**Supplement text**

**Pearson correlation coefficient**: the Pearson product-moment correlation coefficient (or Pearson correlation coefficient, for short) is a measure of the strength of a linear association between two variables and is denoted by r. The Pearson correlation coefficient (PCC) is defined as the [covariance](https://en.wikipedia.org/wiki/Covariance) of the two variables divided by the product of their [standard deviations](https://en.wikipedia.org/wiki/Standard_deviations). Basically, a Pearson product-moment correlation attempts to draw a line of best fit through the data of two variables, and the Pearson correlation coefficient, r, indicates how far away all these data points are to this line of best fit (i.e., how well the data points fit this new model/line of best fit). The Pearson correlation coefficient, r, can take a range of values from +1 to -1. A value of 0 indicates that there is no association between the two variables. A value greater than 0 indicates a positive association; that is, as the value of one variable increases, so does the value of the other variable. A value less than 0 indicates a negative association; that is, as the value of one variable increases, the value of the other variable decreases. The stronger the association of the two variables, the closer the Pearson correlation coefficient, r, will be to either +1 or -1 depending on whether the relationship is positive or negative, respectively.

**The Randomized Dependence Coefficient4 (RDC)** is a measure of nonlinear dependence between random variables of arbitrary dimension based on the Hirschfeld-Gebelein-Renyi Maximum Correlation Coefficient. Given the random samples and and the parameters and , the Randomized Dependence Coefficient between and is defined as:

is a map from to . are pairs of basis vectors such that the projections and of two random samples and are maximally correlated. RDC is defined in terms of correlation of random non-linear copula projections; it is invariant with respect to marginal distribution transformations. RDC is a computationally efficient, copula-based measure of dependence between multivariate random variables. RDC is invariant with respect to non-linear scaling of random variables, is capable of discovering a wide range of functional association patterns and takes value zero at independence.

**SHAP (SHapley Additive exPlanations**) is a game theoretic approach to explain the output of any machine learning model. It connects optimal credit allocation with local explanations using the classic Shapley values from game theory and their related extensions. SHAP values as a unified measure of feature importance. These are the Shapley values of a conditional expectation function of the original model; thus, they are the solution to the following equation:

Where is the number of non-zero entries in , and represents all vectors where the non-zero entries are a subset of the non-zero entries in . Understanding why a model makes a certain prediction can be as critical as the prediction's accuracy in many applications. However, the highest accuracy for large modern datasets is often achieved by complex models that even experts struggle to interpret, such as ensemble or deep learning models, creating a tension between accuracy and interpretability. In response, various methods have recently been proposed to help users interpret the predictions of complex models, but it is often unclear how these methods are related and when one method is preferable over another.

SHAP assigns each feature an importance value for a particular prediction. Its novel components include: (1) the identification of a new class of additive feature importance measures, and (2) theoretical results exemplifying a unique solution in this class with a set of desirable properties. The new class unifies six existing methods, of notable importance due to several recent methods lacking the proposed desirable properties in their class. Based on insights from this unification, SHAP demonstrates improved computational performance and/or better consistency with human intuition than previous approaches. In this study, we used SHAP to make analysis on the impact of model output with respect to different features. In addition, we summarized the impact of socio-economic features and climate features separately for different clusters.

**Accuracy, Weighted Accuracy, Precision, Recall and F1 scores**

Accuracy measures how often the classifier makes the correct predictions. The ratio between the number of correct predictions and the total number of predictions. However, if the dataset is imbalanced, then accuracy may not be a good evaluation metric, since here it only considers the correct predictions and not care the instance from which class. Weighted accuracy computes the accuracy based on samples weight for each class, which is more suitable for imbalanced dataset. Precision and recall are commonly used in evaluation metric for model performance. Precision represents the proportion of positive identifications that were actually correct. Recall indicates the proportion of actual positives that were identified correctly. F1 score is the harmonic mean of precision and recall, which is a measure that combine precision and recall. From Table 1 and table 3 we can see our dataset is imbalanced in that compared to normal cases, our dataset has fewer infected cases.

**10-fold Cross Validation Details**

We split data into 10 nonoverlapping subsets, each time we use one subset as testing set and use the rest data as training set. We repeat this process 10 times by taking different training set and test set. We take the average result as the final result. Cross validation can overcome the overfitting problem.

***Spatiotemporal clusters***

Based on this location list, we sampled the number of CHIKV, DENV, and ZIKV from the whole data. And run the different algorithm to show the influence of socioeconomics and the climate attributes for all clusters.

Socio-economic features have around 38.97% more impact than climatic features on model output in cluster 1 (SHAP value). Climate features have around 10.12% more impact than socio-economic features on model output in cluster 1 (RDC). Climate features (Pearson) have around 0.8% more impact than socio-economic features on model output in the cluster 1 (figure S1).

Socio-economic features have around 37.23% more impact than climatic features on model output in cluster 2. Socio-economic features have around 5.56% more impact than climate features on model output in cluster 2. Socio-economic features have around 26.20% more impact than climate features on model output in cluster 2 (figure S2).

Socio-economic features have around 28.02% more impact than climatic features on model output in cluster 3. Climate features have around 16.72% more impact than socio-economic features on the model output in cluster 3. Climate features have around 4.38% more impact than socio-economic features on model output in cluster 3 (figure S3).

Climatic features have around 9.32% more impact than socio-economic features on model output in cluster 4. Climate features have around 14.40% more impact than socio-economic features on model output in cluster 4. Socio-economic features have around 10.00% more impact than climate features on model output in cluster 4.

Socio-economic features have around 26.84% more impact than climatic features on model output in cluster 5. Climate features have around 23.66% more impact than socio-economic features on model output in cluster 5. Climatic features have around 29.76% more impact than socio-economic features on model output in cluster 5.

Socio-economic features have around 23.60% more impact than climatic features on model output in cluster 6. Climate features have around 12.76% more impact than socio-economic features on model output in cluster 6. Climatic features have around 2.33% more impact than socio-economic features on model output in cluster 6.

Socio-economic features have around 0.84% more impact than climatic features on model output in cluster 7. Climate features have around 7.66% more impact than socio-economic features on model output in cluster 7. Climatic features have around 4.78% more impact than socio-economic features on model output in cluster 7.

Socio-economic features have around 47.21% more impact than climatic features on model output in cluster 8. Climate features have around 11.14% more impact than socio-economic features on model output in cluster 8. Socio-economic features have around 6.84% more impact than climatic features on model output in cluster 8.

Socio-economic features have around 43.96% more impact than climatic features on model output in cluster 9. Socio-economic features have around 23.90% more impact than climate features on model output in cluster 9. Socio-economic features have around 38.51% more impact than climatic features on model output in cluster 9.

Socio-economic features have around 35.58% more impact than climatic features on model output in cluster 10. Socio-economic features have around 6.60% more impact than climate features on model output in cluster 10. Socio-economic features have around 34.96% more impact than climatic features on model output in cluster 10.

Socio-economic features have around 17.58% more impact than climatic features on model output in cluster 11. Climate features have around 1.14% more impact than socio-economic features on model output in cluster 11. Socio-economic features have around 20.83% more impact than climatic features on model output in cluster 11.

Climatic features have around 23.44% more impact than socio-economic features on model output in cluster 12. Climate features have around 8.92% more impact than socio-economic features on model output in cluster 12. Climatic features have around 17.63% more impact than socio-economic features on model output in cluster 12.

**Reference**

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