

Scalable Gaussian Processes for Predicting the Properties of Inorganic Glasses with Large Datasets

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Supplementary Material

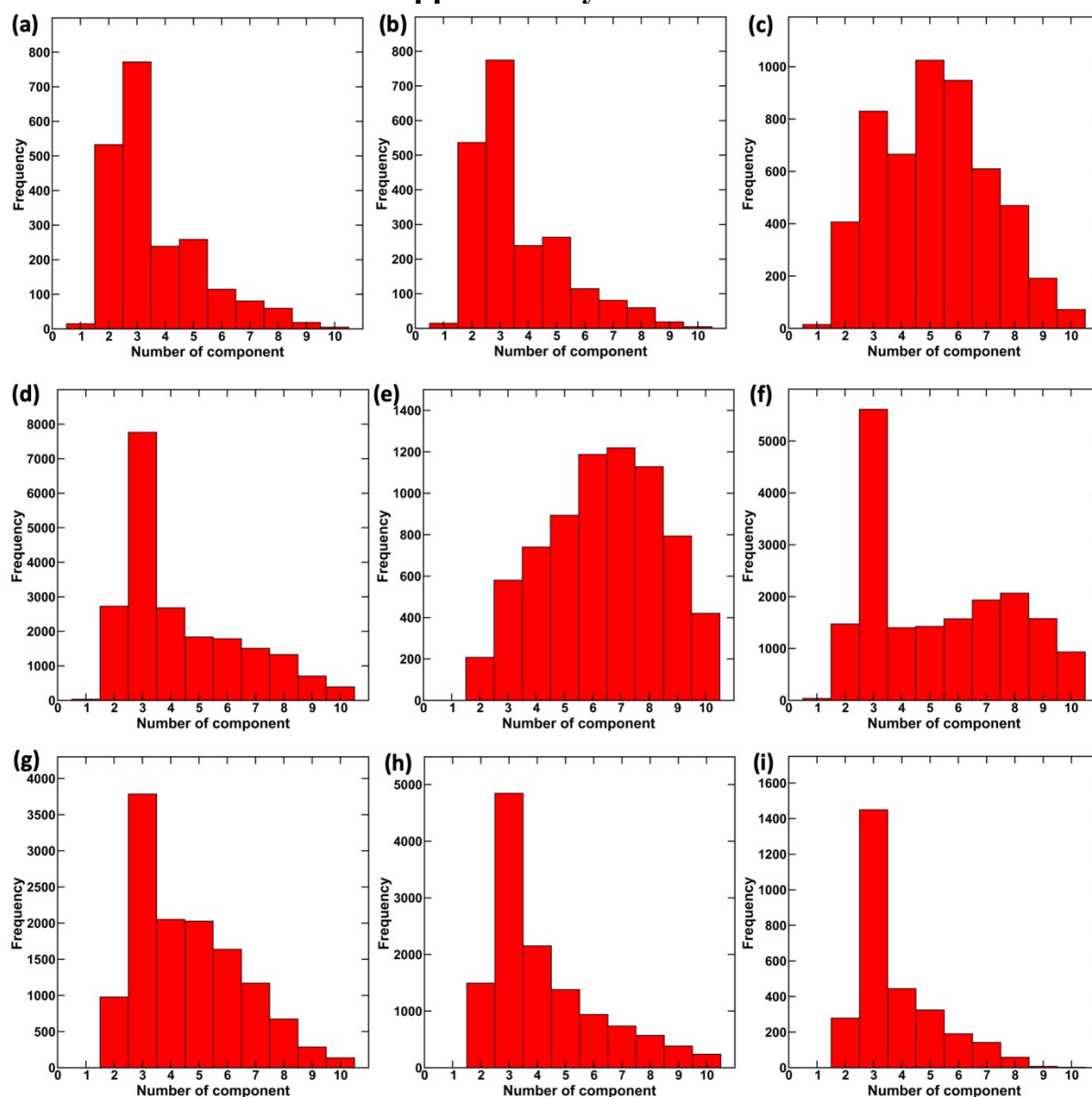
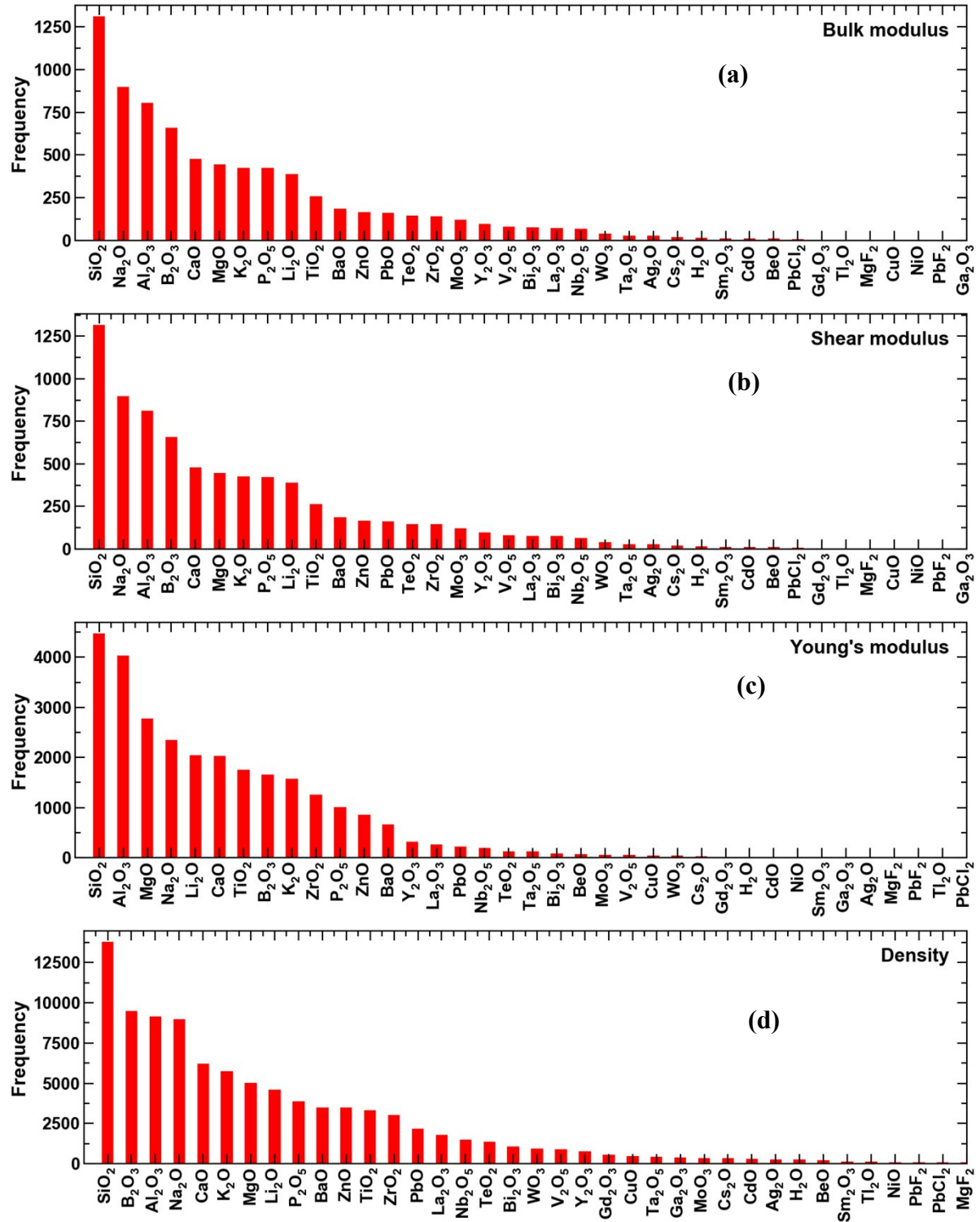
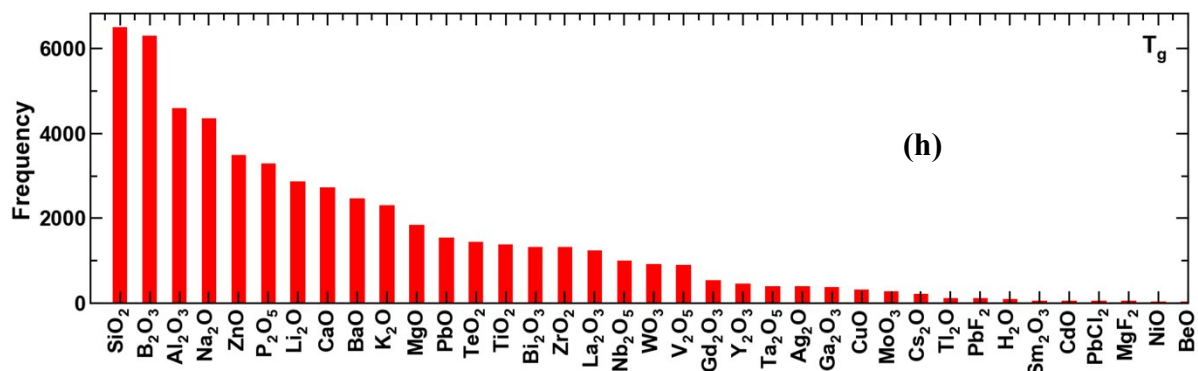
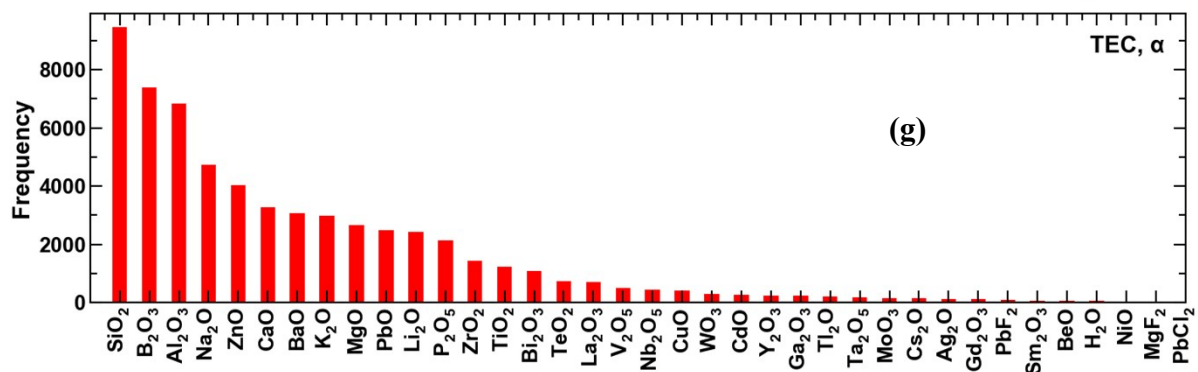
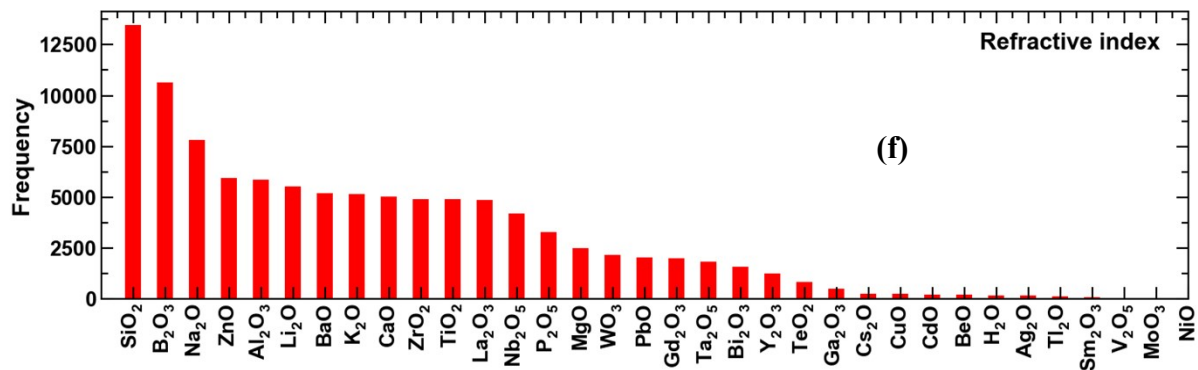
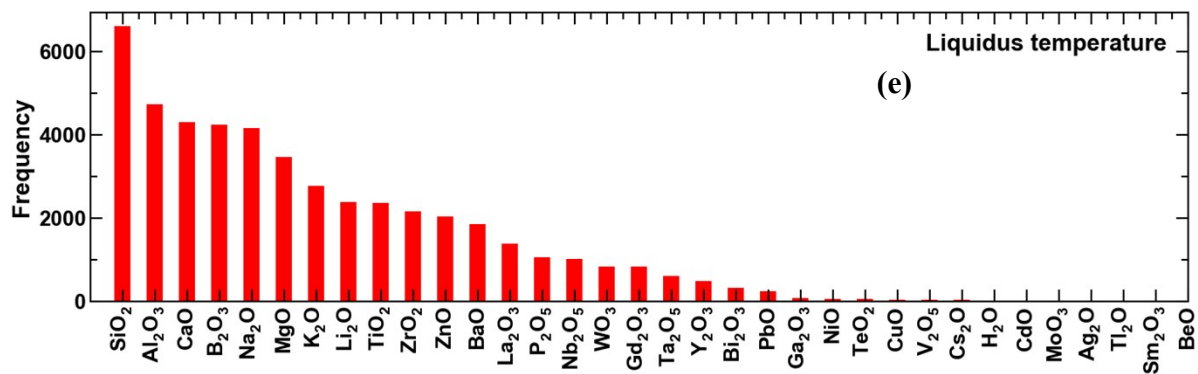


Figure S1. Number of component with respect to frequency plot for (a) bulk modulus, (b) shear modulus, (c) Young's modulus, (d) density, (e) liquidus temperature, (f) refractive index, (g) thermal expansion coefficient (TEC), (h) glass transition temperature (T_g) and (i) hardness.





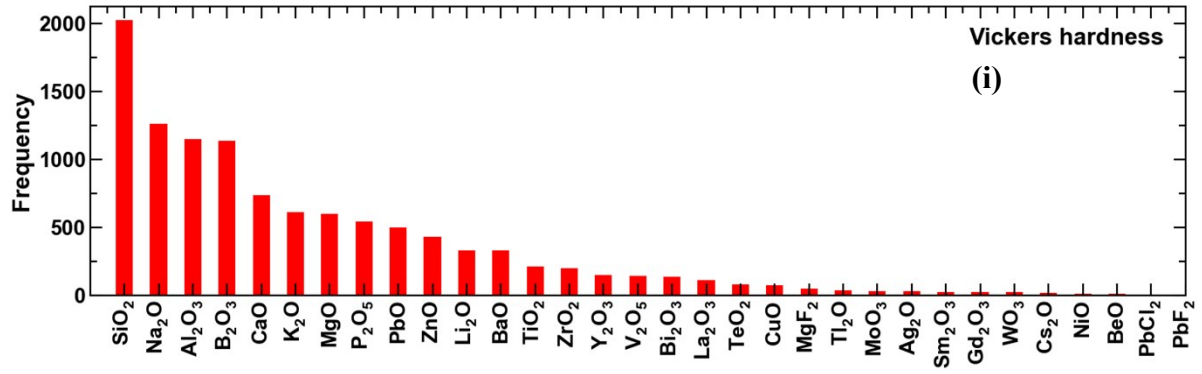
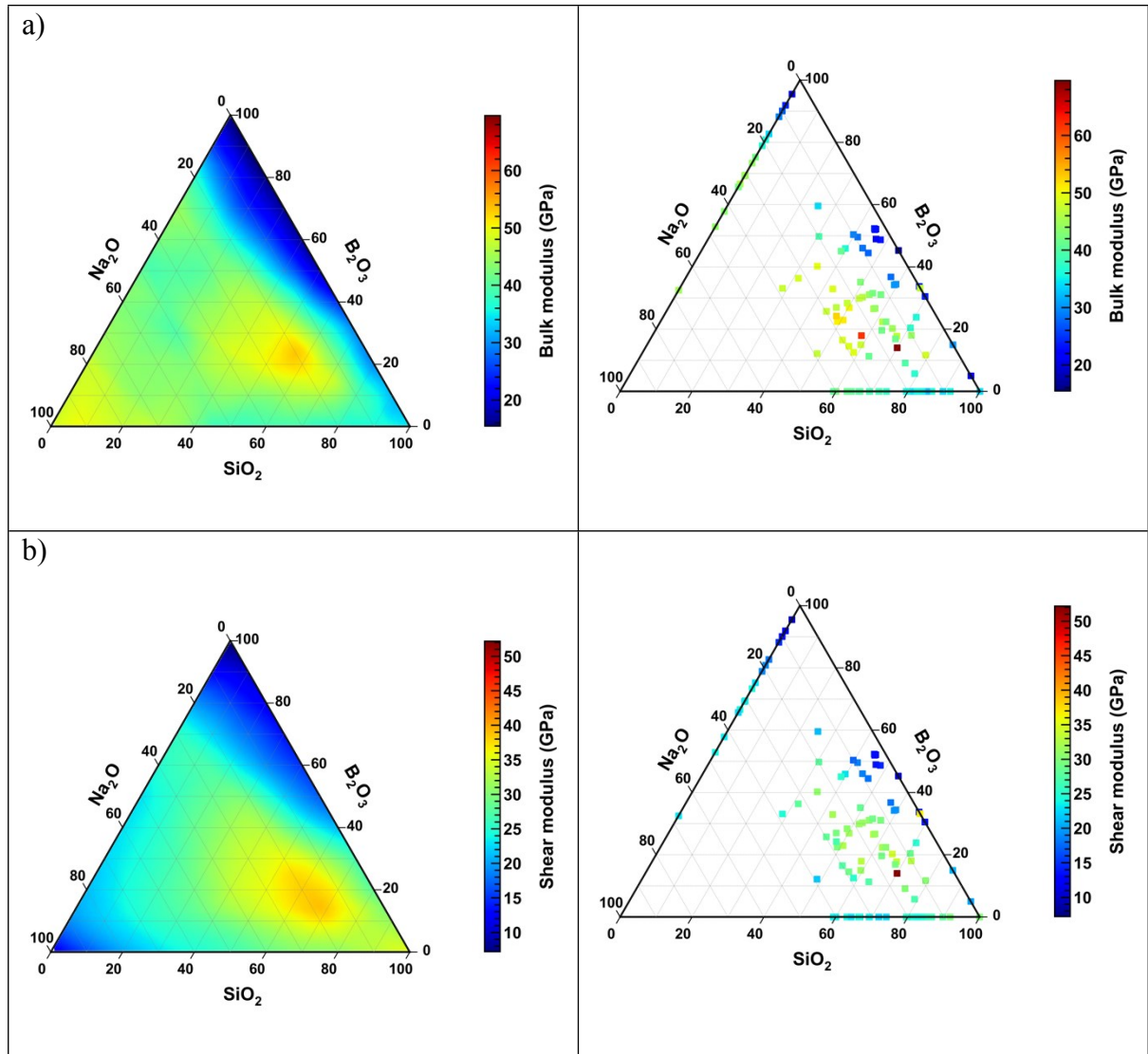
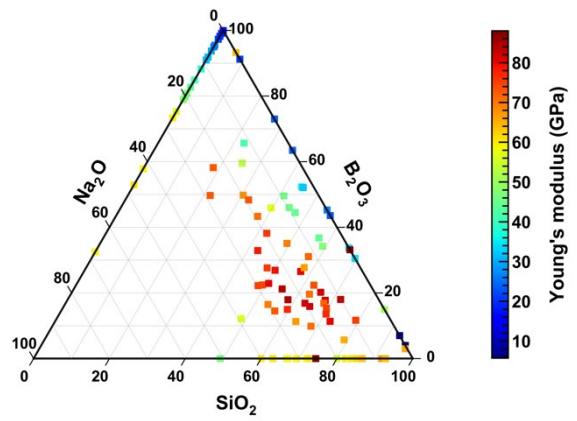
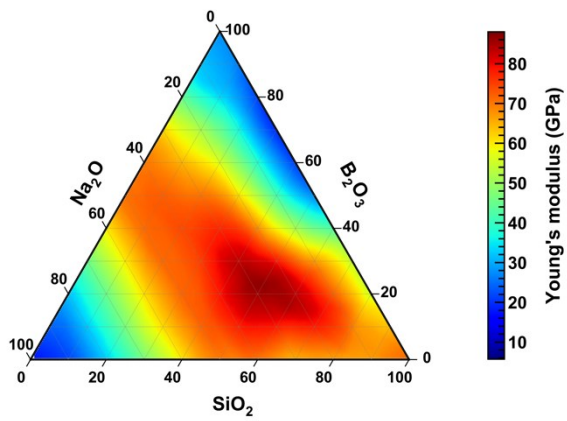


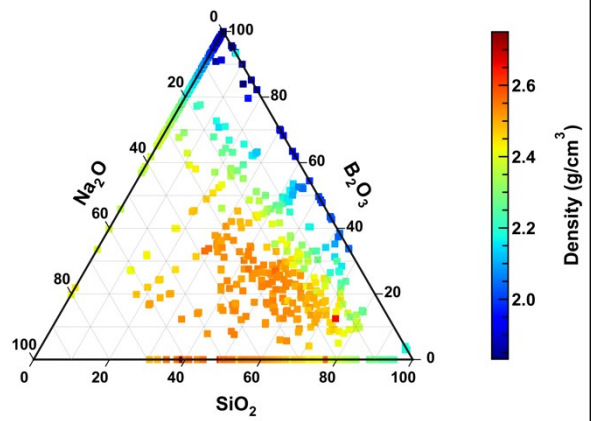
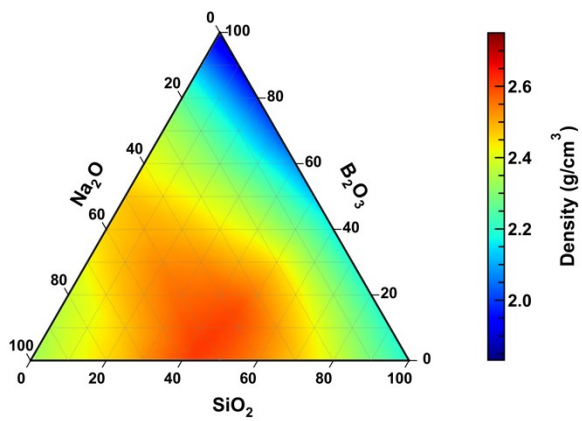
Figure S2. Frequency of glasses with respect to each of the input components for (a) bulk modulus, (b) shear modulus, (c) Young's modulus, (d) density, (e) liquidus temperature, (f) refractive index, (g) thermal expansion coefficient (TEC), (h) glass transition temperature (T_g) and (i) hardness.



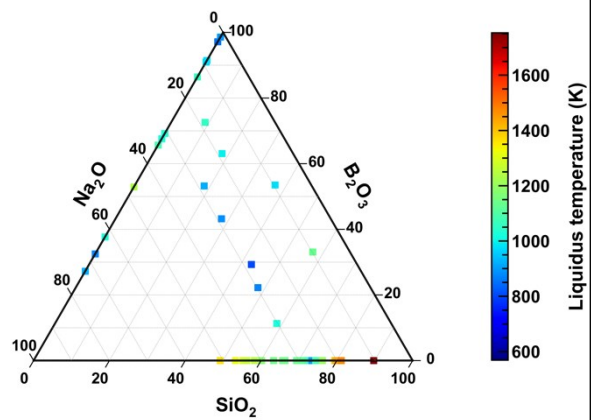
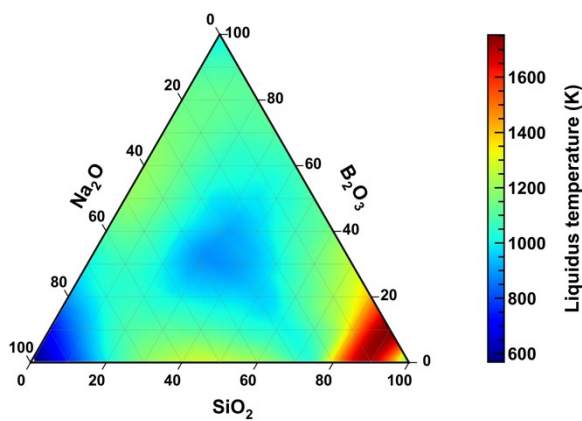
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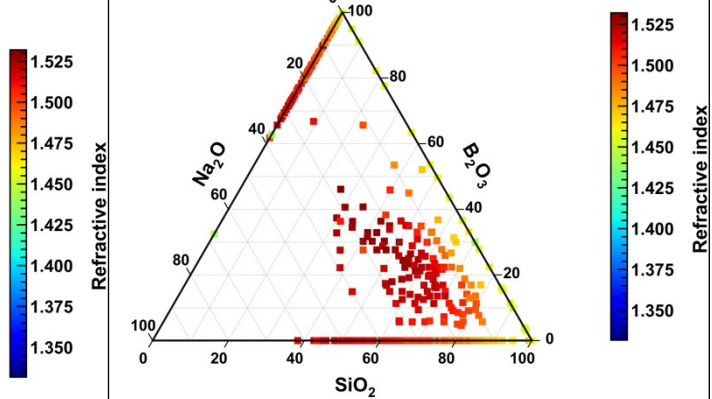
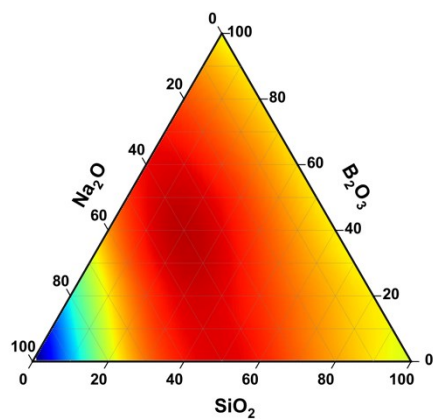
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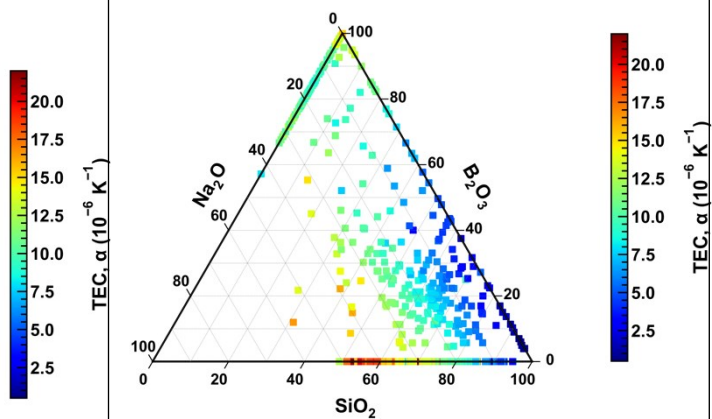
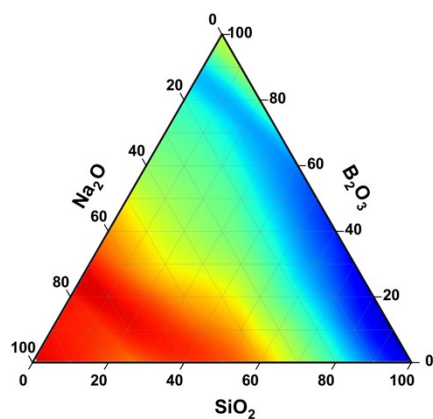
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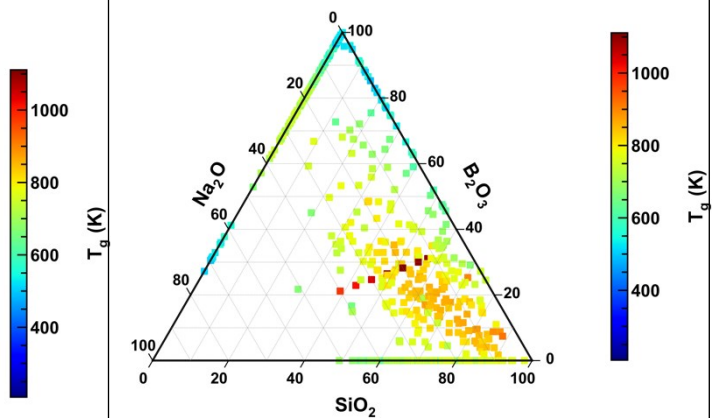
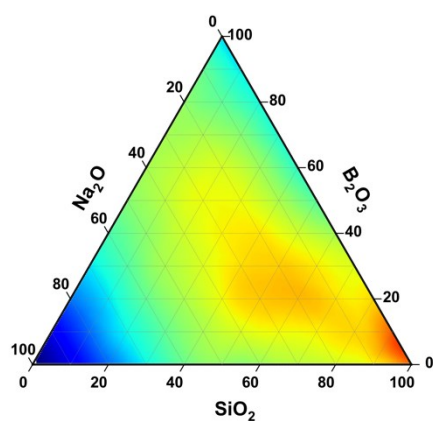
f)



g)



h)



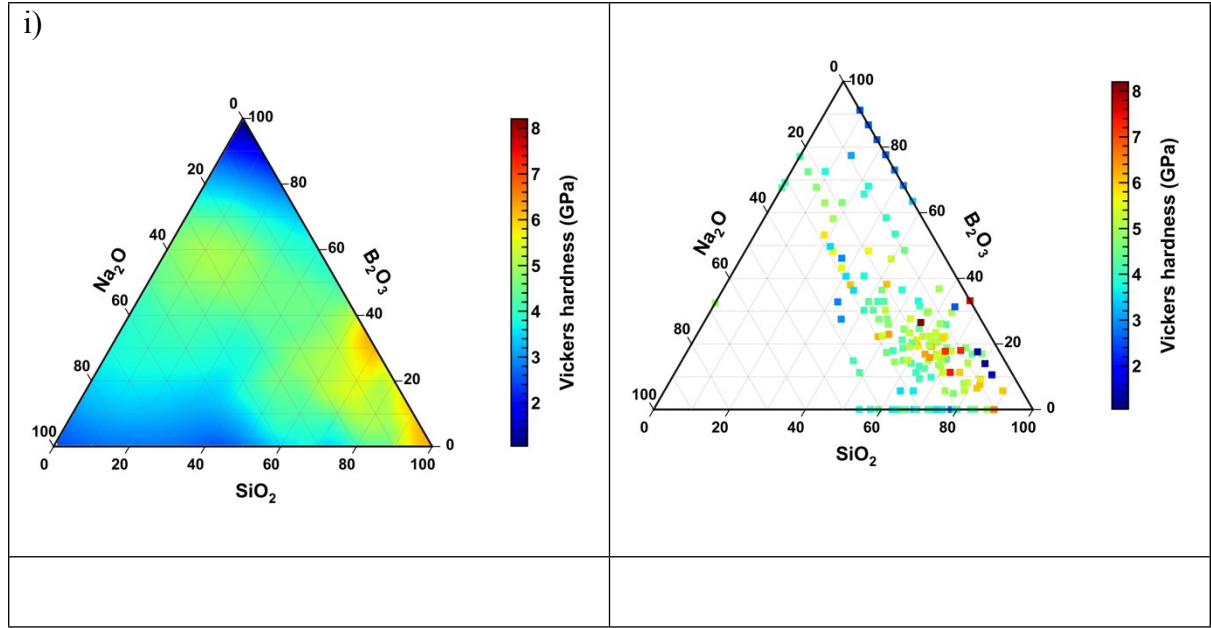
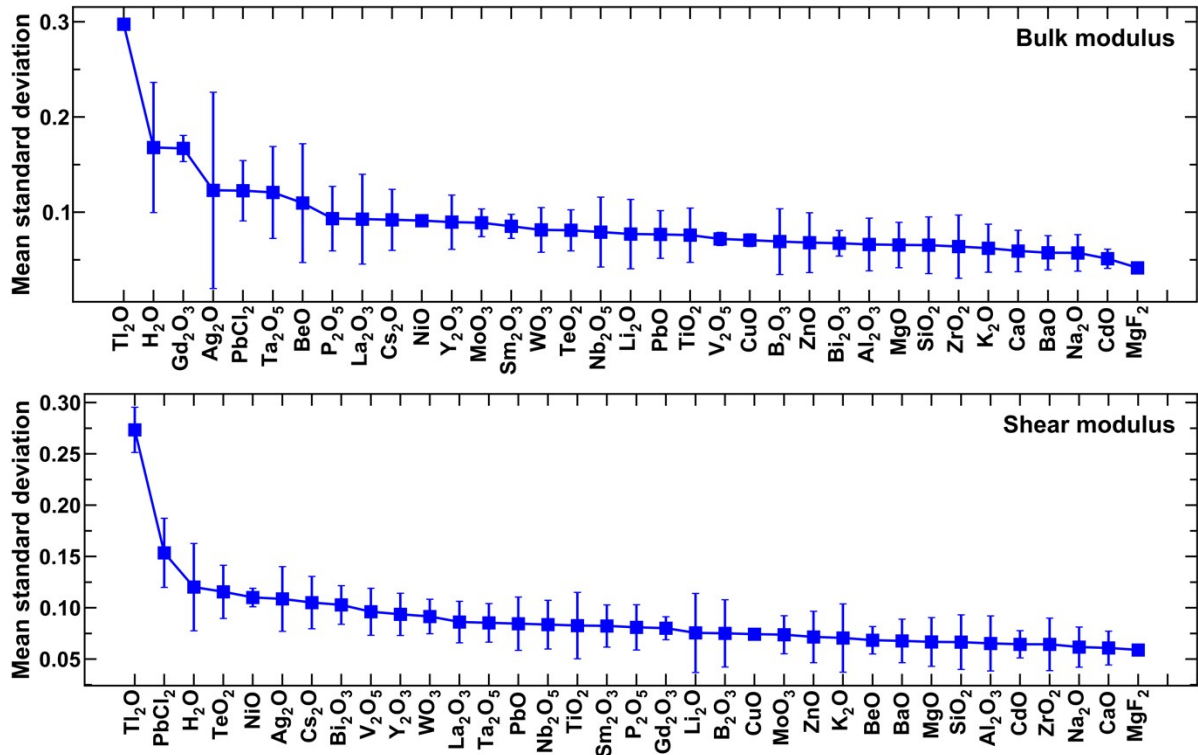
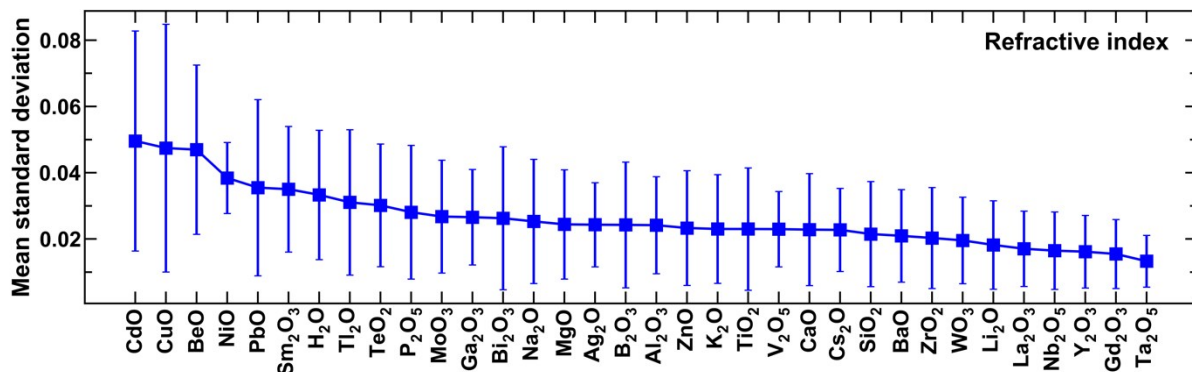
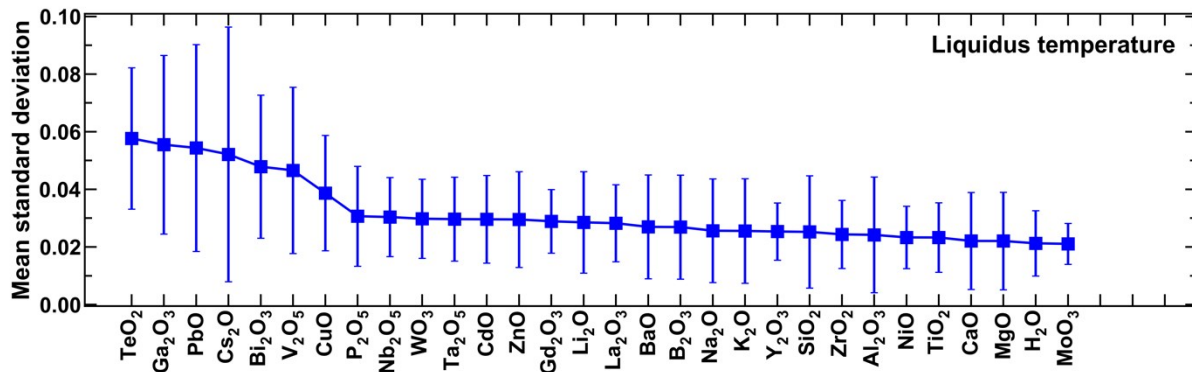
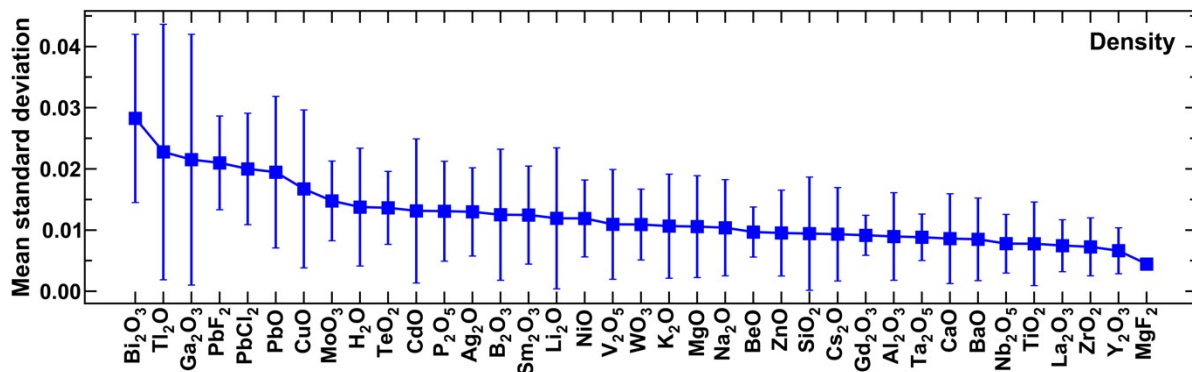
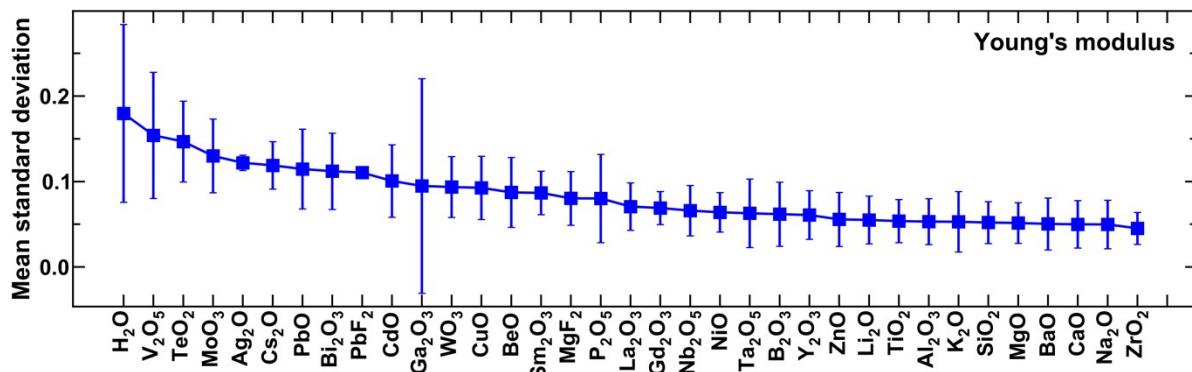


Figure S3. Predicted and experimental values (a) bulk modulus, (b) shear modulus, (c) Young's modulus, (d) density, (e) liquidus temperature, (f) refractive index, (g) thermal expansion coefficient (TEC), (h) glass transition temperature (T_g) and (i) hardness by the trained GPR models for sodium borosilicate glasses. Experimental values are marked in the right panel, while the predicted values are shown in the left panel.





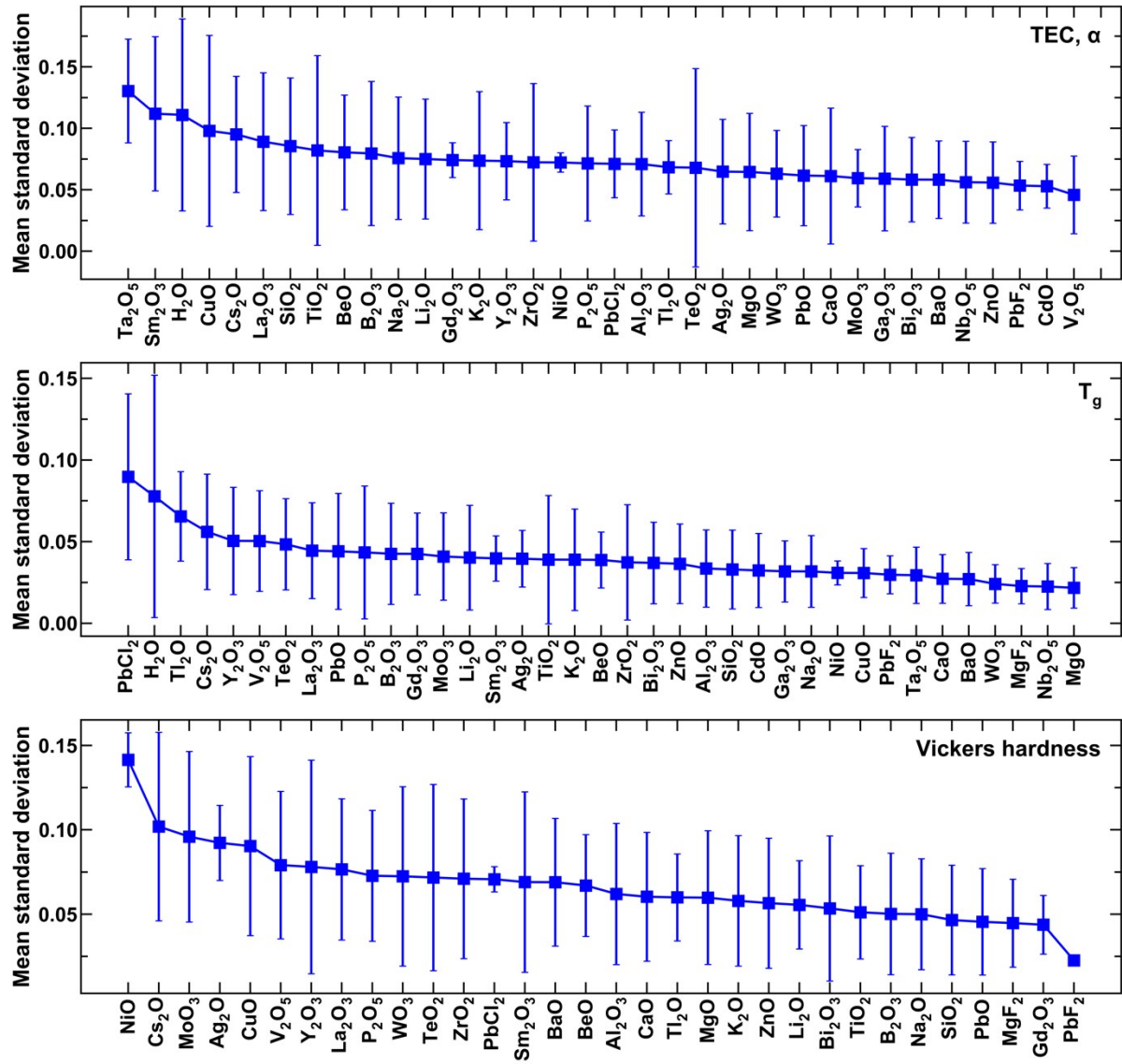


Figure S4: Mean standard deviation for each composition to show how each composition influence the standard deviation of property for (a) bulk modulus, (b) shear modulus, (c) Young's modulus, (d) density, (e) liquidus temperature, (f) refractive index, (g) thermal expansion coefficient (TEC), (h) glass transition temperature (T_g) and (i) hardness.

Least Angle Regression

Figure S5 shows the R^2 and mean squared error (MSE) values with respect to the number of input parameters (that is, oxide components) for a LARS model for (a) Young's modulus and (b) density. We observe that for both Young's modulus and density the R^2 value increases and MSE decreases as number of input parameter increases. Around 30 input components, R^2 value saturates for both the properties. Similar trend is exhibited by other properties as well. Finally, the union of the selected components lead to a total of 37 input components. By doing this, we reduce the dimensionality of the input dataset while ensuring minimal loss in the available information.

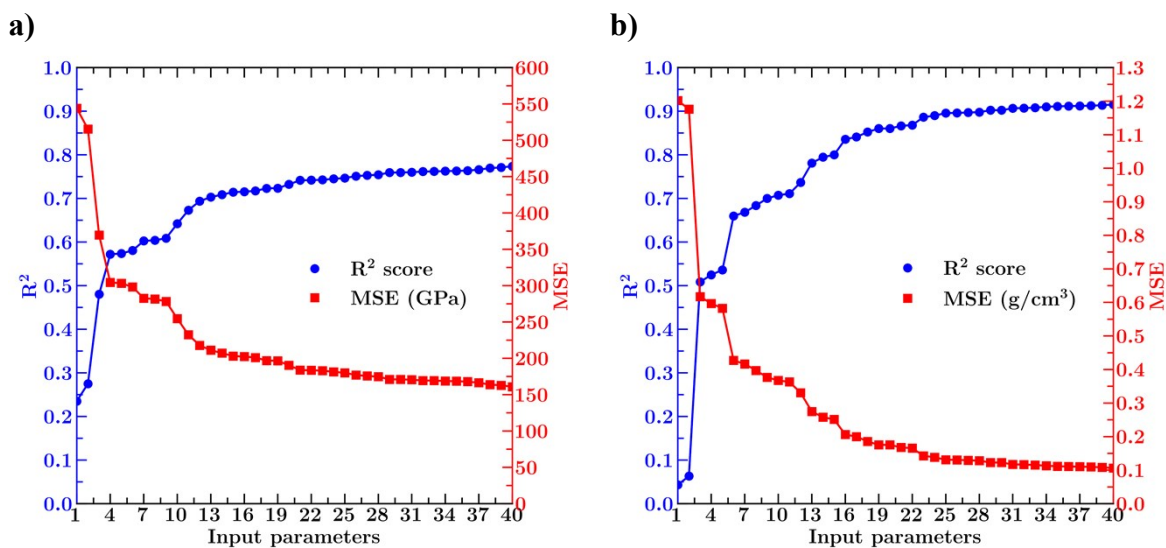
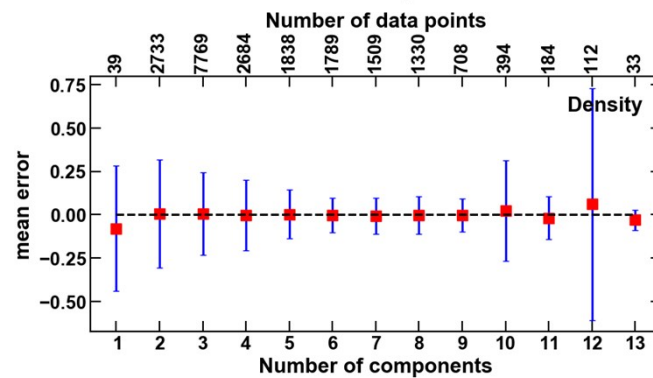
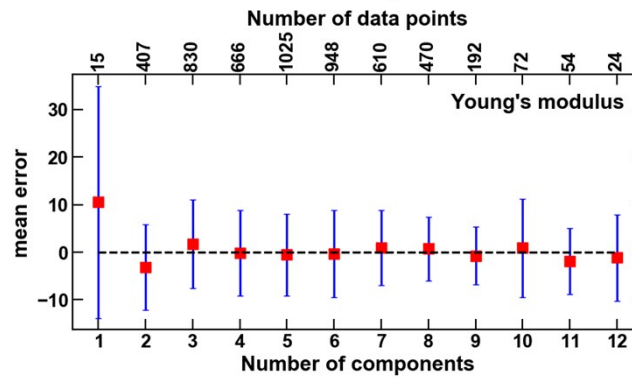
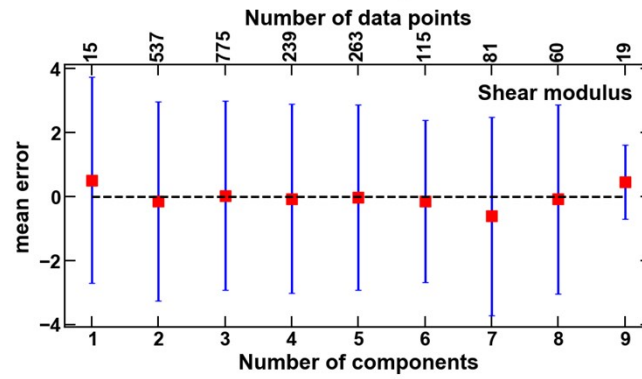
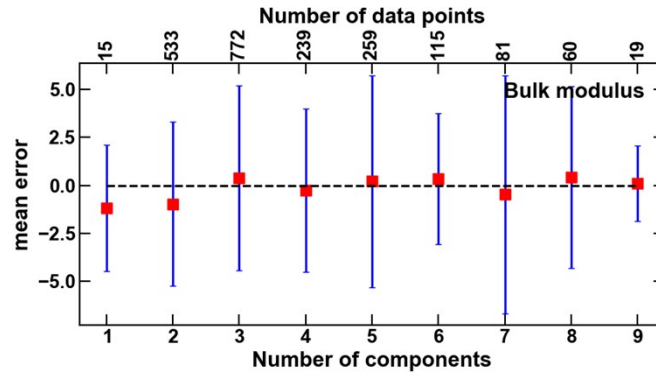
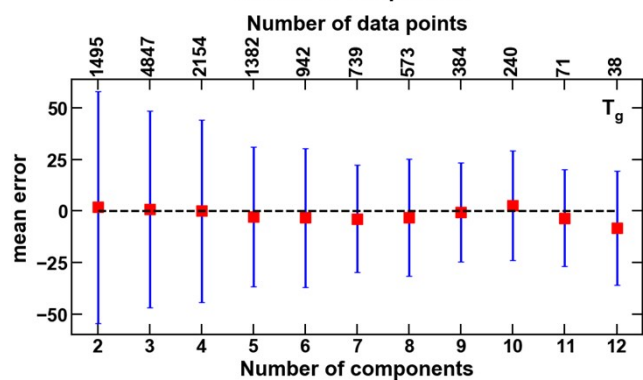
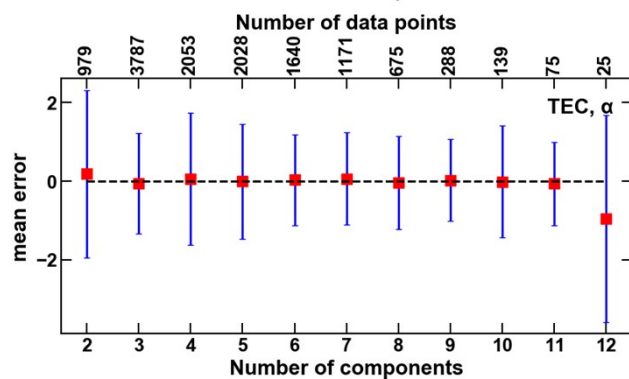
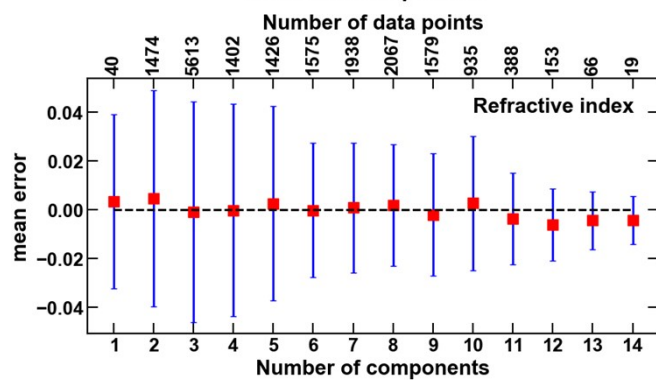
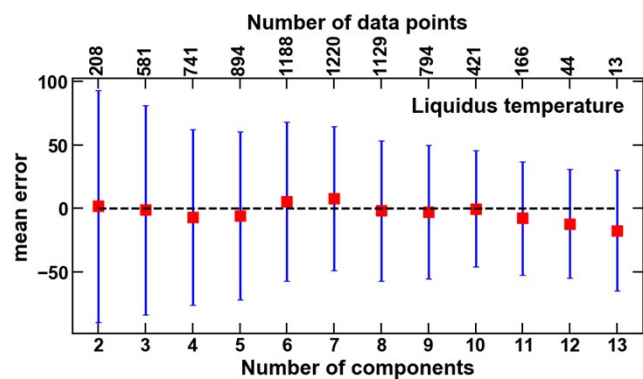
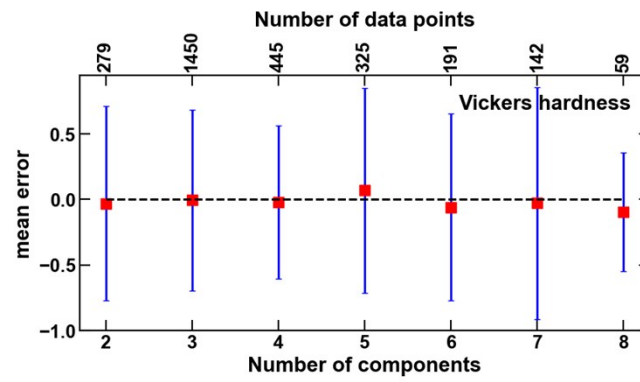


Figure S5. R^2 and MSE obtained from LARS with respect to input parameters (number compositions which are having good covariance with output labels) for **a)** Young's modulus and **b)** Density







FigureS6: Mean error along with standard error w.r.t. number of input components.