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Local and global sensitivity analysis and its contributing factors in reference crop evapotranspiration

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ABSTRACT

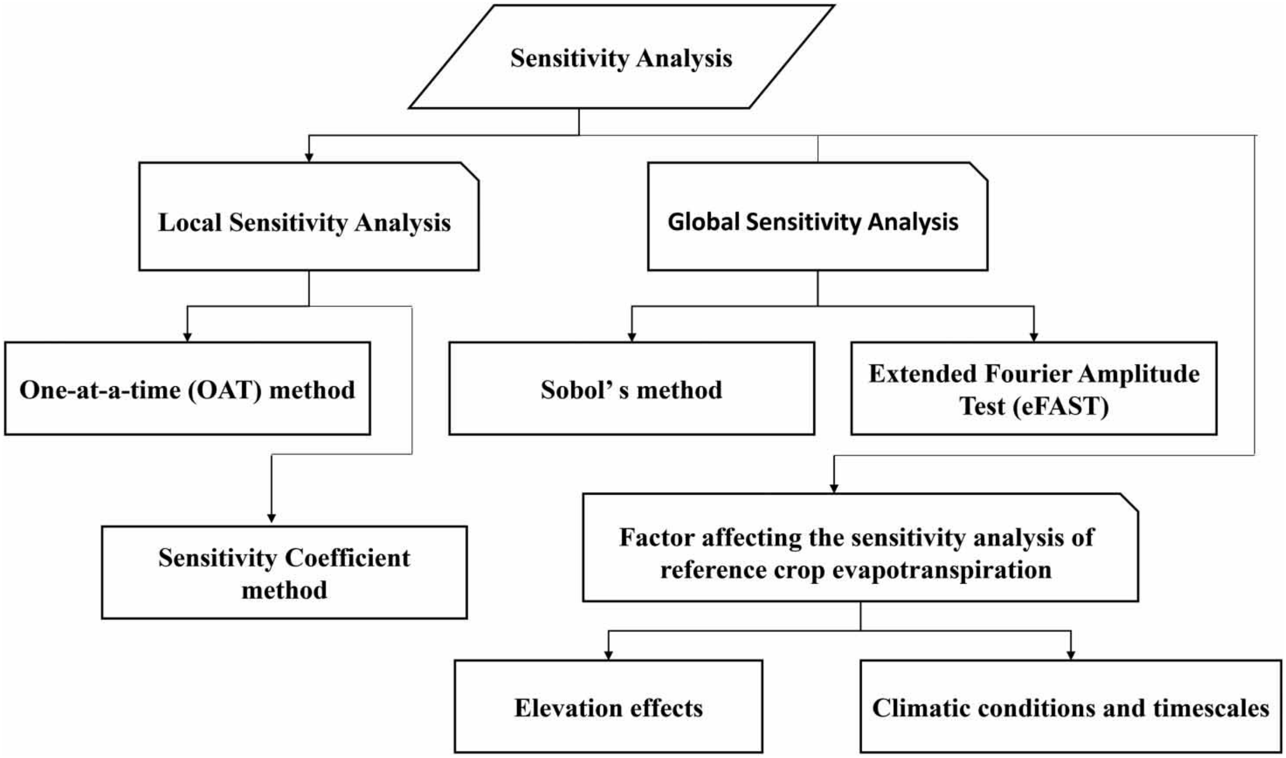
Sensitivity analysis (SA) intends to identify the key meteorological variables that affect the performance of reference crop evapotranspiration (ET_0) models. It is of importance in assessing the variability of meteorological variables and ET_0, especially in the face of increasing climate uncertainties. However, the surging of inconsistencies resulting from global changes in meteorological conditions due to climate change have impacted the ET_0 model estimation in different regions, with detrimental effects on water resources and crop production. Therefore, efficient SA is necessary to evaluate the impact of changes in meteorological variables that influence ET_0 model estimation. This mini review analyses the various SA methods applied in the field of ET_0, based on a comprehensive and comparative analysis of existing SA methods from all around the world. The study discusses the advantages and disadvantages of each SA method, as well as the factors affecting the SA of ET_0. The study also provides future prospects that may contribute to more solid and powerful analysis for ET_0 model estimations and conclusions.

Key words: global sensitivity analysis, local sensitivity analysis, reference crop evapotranspiration, sensitivity analysis

HIGHLIGHTS

- The local and global sensitivity analysis for ET_0 estimation were reviewed.
- The categories, methods, and limitations for SA were examined.
- The factors affecting the SA of ET_0 were discussed.
- The new possible research directions for SA in ET_0 estimations are outlined.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Sensitivity analysis (SA) examines how variations in meteorological variables (input factors) can affect the variations of reference crop evapotranspiration (ET_0). SA is utilized to determine the extent to which each meteorological variable contributes to variations in the ET_0 modelling (Agrawal *et al.* 2022). Conventionally, SA has been implemented through physical calibration, which is arduous and error-prone. SA based on automatic calibration procedures can be split into two categories: local and global methods (Haghnegahdar & Razavi 2017). Local methods focus on the effect of variables on the output by varying each variable (input) individually. Global methods focus on the influences of uncertain input by varying all the parameters simultaneously (Song *et al.* 2015). In practice, various SA methods play an important role in different fields such as medicine (Göksu *et al.* 2018), food and environmental safety (Sharafi *et al.* 2019), biomedical sciences (Qian & Mahdi 2020), building performance analysis (Pang *et al.* 2020) and the list goes on. Despite the limited application of SA methods in ET_0 models, it has been gaining attention in recent years. The precise estimation of various crops water requirement depends on the accurate calculation of evapotranspiration (ET) rate of the reference crop (Malik *et al.* 2021; Gul *et al.* 2022). Accurate ET_0 estimation also plays an important role in achieving sustainable water planning and management (He *et al.* 2022; Malik *et al.* 2022).

It is evident that the major challenges for ET_0 are climate change and the availability of meteorological data. Climate change has influenced the meteorological variables to varying degrees, subsequently affecting the ET_0. The increase in greenhouse gas concentrations in the atmosphere is causing the Earth's surface and lower atmosphere to warm, leading to changes in meteorological variables. Due to global warming, ET_0 is expected to increase with rising of the global temperature (Fan *et al.* 2021; Goh *et al.* 2021; Theng *et al.* 2022). Increasing ET_0 will thus contribute to a decline in irrigation water availability, which could affect crop yields (Sampathkumar *et al.* 2021). To understanding the effects of climate change on ET_0, SA examines how changes in different meteorological variables affect ET_0. The sensitivity of ET_0 can provide critical evaluation for identifying the most suitable models for ET_0 estimation under climate change conditions (Woo *et al.* 2021; Ng *et al.* 2022).

Additionally, the availability of meteorological data, such as temperature, solar radiation, wind speed and relative humidity, plays an important role in ET_0 estimation, as it is sensitive to changes or errors in meteorological data (Zhang *et al.* 2022).

Meteorological data is affected by instrumental and human errors that emerged from various sources, such as sensor calibration, settings of measurement sets, and data reading/recording (Biazar *et al.* 2019). Consequently, this leads to missing or unavailable of the meteorological data, which, in turn, affects the accuracy of ET_0 estimation. Thus, SA is necessary to understand the connection between ET_0 and meteorological variables. SA can help to identify the most important variables in ET_0 estimation, and gain insights into how these missing data might affect ET_0 models and predictions (Ndulue & Ranjan 2021).

The majority of reviews conducted on ET_0 focus on addressing the main differences between empirical ET_0 models in the context of different meteorological variables, performances and drawbacks (Ghiat *et al.* 2021). However, there is a lack of studies concerning the applicability of SA methods for ET_0 estimation under climate change conditions. As such, the purpose of this review is to fill this gap by comprehending the SA methods in one study, and highlighting the correlation among the main factors affecting the SA of ET_0. SA is typically the initial phase towards model calibration because it evaluates the degree of influence of different variables (input) on the models are. SA is effective in the identification of the dominant mechanisms in model behaviour and any relationship between variables The methodology for SA is interchangeable in various types of application in ET_0 estimation. Figure 1 depicts the steps for carrying out the SA in ET_0 estimation.

The goal of this paper is to review and present the application of SA in ET_0 modelling, provide practical examples on each SA method, and make future recommendations for applying SA in ET_0 modelling. The paper is organized as follows: Section 2 presents different types of SA methods typically adopted in ET_0 modelling. Section 3 reviews the degree of influence of ET_0 on its meteorological variables around the world. Finally, the future prospect for the use of SA methods in ET_0 modelling are presented in Section 4.

2. SENSITIVITY ANALYSIS METHODS USED IN ET_0 MODELLING

2.1. Local and global sensitivity analysis method

The methods for SA applied in the ET_0 estimation can be classified into local sensitivity analysis (LSA) and global sensitivity analysis (GSA). The previous developments in SA were mainly based on the obtaining point-based sensitivity measures. However, this definition is ambiguous and potentially misleading due to the limited practice of SA methods in ET_0 fields. This led to the advancement of GSA, which focuses on attributing the variability of the model responses to different factors, including the model variables, forcings, boundary and initial conditions (Razavi *et al.* 2019). The general overview, advantages and disadvantages of various LSA and GSA techniques in ET_0 modelling are outlined in Tables 1 and 2, respectively. Although GSA requires higher computationally efficiency compared to LSA, LSA is inadequate when the model is non-linear and monotonic, which will lead to low accuracy. GSA method can provide high-order interactions therefore it is regarded as a more reliable method.

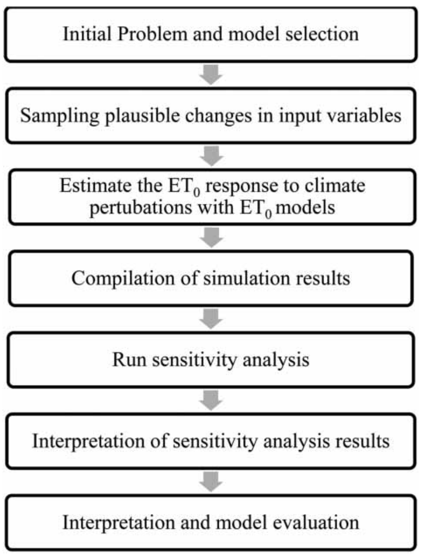


Figure 1 | Schematic flow diagram for SA in ET_0 modelling.

Table 1 | General overview of various LSA and GSA techniques in ET_0 modelling

	Local Sensitivity Analysis (LSA)		Global Sensitivity Analysis (GSA)	
Approaches	**One-at-a-time (OAT) method**	**Sensitivity Coefficient Method**	**Sobol's Method**	**eFAST**
Sampling Strategy	N/A	N/A	Sobol Sequence	eFAST sampling
Computational budget	Low	Low	High	High
Characteristics	Quantitative	Quantitative	Quantitative	Quantitative
Parameter Interaction	No	No	Yes	Yes
Coping with non-linearity	Yes	Yes	Yes	Yes
Robustness	Weak	Weak	High	High

Table 2 | The advantages and disadvantages of various LSA and GSA techniques in ET_0 modelling

Approaches	Advantages	Disadvantages
One-at-a-time (OAT) method	- Easy of operation and interpret, Low computational cost	- Prone to produce uncertain results - Largely rely on the scale of the chosen parameters.
Sensitivity Coefficient Method	- Easy of operation and interpret, Low computational cost	- Does not provide detailed interaction between the combinations of input factors.
Sobol's Method eFAST	- Great precision estimation as it provides error made on indices estimates via random repetition and/or bootstrap methods. - Able to incorporate the influence of input parameters over the whole range of variation. - Model independence (Adequate for non-linear and non-monotonic models)	- High computational cost - Difficult to apply in complex models with a large number of parameters. - If the number of parameters increase, a large number of model evaluations are required to get precise result.

2.2. One-at-a-time (OAT) method

In the One-at-a-time (OAT) method, the effect on model output is established by adjusting one variable (input) at a time while keeping the other variables constant. Since the OAT method does not measure the interaction between various variables, this method is error-prone and can produce uncertain results, especially for models that contain numerous variables with only a few influential inputs (Saltelli *et al.* 2019). The accuracy of sensitivity results for a certain input variable is associated with the value selected for other model variables. In addition, sensitivity results in OAT sampling mostly depend on the scale by which the input variable is varied (Razavi & Gupta 2015). The advancement based on the OAT sampling has developed more model-based methods such as regression, elementary-effect, factorial design and Monte Carlo.

2.3. Sensitivity coefficient (SC) method

Various sensitivity coefficient (SC) methods have been introduced in the application of ET (McCuen 1973; Coleman & Decoursey 1976), hydrological studies (Anderton *et al.* 2002). Saxton (1975) defined the SC method as the ratio of the amount of increase or decrease in ET_0 to the changes in each meteorological variable on a daily basis. The dimensionless SC values allow comparison between each meteorological variable. The larger the SC, the greater of degree of influence of the meteorological variables on ET_0 (Koudahe *et al.* 2018). The correlation between ET_0 and each variable relies on the absolute value of the SC. If $SC > 0$, ET_0 increases as the meteorological variable increases; whereas if $SC < 0$, ET_0 decreases as the meteorological variable increases. A SC of 0.1 for a meteorological variable is equal to a 1% increase in ET_0 when the meteorological variable increases by 10%. However, the method is sensitive to the magnitudes of ET_0 and the meteorological variables. In particular, the SC may not be a good indication of the significance of the meteorological variable sensitivity if the ET_0 or the meteorological variable is zero (Beven 1979).

Furthermore, Coleman & DeCoursey (1976) defined the SC coefficient that eliminated the bias caused by the SC method. More recently, Ambas & Baltas (2012) proposed a new SC that emphasizes the use of standard deviation. This method has several advantages (Table 3) as compared to the previous approaches.

From Table 4, numerous studies have assessed the sensitivity of meteorological variable contributing to ET_0 estimation using the SC method. These studies highlighted changes of each meteorological variable on ET_0 estimation in different climatic conditions and regions. Qi *et al.* (2017) tested the sensitivity of ET_0 of the FAO-56 Penman Monteith model in Heilongjiang Province, China and concluded that relative humidity was the most sensitive variable in spring, summer and autumn seasons and maximum temperature was the most sensitive variable during winter time. Jerszurki *et al.* (2019) tested the sensitivity of a FAO-56 Penman Monteith model to estimate ET_0 under different climate conditions across Brazilian regions. The results demonstrated a strong and linear response of ET_0 to changes in meteorological variables for all climate types and vapor pressure deficit, wind speed and solar radiation were the most sensitive variables. Xie & Wang (2020) performed SA on 10 different ET_0 models, and they concluded that the wind speed and sunshine hours were the major factors influencing ET_0 changes. On the other hand, Yildirim *et al.* (2021) analysed the sensitivity of ET_0 across seven different regions in Turkey and concluded that ET_0 was most sensitive to wind speed, followed by air temperature.

Although the SC method is employed to assess the inconsistencies and root cause of ET_0 change, it does not measure the impact of meteorological variables on ET_0. Hence, to precisely explain the causes of ET_0 change, contribution rate analysis is required to quantify the contributions of change in meteorological variables to change in ET_0 (Liu *et al.* 2020).

2.4. Sobol' method

The Sobol' method is a GSA approach that uses variance decomposition to determine the attribution of each uncertain input variable to the total output variance of a model. It allows for an assessment of the impact of each meteorological variable on the ET_0 model performance, as well as the interaction between the meteorological variables on the ET_0 model, which cannot be achieved by LSA methods (Zhang *et al.* 2019). The variances are estimated by approximate Monte Carlo numerical integration. In addition, the Sobol' method provides first-order and total indices. The first order indices describe the attribution of each meteorological variable on the output variance without accounting the interaction between other meteorological variables. The total indices indicate the attribution of the meteorological variable and the variance caused by the interactions between other meteorological variables. Not only these two indices develop an understanding by providing a quantitative measure of the contribution of the meteorological variables, it also can be used for factor fixing and prioritization (Pang *et al.* 2020).

2.5. Extended Fourier amplitude sensitivity test (eFAST)

The enhanced version of Fourier Amplitude Sensitivity Test (FAST), known as extended-FAST (eFAST) was initially developed by Saltelli *et al.* (1999). This method is developed to resolve the limitation of FAST as FAST is inefficient for high-order interaction terms (Pang *et al.* 2020). One of the key features of eFAST is to allow the input variables of the ET_0 model to oscillate at different frequencies. The eFAST demonstrates which uncertain input variable has the largest degree of impact on the variability of output. Since it is quantitative and model independent, eFAST has been abundantly utilized to evaluate the model acceptability and establish what factors affect model (Cheng *et al.* 2020).

Similar to Sobol' method, eFAST computes both first-order and total-order sensitivity indices of each input variable to the output variance. The first-order sensitivity index accounts for the contribution of an input variable only whereas the total-order sensitivity

Table 3 | The advantages of new SC method proposed by Ambas & Baltas (2012)

	Advantages
New SC method	1. Standard deviation cannot be zero. 2. The coefficient is unaffected by the units. 3. The standard deviation expresses the entire data set. 4. The minimum value relies on the magnitude of the time series. 5. The range width of input variables relies on both minimum and maximum values. 6. Some meteorological variables are limited. For instance, the relative humidity and wind speed. The relative humidity must be valued between 0 and 100% whereas the value of wind speed must be positive values. 7. This SC shows the adjustments caused to the model by the variation of the variable.

Table 4 | The summary of SA methods applied in different regions across the world

SA methods	Regions	Parameters	Key results	Reference
Sensitivity Coefficient method	China	T, RH, SR, WS	ET_0 was most sensitive to Rs, followed by RH and T, and the least sensitive to WS	She *et al.* (2017)
	Songnen Grassland, Northeast China	Tmax, Tmin, T, RH, SR, WS	RH and Tmax were the most sensitive variables to the change in ET_0 over the whole region.	Ma *et al.* (2017)
	Heilongjiang, China	Tmax, Tmin, RH, SR, WS	ET_0 was the most sensitive to RH during spring, summer and autumn whereas Tmax and Tmin were the most sensitive variables during wintertime.	Qi *et al.* (2017)
	Greek	Tmax, Tmin, T_{dew}, T, RH, WS, DL, SR, AR, NR	T and SR were the most sensitive variables for all locations.	Paparrizos *et al.* (2017)
	Côte d'Ivoire, West Africa	Tmax, Tmin, RHmax, RHmin, SR, WS	ET_0 was most sensitive to SR and Tmax, followed by WS. The SC of SR were high in humid condition whereas Tmax and WS were high under semi-arid condition.	Koudahe *et al.* (2018)
	Southwest China	Tmax, Tmin, RH, SR, WS	ET_0 was most sensitive to RH, but a significant reduction in SD caused a great decline of ET_0.	Jiang *et al.* (2019)
	Iran	Tmax, Tmin, RHmax, RHmin, SR,SH	Tmax were the most sensitive variables to the change in ET_0 for most of the stations.	Biazar *et al.* (2019)
	Brazil	Tmax, Tmin, RH, SR, WS, VPD	ET_0 was most sensitive to VPD, WS and SR in all climatic types.	Jerszurki *et al.* (2019)
	Beijing, China	T, RH, SR, WS	RH and SR, alternately were most sensitive variables.	Liu *et al.* (2020
	Iran	Tmax, Tmin, RH, WS, SH	ET_0 was most sensitive to Tmax and RH in all climatic types.	Nasrollahi *et al.* (2021)
	Turkey	T, RH, SR, WS	ET_0 was most sensitive to WS across all regions.	Yildirim *et al.* (2021)
	Senegal River Basin	Tmax, Tmin, RH, SR, WS	ET_0 was most sensitive to RH, Tmax and SR in majority of the regions.	Ndiaye *et al.* (2021)
	South Manitoba	Tmax, Tmin, SR, WS, VPD	ET_0 was most sensitive to Tmax, followed by SR, VPD, WS and Tmin	Ndulue & Ranjan (2021)
Sobol's method	Australia	T, RH, SR, WS	ET_0 was generally most sensitive to T.	Guo *et al.* (2017)
	Global scales	Tmin, VPD, g, C_1, β	MOD16 exhibited the highest sensitivity to β for all biome.	Zhang *et al.* (2019)
	Peninsular Malaysia	Tmax, Tmin, T, RH, AP, WS	Tmin was found the most sensitive variables, followed by WS and RH. ET_0 was least sensitive to SR.	Pour *et al.* (2020)
	Bushland, Texas	37 model input variables for DSSAT	The most sensitive parameters included that initial soil water content, soil parameters, the parameters that controlled crop development, leaf growth or development, seed cotton yield as well as canopy height and width.	Thorp *et al.* (2020)
	China	Tmax, Tmin, RH, SR, WS, AP	ET_0 was highly sensitive to Tmax, RH and SR.	Zeng *et al.* (2021)
eFAST	China	T, RH, SR and WS	ET_0 was more sensitive to SR and less sensitive to T in low latitude than that of high latitude.	Zheng *et al.* (2015)
	China	NDVI, Ts, Ta, α, τ_{sw}, ε_s, ε_a	α and τ_{sw} were the most sensitive parameters whereas the remained parameters were the least sensitive for the coupled SEBAL, indicating their minor roles on regional ET_0 estimations.	Zheng *et al.* (2015)
	Colorado	RHmax, RHmin, Tmax, Tmin, Ws and SR	ET_0 was most sensitive to WS, followed by RHmin (winter) and SR (summer).	DeJonge *et al.* (2015)
	Texas	Root_growth_soil, soil_evap_plant, Microbial_top_soil_coefficient and Max_rain_intercept	'soil_evap_plant' was the most sensitive parameter.	Talebizadeh *et al.* (2018)

Notes: T represents mean temperature (°C); RH represents relative humidity (%) ; SR represents solar radiation (MJ m^{-2}); ER represents extraterrestrial radiation (MJ m^{-2}); NR represents net radiation (MJ m^{-2}); WS represents wind speed (ms^{-1}); SH represents sunshine hours(h) ; DL represents day length (h) AP represents atmospheric pressure; VPD represents vapour pressure deficit (kPa); g represents leaf boundary layer conductance (ms^{-1}); C_1 represents the mean potential stomata conductance (ms^{-1}); β represents the sensitivity of soil evaporation to VPD; NDVI represents Normalized Difference Vegetation Index; Ts and Ta are surface and surface air temperature respectively (K); α represents ground surface albedo; τ_{sw} represents empirical parameter that accounts for transmissivity of both direct of solar beam radiation and diffuse radiation to the surface; ε_s and ε_a denote broadband surface and atmospheric emissivity; 'soil_evap_plant' is a parameter that accounts for the effect of plant cover on reduced evaporation from soil surface; 'Root_growth_soil' is the soil characteristics on root growth that affect ET; 'Microbial_top_soil_coeff' and 'Max_rain_intercept' are the parameters that influence the litter transformation on the soil surface and intercepted rainfall amount.

index accounts for the interactions among all the input variables (Yang *et al.* 2016). The details can be found in Saltelli *et al.* (1999). In comparison with Sobol's method, the study that carrying out SA using eFAST for ET_0 estimation is relatively limited.

This method has been applied by Zheng *et al.* (2015) to investigate the variation of the sensitivity of ET_0 to relative humidity, wind speed, mean temperature and incoming solar radiation in China. The results depicted that the sensitivity of ET_0 varied geographically and seasonally. The stations located in low latitude were more sensitive to solar radiation and less sensitive to mean temperature than the stations in the high latitude. It is apparent that global warming has led to the ET_0 variation especially in northeast China and Tibetan Plateau (cold regions) where the Si values of mean temperature were the highest than other meteorological variables. Apart from that, Tadesse *et al.* (2018) performed SA using eFAST to detect sensitive parameters that influence the ET simulations in Bushland Texas. Among all the parameters, 'soil_evap_plant_cover' was the most sensitive.

3. FACTORS AFFECTING THE SENSITIVITY ANALYSIS OF ET_0

3.1. Elevation effects

The diversity of the elevation is one of the primary reasons that affects ET_0 sensitivity. The variation in ET_0 is especially complex in high-altitude regions as these regions experience a faster warming trend compared to low-altitude regions. Zheng & Wang (2015) assessed the sensitivity of FAO-56 PM model to meteorological variables at 688 meteorological stations in China. The study presented the relationship between sensitivity index (Si) values with latitude and longitude at different timescale. They found the stations located at high latitude exhibited higher Si values of mean temperature and lower Si values of solar radiation compared to stations located at low latitudes. The results also indicated that solar radiation and mean temperature were significant correlated with latitude at both annual and seasonal timescales. However, the correlations between meteorological variables and longitude were equivocal. As mentioned by Qi *et al.* (2017), topography and monsoon circulation have contributed to the changes of ET_0 in the northern province of China. The combined effects of temperature and precipitation variations, corresponding with the topographies, lead to the declining trend of annual ET_0 from low-altitude to high-altitude mountainous areas. Apart from that, Ma *et al.* (2017) found clear spatial patterns of ET_0 in Songnen Grassland, northeast China. In low latitude areas, due to the presence of valleys, the temperature is relatively low in the northeast and east regions. The lower values of ET_0 at high latitude area are due to the continental monsoon climate. The flat topography at low latitude in southwest regions resulted in lower relative humidity and high ET_0 values.

In addition, Qi *et al.* (2017) examined the impact of meteorological variables on ET_0 using daily data provided by the China Meteorological Administration for Heilongjiang province in northeast China. They found that all meteorological variables, including wind speed, maximum and minimum temperature, relative humidity and sunshine duration were interconnected with changes in elevation. All the meteorological variables, except for relative humidity, showed a declining trend at high-altitude mountainous areas (greater than 400 m elevation) across all four seasons. Conversely, the average relative humidity showed an increasing trend with increasing elevation. Overall, ET_0 showed a decreasing trend from low to high-elevation area in spring, autumn and summer. This trend may be due to the interaction of temperature and precipitation variations that are strongly linked to topography and monsoon circulation in the Heilongjiang region.

Similarly, Jiang *et al.* (2019) investigated the impacts of meteorological variables on ET_0 during 1961–2016 in southwest China and found that relative humidity had high SC values (negative values) in high-elevation regions, which would strongly decrease ET_0. In high-elevation areas, relative humidity declined significantly due to a decreasing trend in precipitation in southwest China, leading to a decrease in atmospheric vapour pressure and an acceleration in the process of water vapour released from plants. On the other hand, Sun *et al.* (2020) analyzed the spatial and temporal changes in seasonal and annual ET_0 in the Hengduan Mountains from 1981–2017. They found that the sensitivity of air temperature, actual vapour pressure and solar radiation decreased from low to high-elevation areas, whereas the sensitivity of wind speed increased gradually with increasing elevation. Air temperature was the most sensitive variable at low-altitude regions, whereas wind speed was the most sensitive variable at high-altitude regions.

3.2. Climatic conditions and timescales

Generally, changes in ET_0 in response to climate change vary significantly depending on time scales and climatic conditions. The changes in meteorological factors are strongly associated with the variability of the spatiotemporal scale of the SCs. Several studies have carried out the SA of ET_0 estimation under contrasting climatic conditions and time scales around the world. Dejonge *et al.* (2015) investigated the SA of ET_0 estimation to sensor accuracy in Colorado and Florida, United States. The authors found out that ET_0 was highly sensitive to solar radiation during summer, followed by minimum relative humidity and wind speed in early and late summer, respectively. ET_0 was most sensitive to wind speed and minimum relative humidity during winter. The results also demonstrated that the solar radiation was the most sensitive in humid areas, Florida throughout the study period.

Koudahe *et al.* (2018) evaluated the changes of ET_0 with respect to its meteorological variables under humid and semi-arid condition in Côte d'Ivoire, West Africa. The authors found out that ET_0 was most sensitive to changes in wind speed, solar radiation and maximum temperature at all study areas. Wind speed and maximum temperature showed the highest SC under semi-arid regions, whereas the SC of the solar radiation was highest under humid regions. In semi-arid regions, the increasing wind speed reduced the aerodynamic resistance, which contributed to the increase of ET_0. Maximum temperature was ranked as the third important variable and can be attributed to the fact that the importance of maximum temperature is to calculate the net radiation, slope of saturation vapor pressure and net longwave radiation for ET_0 estimation.

In Brazilian region, SA was carried out by Jerszurki *et al.* (2019) to determine the influence of different meteorological variables on the ET_0 model under different climatic conditions. ET_0 was most sensitive to vapour pressure deficit, followed by wind speed and solar radiation under all climatic conditions. Increased air temperature contributed to the decline of the slope of saturation vapour pressure in the FAO-56 PM model, thus resulting in larger sensitivity during the winter period in the semi-arid region. Besides, the highest sensitivity of wind speed was observed during spring and summer in semi-arid regions due to low relative humidity and high air temperature. Under the conditions of low relative humidity, the wind replaces the saturated air more efficiently, which favours the maintenance of higher vapour pressure deficit and promotes larger ET_0 value. On the other hand, increasing solar radiation has led to an increase of ET_0 under humid, tropical and sub-tropical regions.

Liu *et al.* (2020) assessed the SA and contributions of meteorological variables to ET_0 change on different time scales in Beijing. Over the period of 60 years (1958–2017), the changes of ET_0 varied temporally. On the daily scale, ET_0 was most sensitive to the relative humidity during day and night time, while ET_0 was most sensitive to net radiation during the afternoon. Relative humidity was most sensitive to ET_0 from October to March, and net radiation was most sensitive to ET_0 from April to September. Furthermore, net solar radiation was the most sensitive variable during spring and summer, while relative humidity was the most sensitive variable during autumn and winter. The decline in relative humidity and increasing temperature has contributed to the rise in ET_0.

Moreover, Zeng *et al.* (2021) evaluated SA using CMIP5 projections (2021–2050) based on annual and seasonal timescales in China. ET_0 was most sensitive to maximum temperature, solar radiation and relative humidity during Spring, Autumn and Winter. In summer, solar radiation, maximum temperature, relative humidity and wind speed were the most sensitive variables that influence ET_0. The occurrence of increasing radiative forcing caused by anthropogenic factors of climate change brings abrupt changes in meteorological variables in China. For instance, the most sensitive meteorological variable has changed from maximum temperature to solar radiation and from relative humidity to solar radiation in Summer and Winter respectively.

From the studies above, it is evident that the variation of ET_0 is highly diverse across the different regions around the world. This fact further reinforces the necessity to carry out SA in order to study the change in ET_0 and its driving factors. The knowledge of identifying the variation in ET_0 in terms of spatial and temporal scales is the primary step in estimating the ET_0 (Jiang *et al.* 2019). Studying the effects of meteorological variables on the ET_0 using SA would aid in analyzing the future water demands for sustainable agricultural activities, proper water resources planning and management. Farmers can make better decisions regarding irrigation scheduling, leading to improved crop yields and water-use efficiency (Han *et al.* 2021). For instance, if the ET_0 rate is high, farmers can adjust their irrigation schedule to ensure that the crops receive adequate water, while avoiding over-irrigation, which can lead to waterlogging and other negative impacts on the crop growth. Additionally, farmers can optimize the use of fertilizers and other inputs, reducing waste and environmental impacts (Yamaç & Todorovic 2020).

Apart from improving the agricultural practices, SA plays an important role in climate change adaptation and drought management. ET is also affected by climate change, which has important implications for water resources management (Khaydar *et al.* 2021). By understanding how ET will change in response to climate change, water resources engineers and policy makers can better plan for the future and take steps to adapt to changing water availability. Furthermore, ET_0 can be used as an indicator of water stress during drought events, which can guide water management decisions. By monitoring ET_0, water resources engineers can identify areas that are experiencing water stress and prioritize water allocation to areas that are most in need (Ng *et al.* 2022).

4. FUTURE PROSPECTS

The employment of GSA methods should always be considered in order to overcome the limitations of LSA methods. This would greatly reduce the likelihood of errors when making decision that need to be carried out by policymakers or researchers. The future prospects of this study field can be sorted as follows:

1. Development of multi-method SA toolboxes to resolve the constraints of each SA method.

While some multi-method toolboxes have been developed, it is able to comprehensively resolve the constraints of each SA methods, particularly for such a complex hydrological process. For instance, VARS-TOOL is a toolbox that utilizes directional variogram and co-variogram functions, providing comprehensive sets of global sensitivity indices with minimal computational burdens. It could be a promising approach to explore for the modelling of ET_0.

2. Employment of high-resolution meteorological data

Higher resolution meteorological data with detailed information such as geographical information system (GIS) and satellite data may be utilized for ET_0 modelling. This will be particularly favourable for regions that always encounters issues like scarce or missing meteorological data.

3. Improve methods to study the interactions between meteorological variables (inputs)

Based on the knowledge, it is undeniable that there is no SA method that is capable of studying the interactions between meteorological variables for ET_0 modelling effectively. The information about meteorological variables interactions can be compiled as a by-product of several SA methods. For such, the standard deviation of the elemental effects and the dissimilarity between total-order and first order indices.

4. Analysis of other input factors that are affecting ET_0

Apart from mentioned climatic factors, other factors affecting ET_0 such as leaf area index (LAI) and crop coefficient should be taken into account for ET_0 estimation.

5. CONCLUSION

The application of SA in ET_0 estimation is to determine the degree of influence of the meteorological variables on the ET_0 estimation. The sensitivity of ET_0 can provide critical evaluation to determine the most suitable models for ET_0 estimation under the influence of climate change. Different SA methods are adopted in ET_0 estimation but each of the methods has its own limitations. SA methods are simple and easy in terms of implementation and interpretation; thus, they may be still the first choice due to its low computational burden with ET_0 models. However, the Sobol's and eFAST may be preferred for models with high number of meteorological factors. They can measure the changes of each meteorological variable in the output variance.

While each SA method distinguishes the sensitivity of the ET_0 in a different way, it can be found that the majority of the studies have adopted only one SA method (either LSA or GSA method). It is suggested that both local and global SA methods should be employed for better comparative assessment. To provide a more comprehensive SA, additional factors that affect ET_0, such as LAI and crop coefficient, should be considered. Despite the advancements in the developments of GSA methods, the intensive computational costs remain a major challenge. This fact reinforces the future need to build an integrated and realistic multi-method SA toolbox that integrates various theories and strategies to handle high-dimensional models with minimal computational costs. The development of an efficient and effective multi-method SA toolbox will definitely provide high accuracy and robust results, allowing farmers, engineering and decision makers, to identify adequate solutions for water resources planning and management as well as improving the agricultural crop production.

The paper has reviewed the SA methods in ET_0 modelling. The findings and recommendations of the application of SA in ET_0 modelling are summarized as below.

- The LSA is the simplest and easiest in terms of ET_0 modelling. It requires low computational cost, simple implementation, and easy interpretation. The drawback of this method is that it only explores a small portion of the possible space of input values.
- The application of GSA methods to study the dominant meteorological variables affecting the ET_0 estimation is still limited. It could be a better choice in comparison with LSA methods as it can determine the changes of uncertain inputs over the whole input space.

- The choice of SA methods is dependent on the research purpose, the computational costs and the number of input variables. The feasible suggestions of performing SA are:
  - (a) The SC method may be still the first choice because it only requires low computational cost.
  - (b) The variance-based method (i.e. Sobol and eFAST method) provides more robust analysis provided with high computational demanding.
- It is of importance to select an appropriate SA method for ET_0 estimation. This is because ET_0 is a complex and non-linear process that is difficult to measure and estimate accurately. Thus, adequate SA methods must be selected carefully to achieve the research requirements.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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