average the data might show the same temperature trend, in terms of subsequent building energy consumption, the locally varying temperature fluctuations could play a major role. In the literature it is possible to find examples of linear averages of weather data from multiple years [23]. Nevertheless, if the weather data are used to perform building energy simulations, the user is advised not to directly employ averaged data over a multi-year period when the building's thermal dynamics are of interest.

When the "Download from MesoWest" function is called, multiple iterative loops are nested in it. The first loop is going over each of the selected variables. Then, for each variable, the second loop goes through each selected year. Finally, for each variable and each year, the third loop goes through each identified station in the radius specified by the user starting from the chosen location. Before executing the last loop, the MesoWest API is called to get the number of available stations (for the specific year and variable) and their distance from the user's location.

Inside is the third loop, as shown on the right hand side of Fig. 4.b. The MesoWest API is called again to download the data for each station, each year and each variable. A full explanation of the MesoWest API is provided on their website [48].

The data downloaded from MesoWest have a time step of 5 min and may have some missing time steps randomly distributed in a whole year period. In order to account for this, the function "5 min-to-1 h" is called. This function groups the data into hourly time steps, averaging the available 5-min data in the same hour. Subsequently, it locates where the missing time steps are and applies a linear interpolation to fill the gaps. If the missing data comprise more than 20 consecutive time steps, the quality of the data is considered to be too low and the data are not taken into account.

At the end of the third loop, each yearly vector for each station is averaged. The data from all the considered stations are first interpolated linearly according to the latitude only, then according to the longitude only, and finally the two interpolated values are averaged. This means that the values in each station are weighted geometrically based on their distance from the location chosen by the user; the stations closer to the chosen location influence the final interpolated value more than stations further away. It is the user's responsibility to consider how far from the chosen location the available stations are, and to judge their accuracy based on the local geography. If they are far away, the data probably will not reliably represent the weather in the selected location. If only one station is available, the data from that station is assumed to be representative of the weather in the selected location.

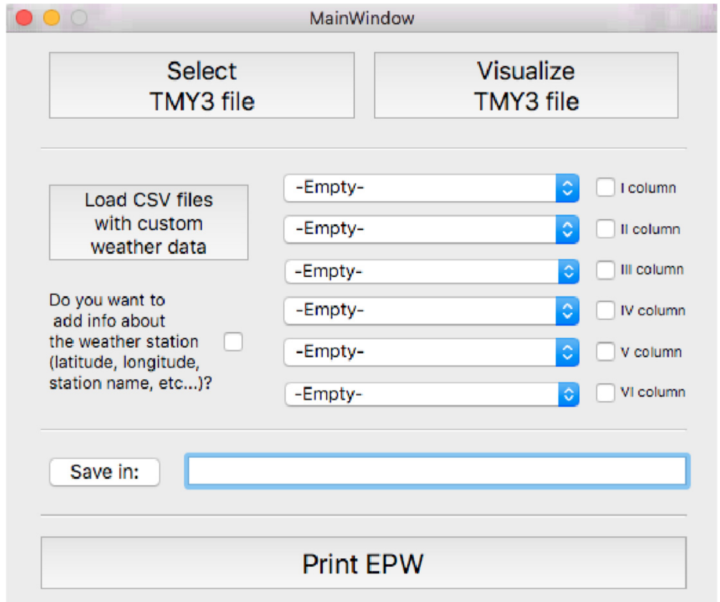
Leaving the second loop, then, each yearly vector has been averaged over the total year-range declared by the user. This procedure has been repeated for each selected variable. Finally, a *.csv* file is output and saved in the path declared by the user. The *.csv* file contains as many columns as the number of declared variables. Each column is formed by a 1 line header, reporting the name of the variable, and 8760 values, corresponding to the total amount of hours in a one year period. The *.csv* contains either actual weather data for a specific weather station or the interpolation of actual weather data from multiple weather stations. Therefore, the *.csv* file represents an Actual Meteorological Year (AMY) file.

EPW module

Fig. 6.a shows the screenshot of the Graphical User Interface for the *EPW module*. The operations related to each button are shown in the flowchart in Fig. 6.b.

Similarly to the previous modules, the user must indicate the location of multiple files to perform the requested task. This module is independent from the previous two, but the files output from those two modules can be directly employed to create a customized *.epw* file with this module. Initially the TMY3 file to be modified is required. Once the user selects it, they may visualize it.

As mentioned by Bhandari et al. "The minimum weather data parameters necessary for whole building simulations accuracy are: dry bulb temperature; wet bulb temperature and/or relative humidity, global, direct normal and diffuse solar radiation (only two variables are required to represent solar radiation); wind speed and wind direction (for natural ventilation and infiltration)" [34]. This is confirmed by other authors as well [11,12,31,33,49,50], although sometimes the relevant variables are reduced to dry bulb temperature, relative humidity and wind speed [12] or to dry bulb temperature and relative humidity only [33]. The customized *.epw* file for a specific location in an urban area will be created starting from the TMY3 file relative to the same urban area. Only the columns corresponding to 6 weather variables are currently available for customization: dry bulb temperature, relative humidity, wind speed, wind direction, atmospheric pressure, and dew point temperature. The rest of the variables are assumed to be homogeneous throughout the same urban environment. Although solar irradiation has been reported to be important for the accuracy of building simulations, the availability of solar radiation data is limited. Additionally it is reasonable to assume the distribution of incoming radiation is more likely to be homogeneous in the same urban area compared



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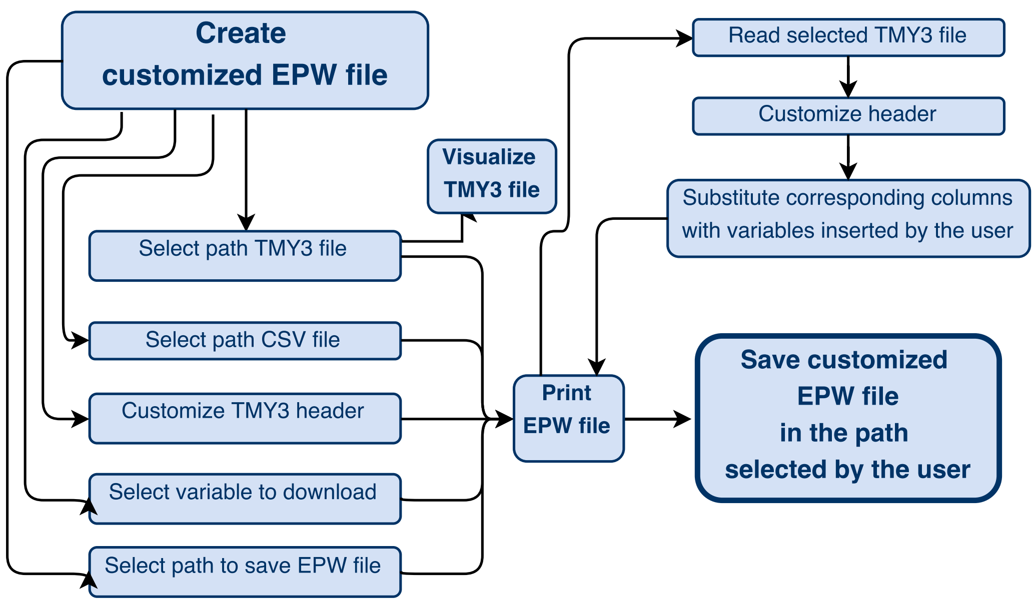


(b)

Fig. 6. Screenshot and flowchart representation of the *EPW module*.

with, e.g., temperature. Atmospheric pressure and dew point temperature have been taken into account in order to respect the proper psychrometric relationships with dry bulb temperature and relative humidity.

The TMY3 file provides solar irradiation values assuming no shading effects or reflections on the considered building by the surrounding urban canopy. If the user is trying to generate a site-specific weather file that would involve alteration of solar irradiation, it is necessary to include these effects directly in the building energy simulation software. For example, in EnergyPlus it is possible to create virtual surfaces around the building model in order to simulate the shading effect of surrounding buildings or trees. The header of the TMY3 file is also read by the module and can be customized by the user to indicate the geographical details of the location of the new weather data.

Next, the user is requested to input a *.csv* file containing the weather variables to be substituted in the original TMY3 file, and to indicate what each column corresponds to. The *.csv* file will contain as many columns as the number of selected variables. Each column contains one line for the header with the name of the variable and 8760 values for each variable. After indicating the path to save the customized weather file, the user may launch the function "Print *.epw* file". This function accepts the selected TMY3 file as input, substitutes the header with the one defined by the user, substitutes the TMY3 columns corresponding to the variable selected by the user with the new data provided by the user, and saves the new *.epw* file in the path indicated by the user.

It is important to emphasize that the psychrometric relationships are preserved. Dry bulb temperature, relative humidity, dew point temperature and pressure are correlated in LAF, so that if any of these four variables is customized by the user,

Table 1
Mean and standard deviation of dry bulb temperature for different years at the William Browning Building (WBB).

	$\overline{T_{DB}}$ [°C]	$\sigma_{T_{DB}}$ [°C]
2004	11.78	10.84
2006	12.45	10.80
2007	12.93	11.67
2008	11.79	10.98
2009	11.62	10.76
2011	11.30	10.79
2012	13.72	10.46
2013	11.31	12.11
2014	13.17	10.10
2015	13.67	10.33
2017	12.95	10.90
Mean	**12.43**	**10.88**
TMY3	**11.87**	**10.59**

it will be used to calculate the corresponding non-customized psychrometric variable or variables.

The generated file has been tested with BEM simulations and can be used to run simulations with EnergyPlus. Using the appropriate converter [51], it is also possible to convert the created *.epw* file into eQUEST and DOE-2 BIN weather files.

3. Illustrative examples

To demonstrate and test LAF's capabilities, a simple analysis was performed for the Salt Lake Valley, Utah, USA, and is shared here. First, the TMY3 file relative to Salt Lake City was downloaded using the *TMY3 module*. Then, using the *MesoWest Module*, weather data for multiple years for the WBB station (Latitude = 40.76623°, −111.84755°) on the University of Utah campus were downloaded. The variables considered were: dry bulb temperature, relative humidity, wind speed and wind direction. The year range downloaded is listed in Table 1, as well as the mean and standard deviation of dry bulb temperature for WBB (William Browning Building, University of Utah) each year. A *.csv* file was output by the *MesoWest Module* and it was employed by the *EPW module*, together with the TMY3 data file for Salt Lake City. A customized *.epw* file was therefore created for each year and employed to run building energy simulations in EnergyPlus.

A commercial reference building model [8], representing a small office, was used to analyze the temporal variability of climate conditions at the WBB station. Building energy simulations were run for all the selected years and the results were compared with the results given by employing TMY3 data. The results for cooling and heating loads, relative to a TMY3 baseline, are shown in Fig. 7.

The relative difference with respect to TMY3 data can be as high as 30% for the heating load and as high as 20% for the cooling load, over the last 13 years at WBB. However, on average the weather conditions are quite similar to the ones described by TMY3 data, making it a reliable reference for generalized building energy simulations even though it cannot capture the expected behavior in a given year.

Additional analyses have been performed to investigate the temporal variability of micro-climate conditions in the Salt Lake Valley. Another station (the Salt Lake International Airport) and two more building models (a primary school and a restaurant) have been taken into account. The figures showing the results for heating and cooling loads, analogous to those shown here for the small office building example, are available in the supplementary material.

4. Limitations

When using LAF, the user should be aware of the following limitations:

• LAF does not provide solar radiation data. They can be quite important for building energy simulations, particularly. However, consistent and reliable measurements for radiation are much more rare than for the variables considered here. The inclusion of solar radiation data will be part of future developments.

• LAF does not control the availability of weather data, nor the availability of weather stations in any specific city. In some cases, the user may not find data for the requested years and/or in the selected location.

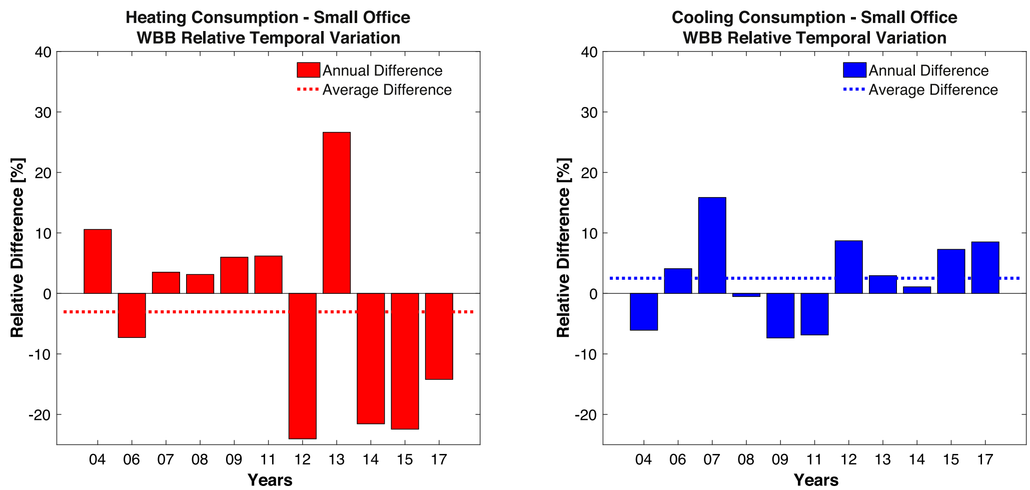
• LAF does not provide data comparable to TMY3 data, which are designed to be "representative" years rather than actual years. TMY data were created using multiple months over as many as 30 years. LAF provides actual weather variable values to be overwritten on existing TMY3 data. This means the user is making an implicit assumption that the variables that were not customized will not affect their simulation results, or that they are homogeneous over space and time. LAF allows the user to average multiple years of data together. As explained in this manuscript, though, this process may seriously affect the statistical characteristics of the data and it is not suggested for simulating building behavior. It is not appropriate to use one specific year as representative for a multi-year portion of the building's lifetime. The user should be aware of any uncharacteristic weather patterns in the location chosen that will show up in the weather data in a given year.

• LAF does not control the quality of the data provided by each network. Each network can be more reliable for some variables and less reliable for some others. The user is advised to refer to the literature [47] for more details about the MesoWest networks. Using data of poor quality can significantly affect the results of building energy simulations. In future versions, quality check algorithms will be implemented. However, the user is always responsible for evaluating the quality of the downloaded data, and may choose to compare them with TMY3 data for reference.

5. Impact and conclusions

The Localized AMY File creator has been tested with EnergyPlus and can produce ready-to-use *.epw* files for building energy simulations. It is equipped with a simple GUI that allows the user to efficiently take advantage of all its capabilities. This innovative tool allows for multiple types of analyses to study the temporal and spatial variability of micro-climate effects and their impact on building energy consumption. It allows for a quick and easy download of site-specific weather data (AMYs) in multiple stations in the same urban area. This extends the analysis of Bianchi et al. [35] to more thoroughly investigate the spatial variability. Likewise, it also allows for a quick and easy download of site-specific weather data for multiple years in the same station. This similarly extends the previous analysis [35] to investigate the temporal variability of site-specific weather effects. It also allows any researcher or practitioner to extend the previous analysis to multiple locations in the United States and Canada, not just to the Salt Lake Valley in Utah. Finally, it provides the user with an efficient way of downloading TMY3 data for building energy simulations.

LAF represents a useful complement to building energy simulations from commonly used building energy modeling software packages for manipulating, visualizing, customizing and converting weather data. It provides site-specific weather files that can increase the accuracy of BEM simulations, thereby promoting building energy conservation and optimal use of distributed energy resources. In contrast to other available tools, LAF provides



(a) (b)

Fig. 7. Temporal variability analysis. Relative difference between each year's (a) heating and (b) cooling consumption and TMY3's consumption for the WBB station.

free access to observed weather data for thousands of stations from a variety of sources across the United States and it provides them in a ready-to-use format for building energy simulations that is highly customizable by the user.

Additional case studies will more widely investigate the variability of microclimate conditions in urban areas, in order to better understand the advantages of using urban weather data over TMY3 data.

Declaration of competing interest

The authors declare that there is no conflict of interest in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.softx.2019.100299.

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