CROSS-BORDER THREAT SCREENING AND SUPPLY CHAIN DEFENSE

A Department of Homeland Security Center of Excellence

SGL Stochastic Geomechanics Laboratory

Actionable Information - Research Briefs - 3 - Analysis on U.S. States COVID-19 Dashboards

Suggested citation:

> Alvarado, J., Allen, A., Medina-Cetina, Z., Pompelli, G., Cochran, M. & Z-Losoya, E. (2021). Actionable Information - Research Briefs - 3 - Analysis on U.S. States COVID-19 dashboards. https://r7-cbts-sgl.engr.tamu.edu/2021/05/01/actionable-information-research-briefs-3-analysis-on-u-s-states-covid-19-dashboards/

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The Research Brief #2, titled U.S., and Mexico COVID-19 Dashboards, presents an exhaustive list of COVID-19 Dashboards developed by official entities of each state (Alvarado et al., 2021). The research brief also shows the number of different variables included for on platform, presenting the information in a spatial manner for the U.S. and Mexico.

This Research Brief #3, and #2 on COVID-19 Dashboards, is focused on the analysis of the variables of U.S. dashboards from different perspectives and classifications. In order to do this, the sequence of activities of Fig. 1 was followed.

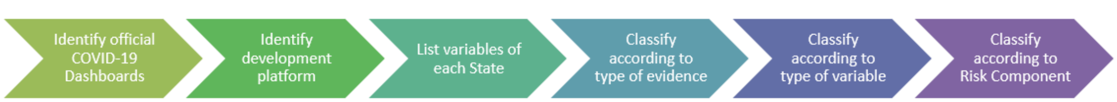

Figure 1: Number of variables presented in U.S. State Dashboards.

As such, the following sections describe the dashboards, and their variables in terms of:

- Development platform
- Distribution of number of variables
- Type of evidence
- Type of variable
- Risk components

An additional section in this Research Brief compares the amount of information presented in each dashboard with social States of Risk such as cases and deaths. The final section summarizes the results and includes the key takeaways and conclusions of the analysis.

Development Platform

Table 1 lists the different platforms used by the State entities to develop their dashboard(s). As it can be seen, a total of 29 out of 50 dashboards, were developed using either solutions by ESRI or Tableau. This is followed by a minority of dahsboards developed in Microsoft Power BI, and some other solutions such as Looker, DataViz, Google APIs, and Plotly.

Table 1: Dashboard development platforms.

Platform	# of dahsboards
ESRI (ArcGIS)	22
Public Tableau	17
Microsoft Power BI	8
Looker	1
DataViz	1
Google APIs	1
Plotly	1

Number of variables

The Fig. 2 shows the total number of variables included in the U.S. State COVID-19 Dashboards. The color scale reflects the quartiles of the distribution. As such, 25% of dashboards present between 9 and 43 variables, 25% between 43 and 57 variables, 25% between 57 and 72, and a final 25% between 72 and 172.

By hovering over the States, a pop-up window will display the total number of variables, and a set of links to visit the dashboards.

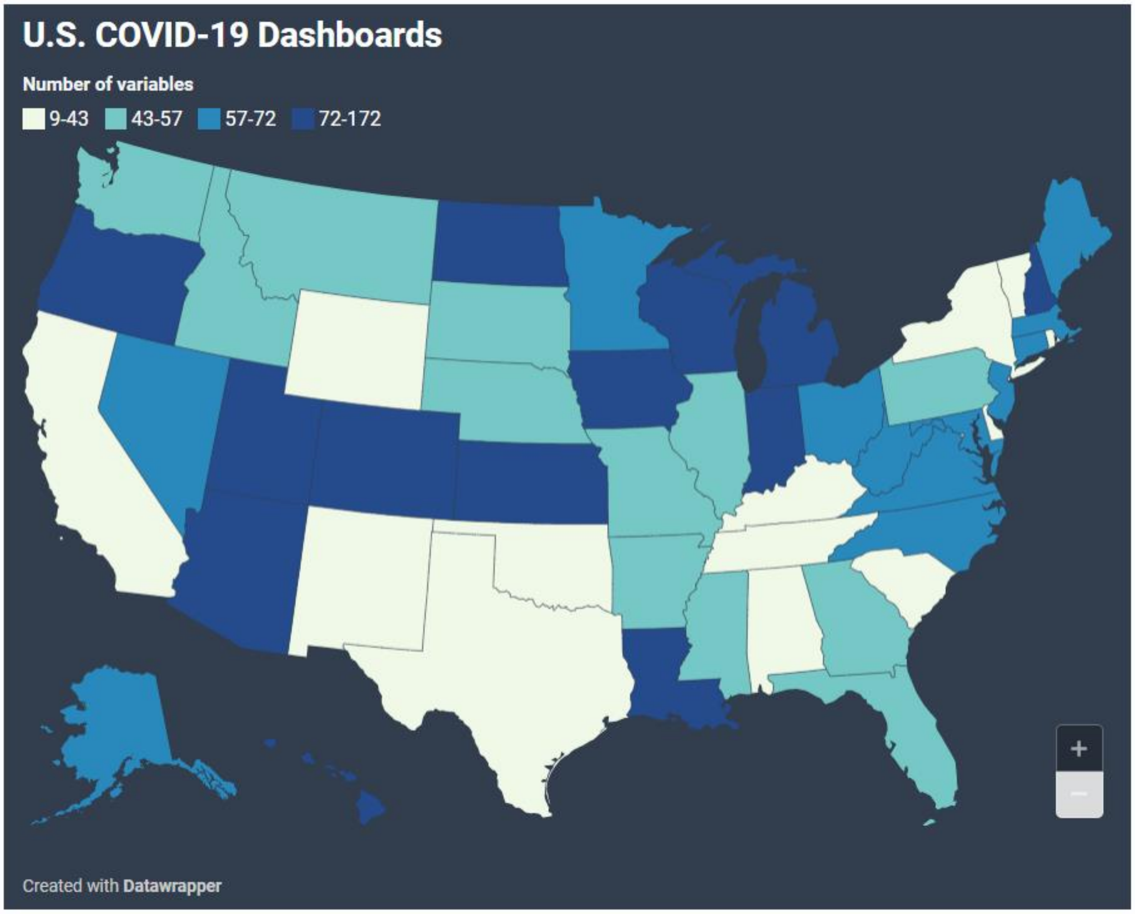

Figure 2: Number of variables presented in U.S. State Dashboards.

To take a better look at the distribution of the number of variables, a relative frequency histogram is included in Fig. 3. Below, some descriptive statistics are shown:

- Minimum: 9. Corresponding to Kentucky
- First quartile: 44
- Second quartile/Median: 59
- Average: 61 variables
- Third quartile: 75
- Maximum: 127. Corresponding to New Hampshire

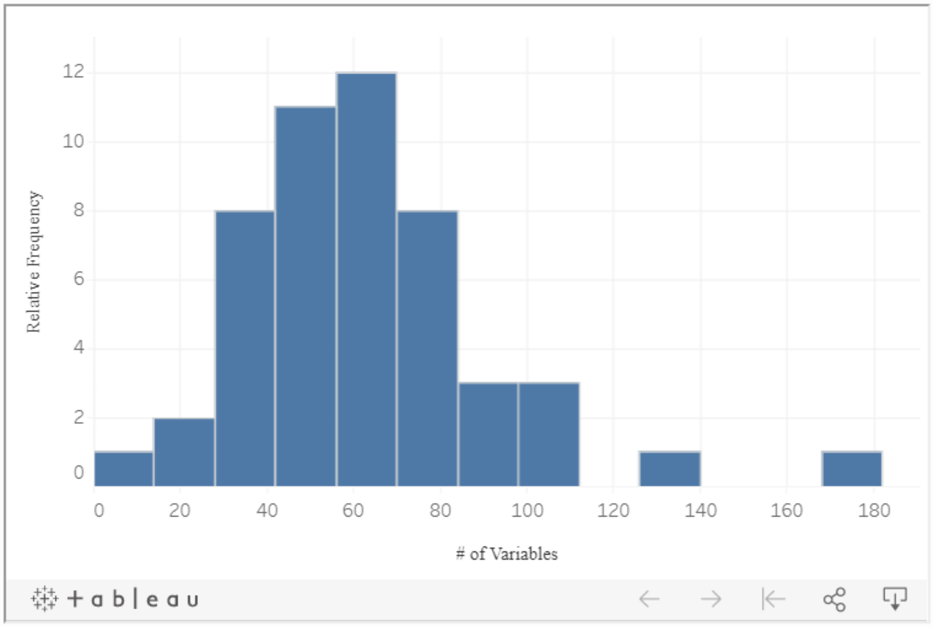

Figure 3: Relative frequency histogram for total number of variables.

Type of evidence

The variables in the dashboard were further classified according to the type of evidence. In Bayesian inference evidence can come from observations, model predictions, expert beliefs, or a combination of them (Medina-Cetina et al., 2016).

After classifying the variables by type of evidence, it is possible to calculate the percentage for each one with respect to the total number of variables in each dashboard. These percentages are:

- Observations: 91% to 100%
- Model predictions: 0% to 9%
- Expert beliefs: 0% to 2%

Most of the variables come from observations from evidence on cases, deaths, and the capacity of health system services. A percentage less than 10% are model predictions, with variables such as the effective reproduction rate or models to predict deaths, and ICU bed occupancy. The only State that present expert beliefs is California, that includes expert opinions to adjust the value of daily COVID-19 tests.

Type of variable

The next classification of variables is by type. The different types are:

- V: regular variable, static in time and space
- V(t): variable changing in time
- V(x): variable changing in space
- V(x, t): variable changing in both space and time

Fig. 4 shows a boxplot for the 4 different types of variables. The distributions for the 4 types are similar, meaning that the variables in the dashboard are roughly equally divided in the 4 categories. Notably, given the nature of the pandemic and the development of the dashboards, there is a considerable number of variables that change in both time and space such as the time series of COVID-19 cases by each county in a state.

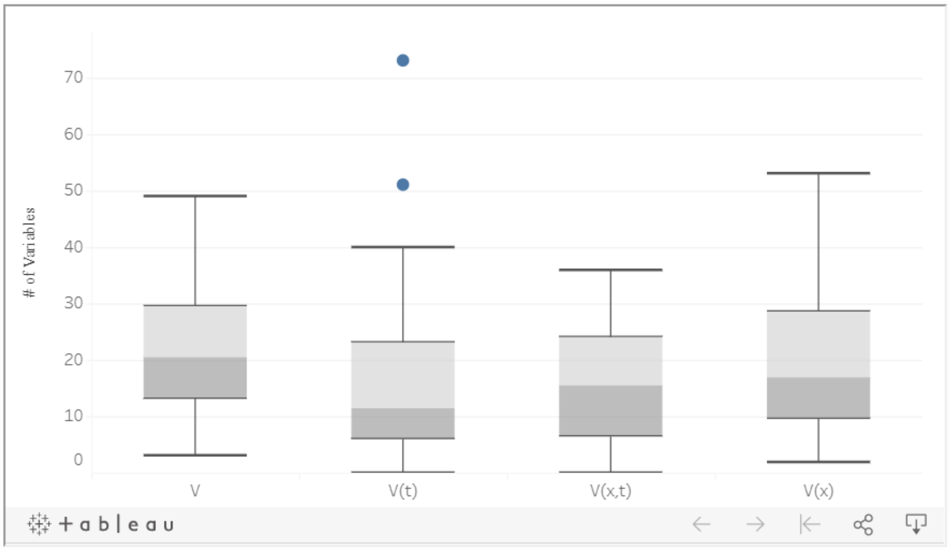

Figure 4: Type of variable distribution.

Classification by Risk Component

According to the Bayesian Risk definition, and framework from (Medina-Cetina & Nadim, 2008), Risk is defined as:

$$Risk = [Hazard] * [Vulnerability] * [Consequences]$$

Where:

- Hazard is the likelihood of occurrence of converging *threats*
- Vulnerability is the likelihood of reaching a Consequence or damage in the *system* of interest, conditioned on a given *Threat Intensity*
- Consequences represents the value of the elements exposed to converging threats

Variables required to estimate the Hazard, Vulnerability, and Consequences, have to depict the *threats*, the *systems*, and the *impacts* respectively.

The Risk Assessment framework is expanded into the following for representing Risk Assessment & Management:

$$Risk = [H * V * C] + [Cost(AC + PC) - AC - PC]$$

Where:

- AC= Active countermeasures
- PC = Passive countermeasures

In order to reduce the *state of risk*, *mitigation* strategies such as active countermeasures (AC), and passive countermeasures (PC) can be applied.

Considering Risk Assessment and Management, the 5 Risk Components are:

- Threat
- Systems
- Impacts
- Mitigation
- States of Risk

Fig. 5 shows a boxplot for the variables classified in the 5 Risk Components. The figure shows a higher number of variables for Systems and Mitigation across the 50 dashboards, with median values of 20 and 19 respectively. In contrast, Impacts and States of Risk have a median value of 7.

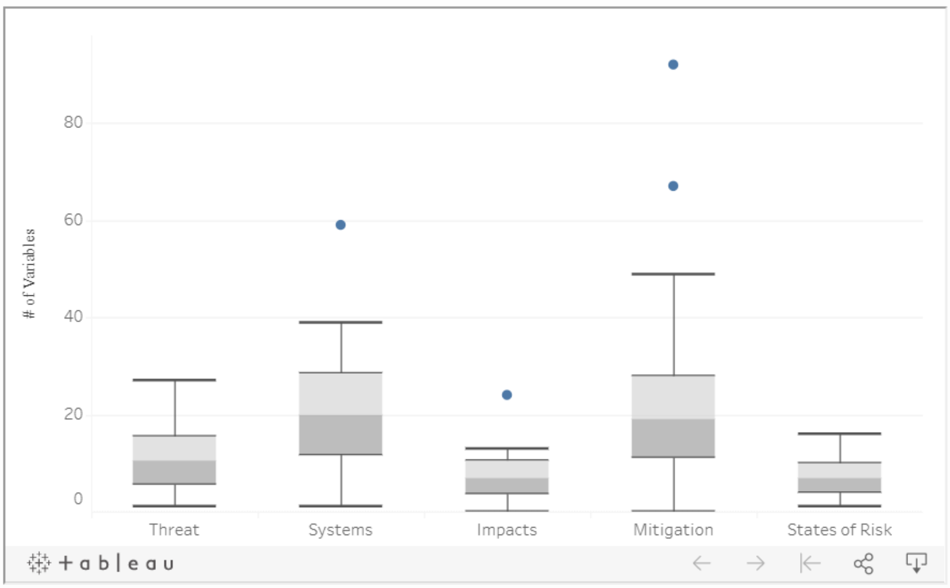

Figure 5: Classification by Risk Component.

Examples of variables in each Risk Component are:

- Threats: Effective reproduction number, Daily COVID-19 cases
- Systems: COVID-19 cases age distribution, Available ICU beds
- Impacts: Fatalities gender/sex distribution, Fatalities race/ethnicity
- Mitigation: Total tests, Vaccine doses administered
- States of Risk: Daily fatalities, Total fatalities

Fig. 6 is a spatial representation of the number of variables on each Risk Component. By hovering over a state, a pop-up window will display the total number of variables for the corresponding Component.

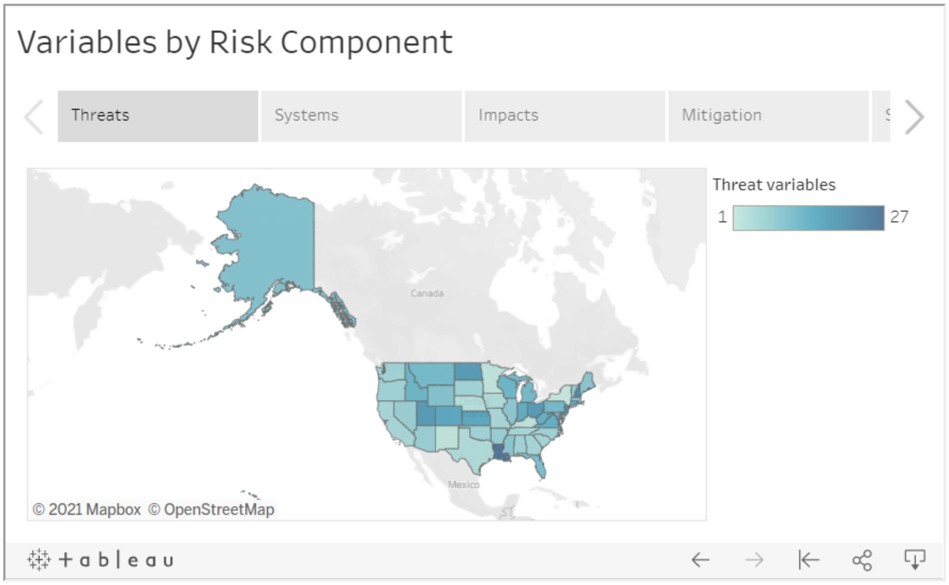

Figure 6: Map of variables classified by Risk Component.

Amount of information presented, compared to normalized COVID-19 cases and deaths

In order to assess the relationship between the amount of information presented in the dashboards with the management of the pandemic in the 50 states, Fig. 7, and Fig. 8 present a scatter plot of the total number of variables (and the number of variables for the 5 Risk Components) and the COVID-19 cases and deaths per 100k population.

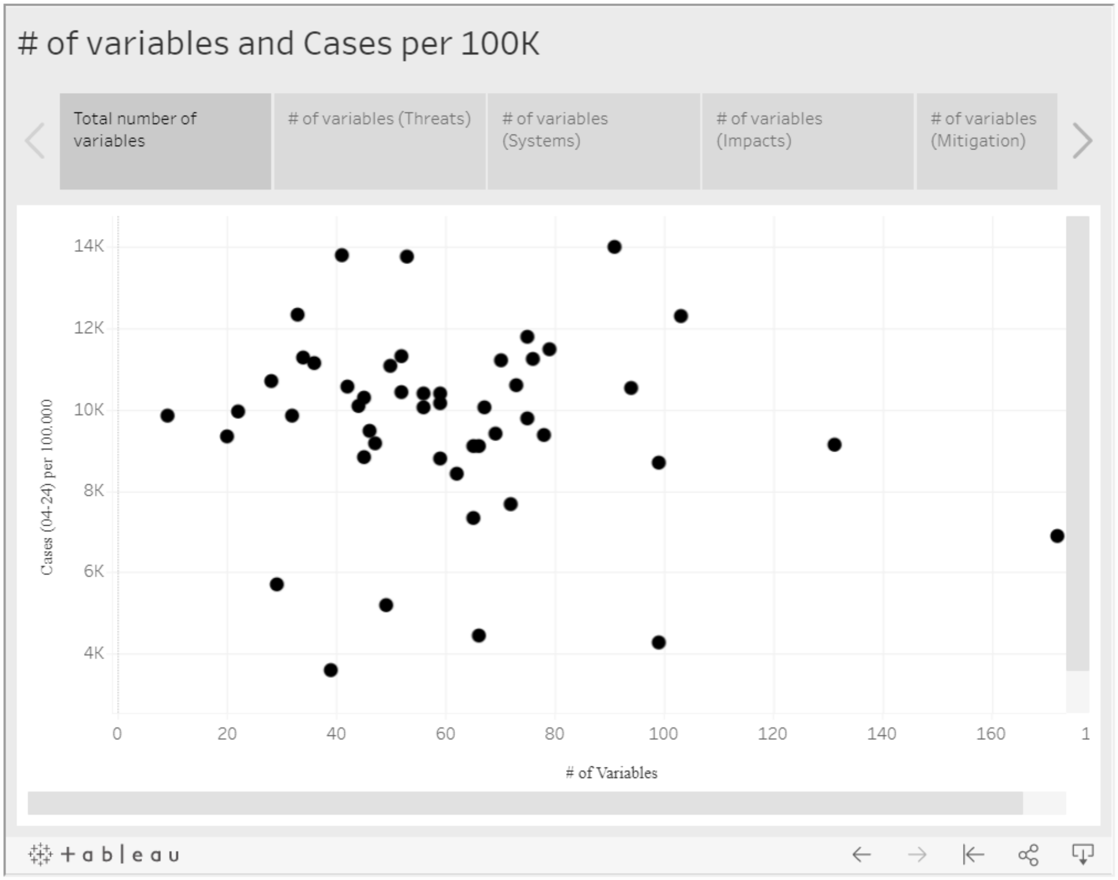

Figure 7: Number of total variables, and variables per Risk Component compared to cases per 100k.

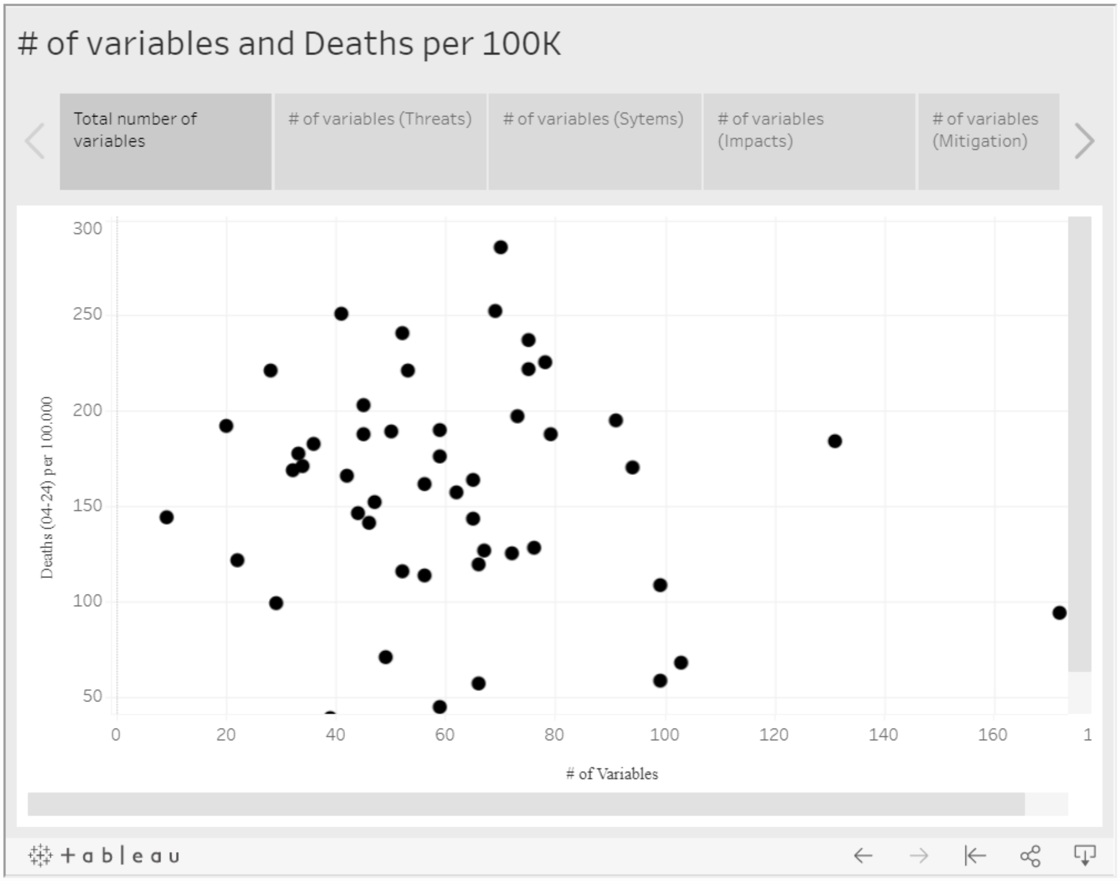

Figure 8: Number of total variables, and variables per risk components compared to deaths per 100k.

The previous figures show no apparent relationship between the amount of information (number of variables) and the social States of Risk represented by the normalized COVID-19 cases and deaths. This is, there is no tendency for the cases and deaths to decrease with an increase on the number of variables from the dashboards.

Bayesian inference, and Bayesian decision-making, suggests that by having information about the components of the Risk equation, the decision making improves. This improvement allows for a better Risk Assessment and Management. This is not what the previous figures suggest.

To explore further the relationship, and the previous affirmation, Fig. 9 presents a similar scatter plot, but this time using the variables needed for Risk Assessment only (Threats, System, Impacts, States of Risk). The color coding on the scatter plots differentiates states that are below the median of the combined number of variables (Threats + Systems + Impacts + States of Risk), between the median and the third quartile, and above the third quartile. Once again, no evident correlation is found in the figures.

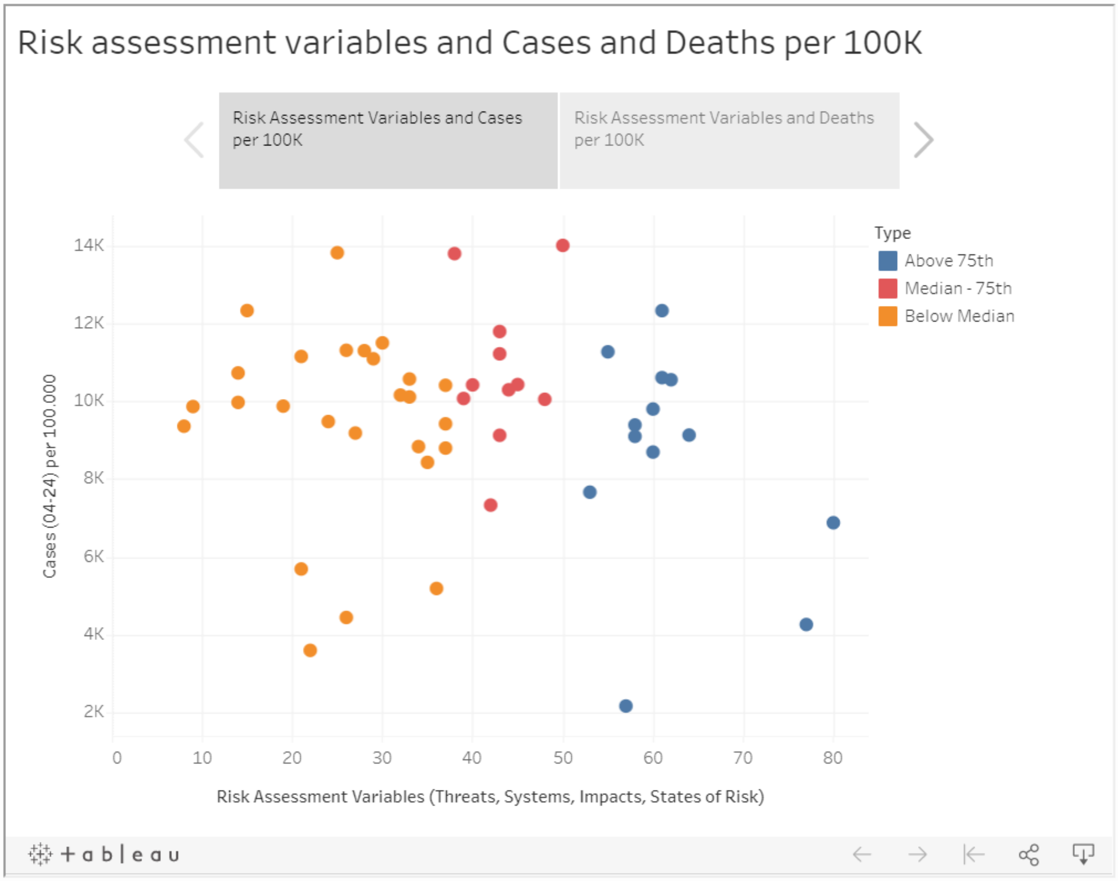

Figure 9: Number of Risk Assessment variables compared to cases and deaths per 100k.

As a last exercise, states that include an aggregate index in their dashboards were identified. Table 2 includes the states, the name of the aggregated indexes, and the variables used to compute them. Finally, these states are marked with yellow in Fig. 10.

Table 2: Aggregated Indexes

State	Index	Variables considered
Alabama	COVID Risk Indicator	Declining new cases (2 weeks), Percent positive declining, Testing goals met, Visits for covid-like symptoms declining
California	County Risk Levels	New COVID cases per day per 100.000, Positivity rate (7 day rolling average), ICU availability
Colorado	COVID-19 dial	New cases (7 day incidence level), Percent positivity of COVID tests , Impact on hospitalizations (Stable or declining)
Connecticut	Leading and secondary indicators for schools	New covid 19 cases per 100.000 per day, Percent test positivity, New covid hospitalizations per 100.000 per day, Percent COVID-19 like illness hospital visits

State	Index	Variables considered
Idaho	County Transmission Risk Levels	New daily cases 7 day rolling average per 100.000, Testing positivity rate, Regional hospital bed ocupancy
Illinois	COVID-19 Resurgence Criteria	Test Positivity 7-Day Rolling Average, Hospital Bed Availability 7-Day Rolling Average, COVID-19 Patients in the Hospital 7-Day Rolling Average
Indiana	Advisory level	7-day positivity rate, Weekly cases per 100.000 residents
Louisiana	Community Risk Level	Cumulative 7 day incidence per 100.000, Cumulative 7 day percent positivity
North Dakota	County Risk Levels	Active cases per 100.000, Tests per 100.000, Test Positivity Rate
Ohio	Opportunity Index	Opportunity domains: Transportation, Education, Employment, Housing, Health, Access, Crime
Oregon	County Risk Levels	Confirmed and presumptive cases, Cases per 100.000 residents, Test Positivity rate
Virginia	Pandemic metrics - Composite score	Cases, Percent positivity, Outbreaks, HC workers, ED visits, ICU hospitalization, Hospital beds, PPE
Washington	Metrics for Risk Assessment	Rate per 100K newly diagnosed cases, Daily molecular testing rate, Percent of positive molecular tests, Percent of adult staffed adult care beds, Beds occupied by COVID patients, Percent of adult ICU staffed beds occupied, Percent of adult ICU staffed beds occupied by COVID-19 cases

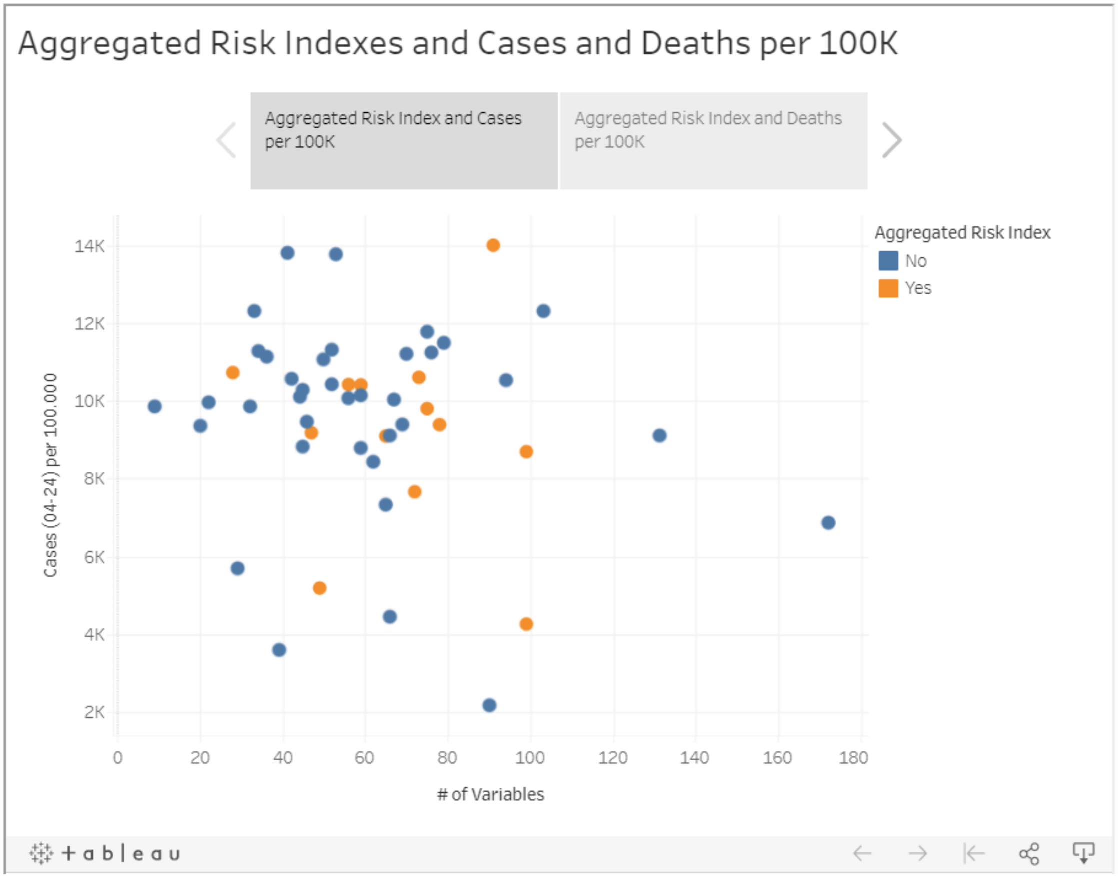

Figure 10: Number of Risk Assessment variables compared to cases and deaths per 100k.

From the figures included in this section, it can be concluded that no evident correlation exists between the amount of information presented and social States of Risk. This holds true for the total number of variables in the dashboards, the number of variables required for a Risk Assessment, and also for those states that presents aggregated indexes, some of which are called Risk Indexes. Potential reasons for these findings are:

- Only social impacts and states of risk were considered in the analysis. No analysis including economic or environmental impacts was made
- Decisions based on the amount of information on the dashboards were intended to manage the economic impacts of the pandemic at state level
- Difficulties with risk communication. People are not assimilating the information, because they are not prepared or educated to do so
- The states have access to the information, and are communicating it through the dashboards, but their decision making could be influenced by external factors such as geopolitics
- The different levels of uncertainty on the information for different Risk Components, creates an added complexity on the decision-making processes
- This analysis doesn't deal with, or considers, the acceptable levels of social risk that could be considered at state level

Conclusions

- This research brief on U.S. COVID-19 state dashboards presents a detailed description on the development platforms, and on the variables reported in terms of type of evidence, type of variables, and Risk Components.
- The amount of information presented in the dashboards was compared to social impacts such as normalized COVID-19 cases, and deaths
- No evident correlation was found between the amount of information and the social States of Risk
- Some reasons for this include the fact that only social impacts were considered, and also the particularities of decision-making at state level
- The findings of the research brief emphasize the importance of risk communication during a pandemic event
- There is a considerable room for research in order to understand why the correlations are not apparent, given that the theory suggests that decision-making improves when evidence on every Risk Component becomes available

References

Alvarado, J. P., Allen, A., Medina-Cetina, Z., Pompelli, G., Cochran, M., & Z-Losoya, E. (2021). *Actionable information - research briefs - 2 - u.s. And mexico COVID-19 dashboards*. https://r7-cbts-sgl.engr.tamu.edu/2021/04/30/actionable-information-research-briefs-2-u-s-and-mexico-covid-19-dashboards/

Medina-Cetina, Z., Eidsvig, U. M., Kveldsvik, V., Glimsdal, S., Harbitz, C. B., & Sandersen, F. (2016). Bayesian risk assessment of a tsunamigenic rockslide at Åknes. In P. Gardoni & J. M. LaFave (Eds.), *Multi-hazard approaches to civil infrastructure engineering* (pp. 413–442). Springer International Publishing. https://doi.org/10.1007/978-3-319-29713-2_19

Medina-Cetina, Z., & Nadim, F. (2008). Stochastic design of an early warning system. *Georisk: Assessment & Management of Risk for Engineered Systems & Geohazards*, *2*(4), 221–234. http://proxy.library.tamu.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=bcr&AN=35523788&site=eds-live