
Blindspots: Pandemic Response Atlas for Testing Visibility and Local Conditions¹

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Apart Research

Abstract

Pandemic response depends on accurate detection and measurement. However, testing data has blind spots or poor visibility in many areas. During the critical early pandemic stage, predicting which communities and neighborhoods have blindspots can help control pandemic spread. Missing tests also matter in determining population antibodies, group vulnerability and several other pandemic measures. In contrast to extensive work on pandemic mortality, the data of who takes tests and who does not is just as relevant in Pandemic management.

This project builds a prototype pandemic response atlas using Covid-19 France and the greater Paris area as a case study.² The prototype is an R Shiny web application that provides three map layers: COVID testing visibility across Île-de-France, IRIS-level socioeconomic conditions, and a high-resolution 200m Paris socioeconomic layer.³ Its main contribution is predicting better public-health surveillance interpreted with local socioeconomic context. Based on socio-economic conditions, policy makers should then better preventively protect the blindspot areas.

¹ Research conducted at the [AIXBio Hackathon](#), April 2026

² Atlas demo: mightbeuseless.com

³ Github repository: <https://github.com/Hamza-Anver/mightbeuseless-ali/>

1. Introduction

Pandemic response depends on detection. If infections are not detected early, public-health teams may underestimate local transmission and respond too late. This makes testing visibility a core part of biosecurity and pandemic early warning.

However, testing data can have social blindspots. In an ideal surveillance system, the decision to test would depend only on infection risk. In reality, testing behavior can also depend on income, education, housing, ability to isolate, distance to testing facilities, work constraints, and trust in public-health systems. This means measured incidence may partly reflect who gets tested, not only who is infected.

This problem matters for future outbreaks. If testing is lower in some communities, a public-health dashboard may understate risk in those places. Broad restrictions can also impose unequal burdens across areas, depending on local income, household size, age structure, housing, and employment conditions. A better early-warning tool should therefore show both testing visibility and the local socioeconomic conditions that shape feasible interventions.

This project turns that idea into a prototype atlas. Using public French data, it maps COVID testing indicators and socioeconomic indicators at small geographic scales. The goal is not to estimate true infection prevalence or prove causal under-testing. The goal is to give public-health users a practical way to inspect where surveillance may be weak and what local conditions should shape targeted support.

Our main contributions are:

1. A working R Shiny prototype mapping COVID testing visibility and socioeconomic burden.
2. A multi-scale data pipeline combining IRIS COVID data, IRIS socioeconomic data, and 200m Filosofi grid data.
3. Policy Framework combining undervisibility and interventions based on local conditions

2. Related Work

This project is mainly motivated by my Master thesis supervisor Pierre-Yves Geoffard's work. As this is a component of my own Master thesis, the two papers below were the theoretical foundation. Geoffard, Jusot, Sireyjol, Warszawski, and Bajos (2025). Using the French EpiCoV cohort, they study whether access to COVID-19 testing in France was associated with socioeconomic conditions. France is an important case because tests were free of charge until mid-October 2021 and became widely available after June 2020.

Their findings show that free testing did not fully eliminate inequalities in testing. Among symptomatic individuals without a known positive close contact, testing was more common among people living in urban areas, more educated individuals, and higher-income individuals. The authors suggest that isolation requires resources. A positive test is more useful when a person can realistically isolate, avoid income loss, and protect others in the household.

The second motivation is the IHE report by Persson, Geoffard, Möller, and Brådvik (2025) on behavior, health, and GDP during the COVID-19 pandemic in Europe. Their report emphasizes that NPIs and behavioral change were intended to reduce physical interaction, but also carried costs in quality of life and production losses. For this project, the key lesson is not that broad restrictions are always wrong. It is that pandemic policy involves tradeoffs, and those tradeoffs vary across social and geographic contexts.

Most COVID dashboards show incidence, positivity, hospitalizations, vaccination, or mortality. This project differs by treating surveillance data as potentially shaped by access and behavior. It asks where measured infection indicators may be less visible because of testing patterns, and what local socioeconomic conditions should be considered before choosing interventions. While this may seem an essential part of Pandemic management, there exists a considerable gap in policy makers not knowing which areas undertake free and widely available tests in pandemics and how this is associated with factors like income and education.

3. Methods

3.1 System overview

I built an interactive R Shiny prototype called **Blindspots**. The app has three operational spatial layers:

1. **COVID testing visibility layer:** IRIS-level COVID incidence, testing-rate, and positivity classes.
2. **IRIS socioeconomic layer:** IRIS-level poverty and median living standard indicators.
3. **Paris 200m socioeconomic layer:** high-resolution Filosofi grid indicators for Paris, including poverty share, standard-of-living proxy, age structure, household size, and population.

The current geographic scope is Île-de-France at IRIS level, because the IRIS boundary file used in this prototype covers Île-de-France. The 200m layer is currently extracted for Paris. The pipeline is designed to extend to metropolitan France once national IRIS contours are substituted.

3.2 Data sources

The prototype uses four main data sources.

Santé publique France SI-DEP IRIS data. The file `sg-iris-opendata.csv` contains IRIS-level COVID indicators, including incidence class, testing-rate class, and positivity class. The key fields used are `iris2019`, `semaine_glissante`, `clage_65`, `ti_classe`, `td_classe`, and `tp_classe`.

IRIS contours. The file `iris.geojson` contains IRIS boundary polygons. In this prototype, it covers Île-de-France and is used to map COVID and socioeconomic indicators at IRIS level.

INSEE Filosofi IRIS data. The file `BASE_TD_FILO_IRIS_2021_DISP.xls` contains IRIS-level indicators on disposable income, poverty, and living standards. The prototype uses it to display median living standard and poverty rate.

INSEE Filosofi 200m grid data. The 200m Filosofi GeoPackage provides high-resolution socioeconomic indicators. The prototype extracts Paris-area cells and derives interpretable local indicators.

3.3 Data processing

The prototype was implemented in RStudio using `sf`, `dplyr`, `readr`, `readxl`, `leaflet`, and `shiny`.

For the COVID IRIS layer, I read `sg-iris-opendata.csv`, filtered to all-age rows using `clage_65 == 0`, extracted the end date from `semaine_glissante`, selected the latest available rolling week, and joined the COVID indicators to IRIS polygons using `code_iris = iris2019`.

For the IRIS socioeconomic layer, I read `BASE_TD_FILO_IRIS_2021_DISP.xls`, skipped metadata rows, converted income and poverty fields to numeric format, joined the indicators to IRIS polygons using the IRIS code, and created display variables such as `median_living_standard` and `poverty_rate`.

For the Paris 200m layer, I read the Filosofi 200m GeoPackage, extracted cells in the Paris area using a bounding box in Lambert-93, derived interpretable variables, transformed the result to WGS84 for Leaflet, and saved the processed object for faster loading.

The derived 200m variables include:

- `poverty_share = men_pauv / men`
- `mean_snv = ind_snv / ind`
- `elderly_share = (ind_65_79 + ind_80p) / ind`
- `children_share = (ind_0_3 + ind_4_5 + ind_6_10 + ind_11_17) / ind`
- `household_size = ind / men`

3.4 Application design

The app is organized around map-based exploration. Users can switch between the three layers and select the variable used to color the map.

In the COVID testing visibility layer, users can inspect incidence class, testing-rate class, and positivity class. The main interpretive rule is simple: **low testing-rate class plus high positivity class is a possible under-detection signal**. This is not proof of hidden infections, but it is a useful flag for further investigation.

In the IRIS socioeconomic layer, users can inspect poverty and median living standard. These variables help describe the local context behind testing behavior and policy feasibility.

In the Paris 200m layer, users can inspect finer local heterogeneity within the city. This layer shows how poverty, household size, population structure, and standard-of-living proxies can vary within small areas that are hidden at larger administrative scales.

4. Results

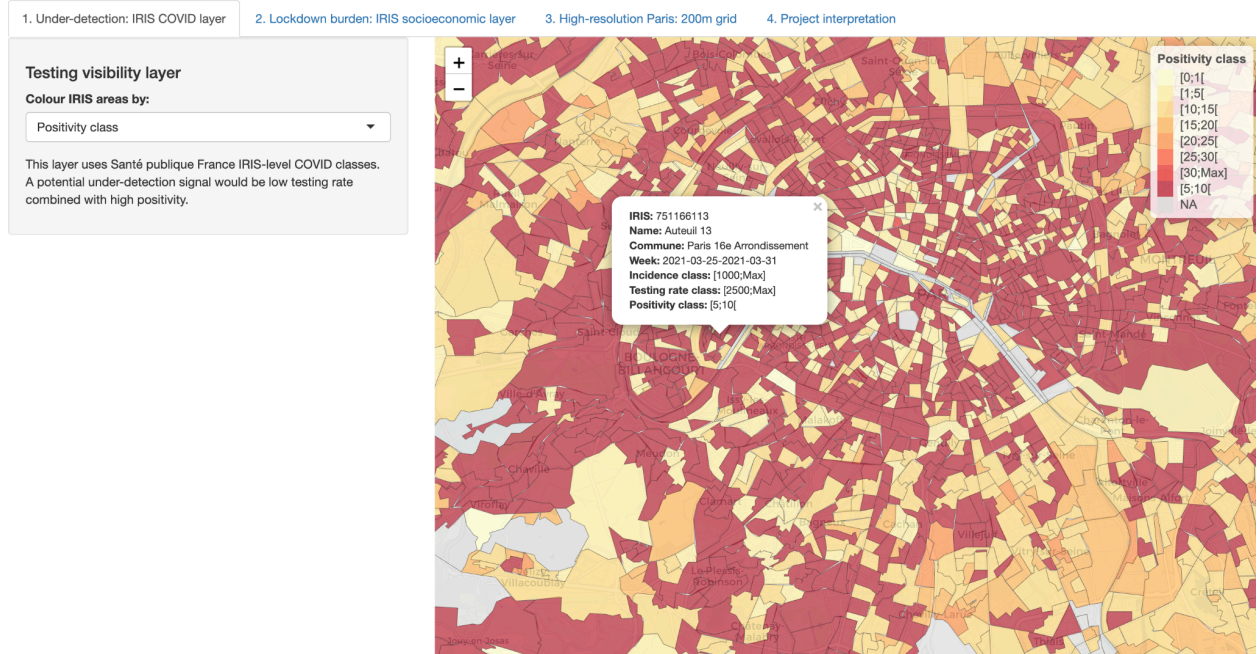
The main result is a working prototype that links public-health surveillance data with local socioeconomic data. The app successfully renders three interactive spatial layers: an IRIS-level COVID testing visibility map for Île-de-France, an IRIS-level socioeconomic map for Île-de-France, and a 200m socioeconomic grid map for Paris.

The COVID layer allows users to inspect incidence class, testing-rate class, and positivity class. This makes it possible to identify areas where low testing and high positivity may indicate weak surveillance visibility. The prototype treats this as a signal for further investigation, not as a direct estimate of true infection prevalence.

The socioeconomic layers allow users to inspect poverty, median living standards, age structure, household size, and population. These indicators are not direct measures of GDP loss, mental-health loss, or QALY loss. They are proxies for local conditions that may shape testing behavior, isolation feasibility, communication strategy, and the burden of broad restrictions.

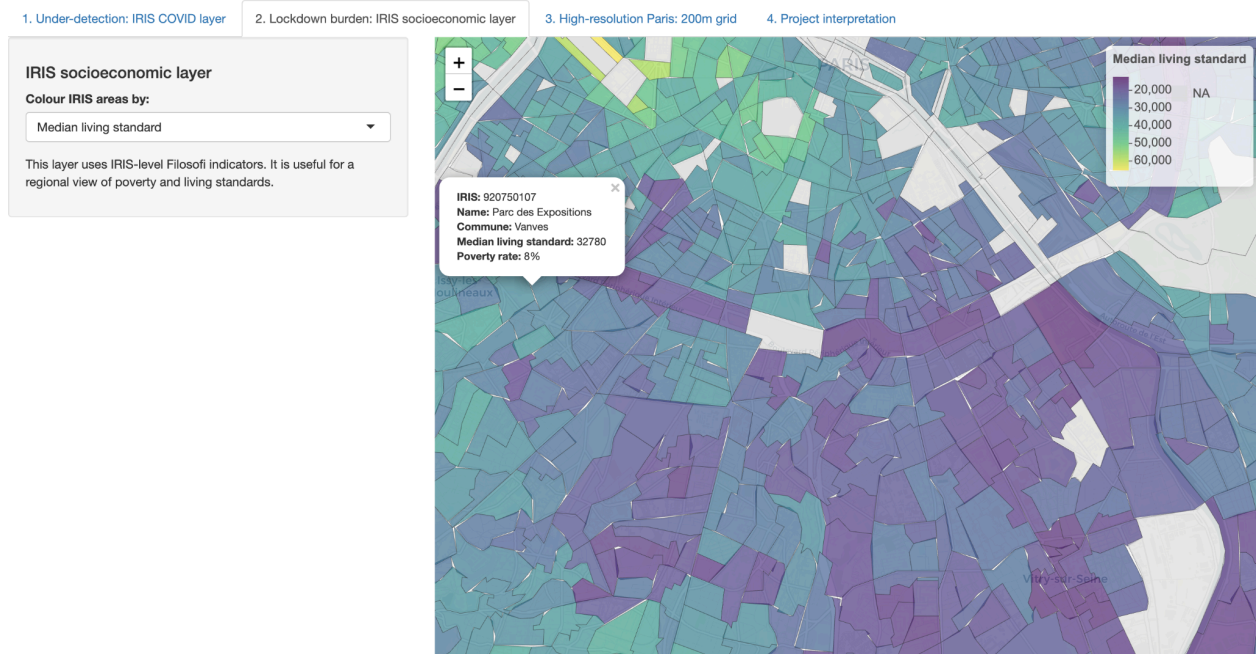
Together, the layers demonstrate the feasibility of a surveillance-context atlas. Instead of showing COVID indicators alone, the tool places those indicators in their social and geographic context.

Figure 1. COVID testing visibility layer.



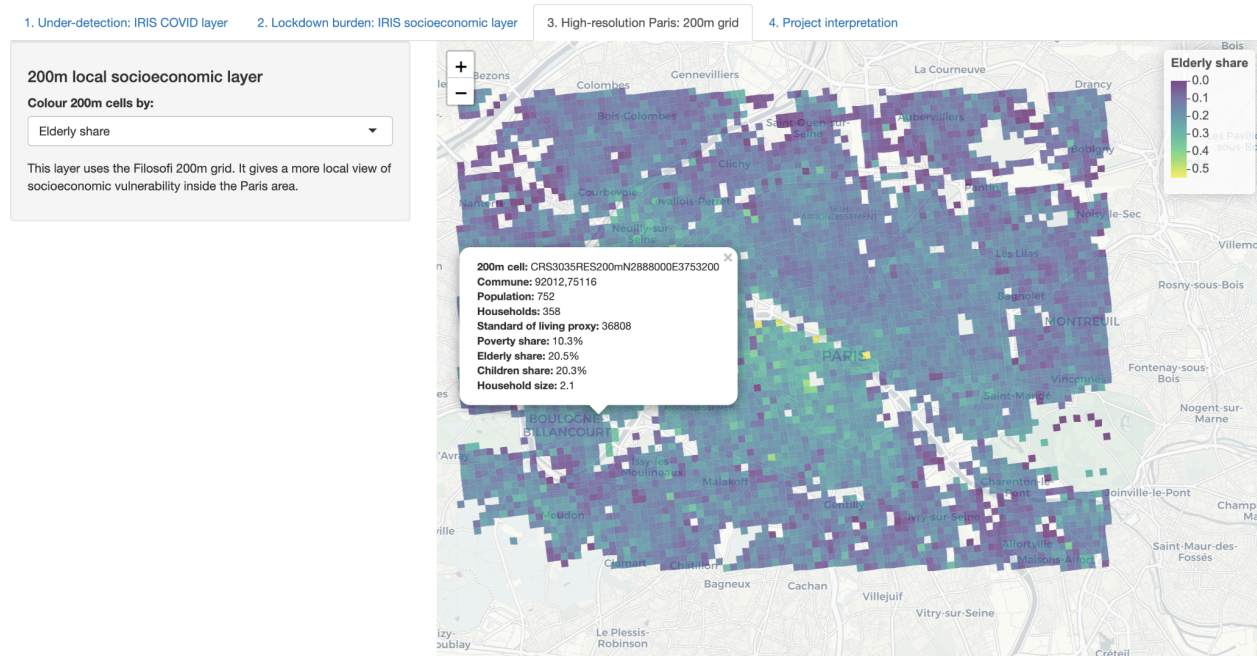
The COVID testing visibility layer allows users to inspect incidence, testing-rate, and positivity classes by IRIS. Areas with low testing-rate class and high positivity class are possible candidates for under-detection.

Figure 2. IRIS socioeconomic conditions layer



The IRIS socioeconomic layer maps local poverty and living standards. These variables help describe the conditions that may shape testing behavior and the feasibility of targeted interventions.

Figure 3. Paris 200m socioeconomic layer



The high-resolution Paris layer shows within-city socioeconomic variation that may be hidden at larger administrative scales.

5. Discussion and Limitations

This project reframes pandemic early warning as a socially conditioned surveillance problem. A surveillance system can fail even when testing exists if testing behavior is unequal across communities. For AIxBio and biosecurity, this matters because AI systems trained or deployed on biased surveillance data may optimize responses around what is easiest to observe, not where risk is greatest.

The practical use case is a local public-health analyst or crisis-response team. In a future outbreak, the tool could help identify neighborhoods where testing visibility is weak and where socioeconomic conditions suggest that targeted support is needed. Possible responses include mobile testing, isolation accommodation, paid-leave support, local communication campaigns, clinics, and resource allocation. The goal is not simply to increase restrictions. The goal is to make interventions more targeted and better matched to local conditions.

The prototype also suggests a design principle for AI-assisted pandemic tools: they should surface uncertainty and context. A future AI policy brief generator could summarize the risk profile of a selected IRIS or 200m cell and suggest targeted responses. However, that extension should only be added after validating the data layers and clearly separating descriptive signals from causal claims.

5.1 Limitations

The current prototype has several limitations. First, the IRIS contour file currently covers Île-de-France only for the prototype, so the app is not yet a national France prototype as it is currently unsuitable for a light web application. However, this could cover all of Europe due to the standardization and also due to the data access that I currently have as a graduate student under my supervisor. I do not currently have authorization to openly share the data without getting external approval, so this would be a future project.

Low testing plus high positivity is only a possible under-detection signal. It is not proof of true infection prevalence. Proper validation would require independent prevalence data, representative testing, serology, wastewater surveillance, or another external benchmark. Socioeconomic variables such as poverty, living standards, household size, age structure, and population are proxies.

Finally, this work uses COVID-19 as a case study. Other pathogens may differ in symptoms, transmission, severity, available diagnostics, and public trust. The method should therefore be adapted and validated before use in a different outbreak.

5.2 Future work

Future work should:

1. Extend the prototype to all metropolitan France.
2. Add education, employment, housing, and occupational exposure variables.
3. Build and validate an under-detection score.
4. Build an intervention-burden or local-conditions score.
5. Add an AI-assisted policy brief generator after validating the data layers.

6. Conclusion

Pandemic surveillance data are not socially neutral. Testing data may reflect both infection risk and the unequal ability or incentive to get tested. A useful early-warning tool should therefore show not only where measured incidence is high, but also where testing visibility may be weak and where local socioeconomic conditions may shape the right response.

This project demonstrates a working prototype of that idea using public French data. The current R Shiny app combines COVID testing indicators, IRIS socioeconomic indicators, and high-resolution Paris 200m grid data. Its main contribution is a practical decision-support framing: identify surveillance blindspots, describe local conditions, and support more targeted pandemic responses.

References

Geoffard, P.-Y., Jusot, F., Sireyjol, A., Warszawski, J., and Bajos, N. 2025. "Socio-economic inequalities in access to COVID-19 tests in France in 2020: evidence from the EPICOV socio-epidemiological cohort." *Frontiers in Public Health*, 12:1434370. DOI: 10.3389/fpubh.2024.1434370.

Persson, U., Geoffard, P.-Y., Möller, J., and Brådvik, G. 2025. *An analysis of behaviour, health, and GDP during the Covid-19 pandemic in Europe*. IHE Report 2025:1. Swedish Institute for Health Economics, Lund, Sweden.

Data Appendix and Repository

Github repository - <https://github.com/Hamza-Anver/mightbeuseless-ali/tree/main>

Website Access - mightbeuseless.com

Pandemic Atlas - <https://mushraf-ali-anver.shinyapps.io/lockdown-atlas/>

Public Access on data.gouv.fr

File	Status and use
Filosofi 200m GPKG	Raw high-resolution INSEE socioeconomic grid used for the Paris 200m layer.
grille200m GPKG	Raw 200m grid geometry or grid reference file. Used to support high-resolution spatial mapping if separated from the indicator file.
sg-iris-opendata.csv	Raw Santé publique France SI-DEP file with IRIS COVID incidence, testing-rate, and positivity classes.

<code>iris.geojson</code>	Raw IRIS boundary file currently covering Île-de-France. Used as the geometry base for IRIS maps.
<code>BASE_TD_FILO_IRIS_2021_DISP.xls</code>	Raw INSEE Filosofi IRIS file with income, poverty, and living-standard indicators.
<code>fichier_diffusion_2021.xlsx</code>	Raw INSEE diffusion or metadata file. Used to understand variable definitions and file structure.
<code>paris_filosofi_200m.rds</code>	Processed Paris 200m socioeconomic layer for fast loading in Shiny.
<code>paris_covid_iris.rds</code>	Processed Paris or Île-de-France COVID IRIS object, depending on final scope. Used for the COVID visibility map.
<code>france_covid_iris.rds</code> or <code>idf_covid_iris.rds</code>	Processed COVID IRIS layer. Current prototype uses Île-de-France; national version is future work.
<code>france_filo_iris.rds</code> or <code>idf_filo_iris.rds</code>	Processed Filosofi IRIS socioeconomic layer. Current prototype uses Île-de-France; national version is future work.

LLM Usage Statement

LLM assistance (ChatGPT) was used for both the report writing and data analysis. The main LLM technical contribution was assistance in debugging, visual graphics and hosting the interactive Shiny app while the author was already highly familiar and primarily responsible for the Data Analysis in R. For the written report, the LLM was used as an editor and to reduce the length of the final report. Project Design, Interpretation, Dataset selection and report outline were solely done by the author.