Dear Reviewer,

We sincerely appreciate your time and valuable comments on our manuscript. Your insightful suggestions have significantly helped us improve the quality of this work. We have carefully addressed all your concerns point-by-point in the revised manuscript, which are highlighted in blue font for your convenience. The detailed responses to each comment are provided below (all suggestions and comments are colored in red).

By using Python, this study developed a new spatial statistics toolbox named FZStats v1.0. It provides details on the development process, raw code, and a user-friendly software product. This toolbox not only includes two categories of traditional general spatial statistical tools but also integrates the new developed Focal-Zonal Mixed Statistics method, which I believe is the core contribution of this research. The manuscript is well-structured, showcasing the necessity and advantages of the proposed Focal-Zonal Mixed Statistics method through a comprehensive review of existing research, methodology, model development, and applications, with thorough discussions, making it a clearly contributive and well-written article. To further enhance the quality of this manuscript and better serve its potential readers, I offer the following suggestions for the authors' consideration:

Thank you very much for your careful reading and encouraging comments. We are especially grateful for your constructive suggestions, which have significantly contributed to improving the quality of our work. Below, we provide point-by-point responses to each of your suggestions and comments. We sincerely hope that the revised manuscript meets your expectations and is now more informative and useful to potential readers.

1.As instructed by the authors, the new model requires two input layers: value raster and zonal raster. In lines 214-219, the acquisition of the zonal raster is evidently based on reclassification, or in other words, the discretization of spatial variable. However, *how should the discretization scheme, including the number of classes and classification methods, be determined? Could the authors provide some recommendations on this? Since different reclassification parameters may significantly influence the results.*

Thank you for your insightful comment regarding the determination of the discretization scheme for the zonal raster. This is indeed a key component of the proposed methodology and deserves further clarification.

First, as a new method, the Focal–Zonal Mixed Statistics inherits the input structure and design logic of the two classical methods. From this perspective, its zonal raster is essentially consistent with the zonal raster used in traditional Zonal Statistics.

Second, from an application perspective, it is sometimes necessary to apply constraints to the construction of the zonal raster so that the resulting statistics are more accurate and meaningful.

In our specific case study of geothermal anomaly detection, we aim to identify a group of highly comparable background samples—i.e., locations that would exhibit similar surface temperature values in the absence of geothermal influence. To improve this comparability, we considered two aspects: (1) spatial proximity, which we will address in response to your next comment; and (2) environmental similarity, which is achieved through the construction of Unique-Value Environmental Characteristic Zonal Raster (UV-ECZR).

To construct the UV-ECZR, each environmental variable is first discretized, and then these layers are overlaid to form a composite zonal raster. This process involves determining both the number of classes for each variable and the appropriate classification method. Below are our recommendations:

(1) Number of Classes

A good classification scheme should aim to minimize within-zone variance and maximize between-zone variance. In practice, we found that using 5–8 classes often achieves a good balance between capturing environmental heterogeneity and maintaining sufficient sample sizes within each zone. This choice is empirical but has proven robust in our tests.

(2) Classification Methods

For continuous variables, Natural breaks (Jenks) are suitable when the data show clear clustering. Equal interval is appropriate for uniformly distributed variables. Quantile classification ensures even representation across the value range. For categorical variables, we generally retain their original classes unless aggregation is required for specific analytical purposes.

Finally, a trade-off must be made between similarity and statistical robustness: increasing the number of classes or including too many environmental variables can yield purer environmental zones but may reduce sample sizes and model stability. Therefore, both theoretical considerations and empirical validation are necessary in setting up the zonal raster.

We have added a new description under "(2) Construction of Unique-Value Environmental Characteristic Zonal Raster (UV-ECZR)" in Section 3.1 "Modeling Process for Focal–Zonal Mixed Statistics," which provides specific recommendations on both classification methods and the number of classes. The relevant content is copied below for your reference.

In this step, environmental factor rasters—whether continuous or categorical—are reclassified into discrete categories using a well-defined discretization scheme. For continuous variables, the classification method should be selected according to the data distribution and research objectives: natural breaks (Jenks) are recommended for datasets exhibiting clear clustering, equal interval classification suits uniformly distributed data, and quantile classification ensures balanced representation across value ranges. For categorical variables, original classes are typically retained unless aggregating categories improves analytical validity. The optimal number of classes, usually between 5 and 8, should balance environmental heterogeneity with adequate sample size within each zone. Classification performance can be evaluated by minimizing within-zone variance, maximizing between-zone variance, and assessing clustering validity through the silhouette coefficient. (Newlines 263-273)

2. Line 220, the configuration of model input parameters is crucial for practical applications, but the introduction to how to set and choose window size, window shape, and statistic selection is somewhat insufficient, and readers may need guidance on this aspect.

Thank you for this important suggestion. We fully agree with your point.

Regarding the first part of your comment, as mentioned in our response to your previous question, spatial proximity is another key consideration (in addition to environmental similarity) for improving the comparability of samples in geothermal anomaly detection. The configuration of window parameters directly reflects this spatial proximity. Therefore, when setting the window size, it is essential to ensure that samples within the window are more consistent in land surface temperature (LST) compared to those outside. At the same time, a balance between similarity and statistical robustness must be considered: smaller windows tend to ensure stronger internal consistency but may result in fewer samples, reducing statistical reliability.

As for window shape, when the spatial distribution of the variable exhibits evident anisotropy, an elliptical window may be more appropriate. Otherwise, circular windows are generally recommended due to their simplicity and symmetry.

Regarding the second part of your question—the selection of the statistical measure—it should be tailored to specific application scenarios. In our geothermal case, we use the following standardized index as the statistical measure: (T_cell – T_mean) / SD_window, where the numerator reflects how much the target cell's temperature exceeds the neighborhood mean, and the denominator (standard deviation) quantifies variability within the window. This standardization improves the comparability of anomaly scores across different regions.

We have added more descriptions under "(3) Determination of neighborhood window and statistical parameters" in "Section 3.1 Modeling Process for Focal–Zonal Mixed Statistics", where we now offer concrete recommendations on window size, shape, and the selection of statistical functions for different application contexts. Please refer to new lines 282-290 for details, as copied below.

The window size should be selected based on several considerations, including the spatial scale of the studied phenomenon (e.g., local versus regional patterns), the resolution of the input rasters (with coarser resolution favoring larger windows), and computational efficiency (as larger windows significantly increase processing time). The window shape should be chosen according to the nature of spatial anisotropy (elliptical for directional patterns), processing efficiency (rectangular shapes are computationally faster), mitigation of edge effects (circular windows help reduce boundary artifacts), and data characteristics (rectangular for grid-aligned features and circular for isotropic phenomena). (Newlines 282-290)

3. Line 248, the coding method proposed by the authors is concise and clear, but there is an issue: if used over a larger area with many factor classifications, it implies more placeholders. Will using this algorithm for coding risk exceeding computer reading limits?

We sincerely appreciate the reviewer's insightful concern regarding computational scalability. Here are our detailed explanations:

(1) Data Type Efficiency

UV-ECC values are stored as 64-bit integers (not strings), supporting up to 19 digits ($2^{64} \approx 1.8\times10^{19}$). For example, 8 factors with ≤10 classes each require only 8 digits—well within this limit while ensuring numerical processing efficiency.

(2) Technical Safeguards

Memory-mapped I/O: Large rasters are processed by chunks to avoid full loading.

Parallelization: Multi-core CPU support distributes computational loads.

We confirm that the method's design and implementation ensure robustness across scales. Thank you for this valuable comment!

4. Line 392, Figure 4 lacks units.

Thank you for your comments. We have updated Figure 4 (now it is Figure 3) by adding the units. Please refer to the new Figure 3, which is copied below.

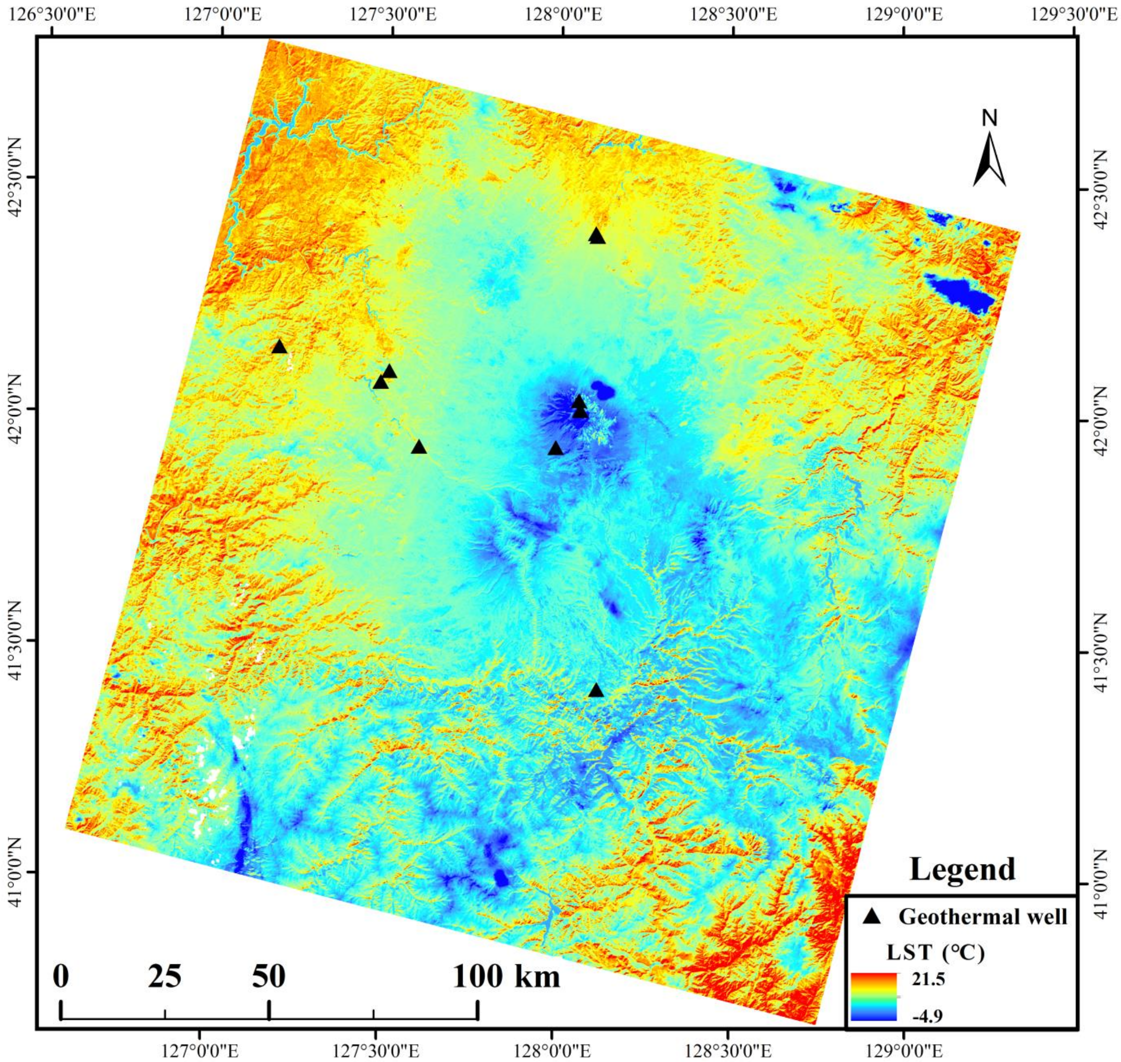


***Figure 3.** Spatial distribution of land surface temperature (LST) in the study area on March 20, 2023.*

5. Line 394, the authors only mention the spatial coupling of LST with slope aspect but do not empirically test whether slope and aspect are major environmental factors influencing LST. Additionally, within a 7.2 km radius, can the effect of elevation on LST be ignored, especially in relatively complex mountainous terrain?

Thank you for your insightful comment. This is indeed an important point that we have now addressed by adding an empirical analysis of the relationship between LST and several key environmental variables, including slope, aspect, elevation, and vegetation index (NDVI). The results demonstrate that slope aspect emerges as the dominant driver of land surface temperature (LST) variations at the local window scale, whereas elevation and NDVI exhibit less pronounced effects. This observation aligns with previous studies showing topographic orientation as a critical modulator of microclimate patterns (He et al., 2019). The underlying mechanism likely stems from two inherent properties of local landscapes:

(1) Limited terrain heterogeneity: Elevation differences within localized windows typically show constrained variability, diminishing the relative impact of absolute elevation on thermal regimes (Zhang et al., 2019).

(2) Vegetation uniformity: Vegetation composition and density tend to stabilize within small topographic units due to similar micro-environmental conditions (Yan et al., 2017).

To enhance topographic characterization, we introduced slope degree as a complementary parameter. The synergistic integration of slope aspect and slope degree achieves three critical improvements:

(1) Comprehensive terrain representation: Aspect-direction defines solar exposure patterns, while slope steepness governs surface runoff and energy retention.

(2) Microhabitat homogenization: Land units sharing equivalent aspect-slope combinations inherently exhibit reduced vegetation variability through water-energy balance constraints.

(3) Thermal regime differentiation: The aspect-degree matrix creates distinct solar radiation geometries that amplify LST contrasts between adjacent terrain units.

Accordingly, we have revised the manuscript to include these findings and have further clarified our rationale for choosing slope aspect and slope degree as the basis for constructing the Unique-Value Environmental Characteristic Zonal Raster (UV-ECZR). This decision ensures that the zonal raster reflects the most relevant terrain-driven drivers of LST variation at the target spatial scale.

Taking the LST retrieved from the Landsat 8 image acquired on March 20, 2023, as an example, a comparison between Fig. 3 and the terrain information presented in Fig. 4 reveals a strong spatial correlation between LST patterns and topographic *factors, particularly slope aspect. Given that the local overpass time of Landsat 8 over the study area was approximately 11:00 AM, with a corresponding solar azimuth angle of 153°, LST values were significantly higher on southeast-facing slopes compared to northwest-facing slopes (Fig. 4a). This highlights the pronounced influence of solar radiation on the spatial variability of LST within the study area.* (Newlines 474-481)

References

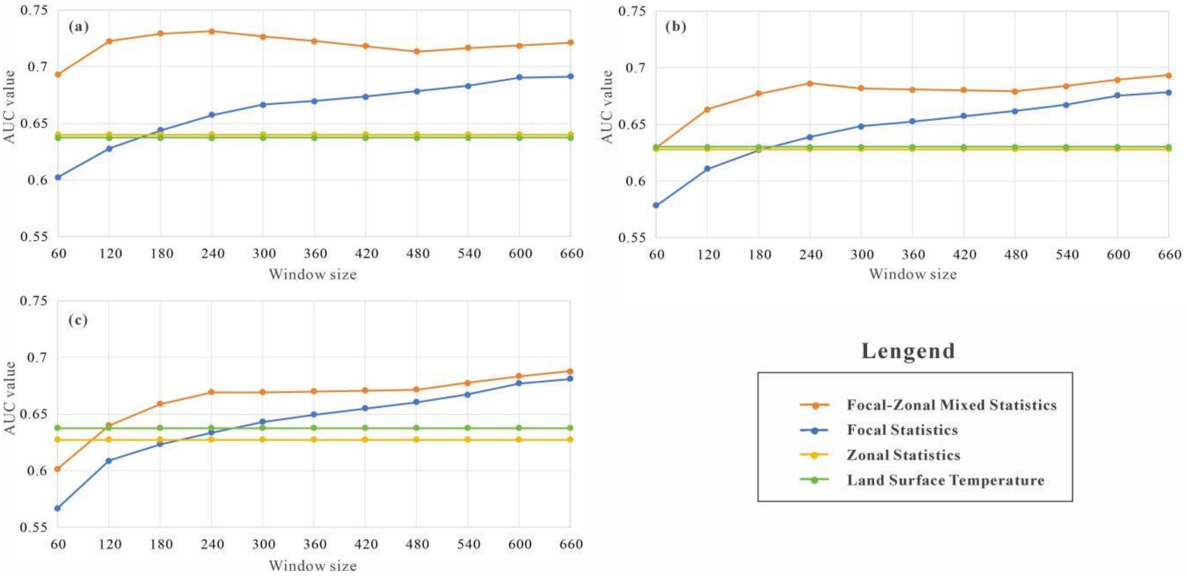
He, J., Zhao, W., Li, A., Wen, F., and Yu, D., 2019. The impact of the terrain effect on land surface temperature variation based on Landsat-8 observations in mountainous areas. International Journal of Remote Sensing, 40(5-6), 1808-1827.

Yan, B., Qiu, S., Xiao, C., and Liang, X., 2017. Potential Geothermal Fields Remote Sensing ldentification in ChangbaiMountain Basalt Area. Journal of Jilin University (Earth Sciente Edition), 47(6), 1819-1828.

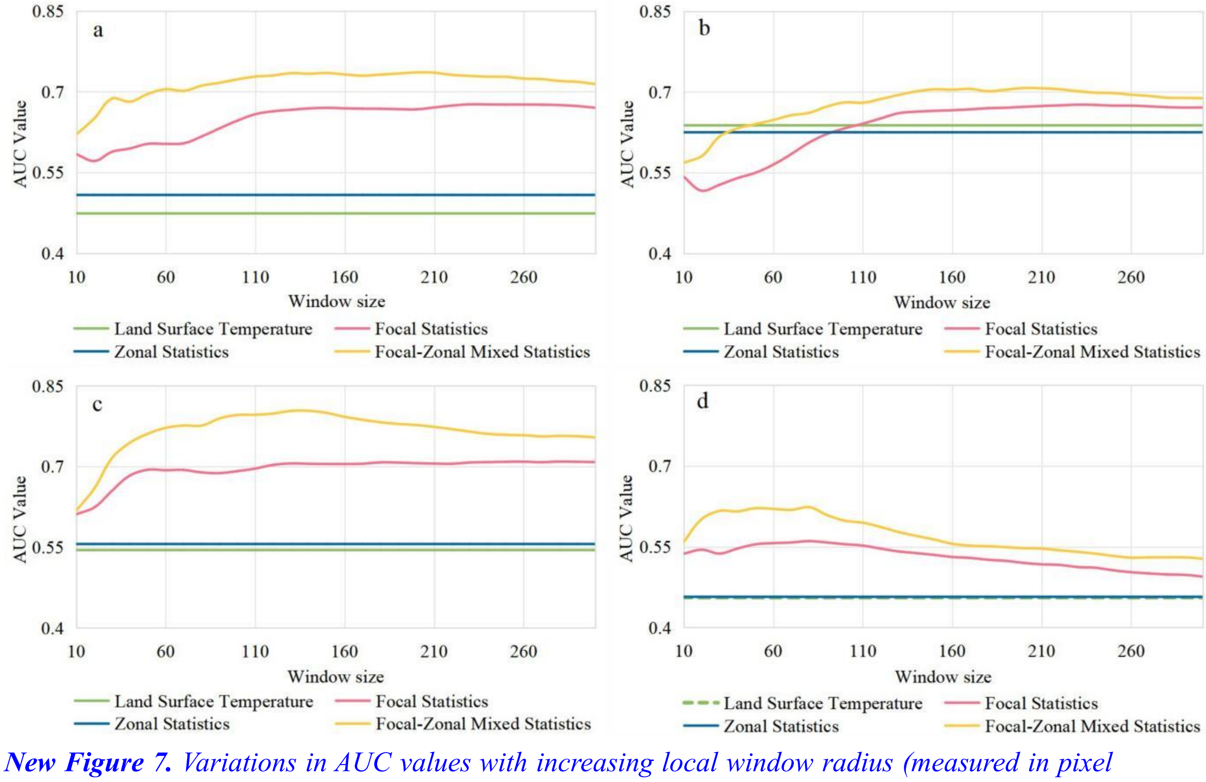
Zhang, D., Xu, X., Yao, S., Zhang, J., Hou, X., and Yin, R., 2019. A novel similar habitat potential model based on sliding-window technique for vegetation restoration potential mapping. Land Degradation & Development, 31(6), 760-772.

6. Line 423, while the mapping in the manuscript is very standardized and exquisite, some figure fonts are too small, such as in Figure 8.

Thank you for your helpful suggestion. We have carefully revised the font sizes across all figures to ensure consistency and improved readability. Specifically, the font size in the original Figure 8 has been enlarged, and this updated figure now appears as new Figure 7 in the revised manuscript. A comparison between the old and new versions has been provided below for your reference.



Old Figure 8*. The changes in AUC values with the window size of Land Surface Temperature (LST) and its three enhancement indicators obtained by Focal Statistics, Zonal Statistics, and Focal-Zonal Mixed Statistics, when a geothermal well represents circles with a radius of (a) 0.1km, (b) 0.2km, and (c) 0.3km, respectively.*



New Figure 7*. Variations in AUC values with increasing local window radius (measured in pixel units) for Land Surface Temperature (LST) and its three enhancement indices derived from Focal Statistics, Zonal Statistics, and Focal–Zonal Mixed Statistics. The geothermal wells are represented as circles with an area of 0.035 km². Panels (a) through (d) correspond to the LST data acquired in the spring, summer, autumn, and winter of 2023, respectively.*

7. Line 458, I am unclear about the reason for setting different representative areas for the mines.

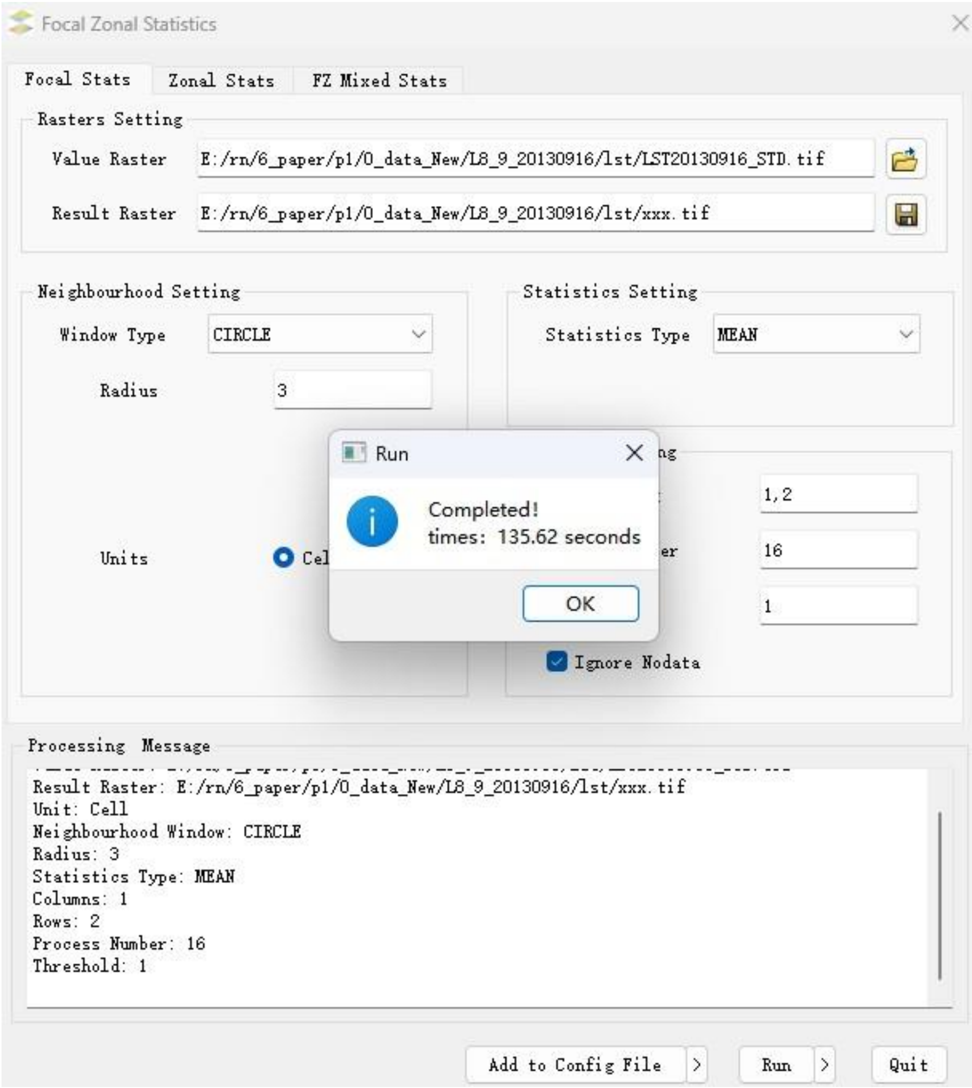
Thank you for your comment. The initial reason for assigning different representative areas to geothermal wells was to address potential spatial inaccuracies in their recorded locations. By using a surrounding area instead of a single pixel, we aimed to accommodate minor geolocation errors and spatial uncertainty in well positioning.

However, as shown in our previous analyses, the prediction performance does not significantly vary with changes in the representative area. This is likely because modern mapping technologies ensure reasonably accurate point locations, and clustered geothermal features are often recorded as multiple, partially overlapping points (e.g., as seen with the northernmost geothermal site in Figure. 4).

Based on these findings, in the revised version, we adopt the pixel where the geothermal well is located as the default representative area. Nevertheless, we retain both settings—a single 30m × 30m pixel (0.0009 km^2) and a 0.035 km^2 circular area—as part of our robustness evaluation. This evaluation also includes variations across different years (2015, 2019, and 2023), seasons (spring, summer, autumn, winter), and a wide range of local window sizes (radii from 0.3 km to 9 km in 0.3 km intervals), providing a comprehensive robustness assessment.

8. At last, after testing the software toolbox provided by the authors, I noticed that there seems to be no popup

Thank you for your suggestion. We have added a popup notification feature to the software toolbox. Upon completion of a task, a message box will now automatically appear indicating that the process has finished, along with the total runtime. This enhancement aims to improve user experience and provide more intuitive feedback on operation status. Please see the following figure for details.


Focal Zonal Statistics
Focal Stats
Zonal Stats
FZ Mixed Stats
Rasters Setting
Value Raster
E:/rn/6_paper/p1/0_data_New/L8_9_20130916/lst/LST20130916_STD.tif
Result Raster
E:/rn/6_paper/p1/0_data_New/L8_9_20130916/lst/xxx.tif
Neighbourhood Setting
Window Type
CIRCLE
Radius
3
Units
Statistics Setting
Statistics Type
MEAN
1,2
16
1
Ignore Nodata
Run
Completed!
times: 135.62 seconds
OK
Processing Message
Result Raster: E:/rn/6_paper/p1/0_data_New/L8_9_20130916/lst/xxx.tif
Unit: Cell
Neighbourhood Window: CIRCLE
Radius: 3
Statistics Type: MEAN
Columns: 1
Rows: 2
Process Number: 16
Threshold: 1
Add to Config File
Run
Quit