Measuring movement to prospectively manage COVID-19 resurgence

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Background

The successful control of infectious diseases in the absence of pharmaceutical interventions has often relied on behavioral interventions (BI) (*1, 2*) (*3*). Strategies to slow transmission of the current outbreak of coronavirus disease (COVID-19) have leaned heavily on BI, such as physical distancing and movement restrictions. Rapid assessment of the spatiotemporal efficacy of BI is critical (*4*).

Reported cases of disease are delayed indicators of underlying behavior, contact rates, transmission dynamics, and total cases (fig. 1). The underlying mechanistic processes are difficult to measure, but are critically important early indicators of the impact of BI on transmission dynamics, i.e., reported cases today reflect physical distancing from two weeks ago (*5*). We will prospectively monitor activity levels starting in areas where the relaxation of BIs presents an immediate risk of a subsequent wave of transmission (China, South Korea, Italy). *Rapid action will be particularly critical in areas where early behavioral interventions were successful*. The prevention of cases during the initial outbreak leaves a large susceptible population vulnerable to secondary waves of transmission (*6*). **Monitoring movement indicators to guide preventative efforts is more effective than using epidemic data to inform reactive interventions**.

Project aims

Aim 1: We will measure indicators of changes in movement and contacts in cities and towns (*7*). We will do this by quantifying remotely sensed changes in illumination and air pollution and explore the detection of vehicular traffic and radio frequency emissions before, during, and after BI. The ongoing satellite data collection allows us to monitor previous years to establish baseline non-crisis dynamics and develop a timeline of behavioral change dynamics and disease incidence.
Aim 2: We will use movement and behavior data with epidemiological data to fit stochastic epidemic models and estimate the impact of changes in movement on disease transmission.

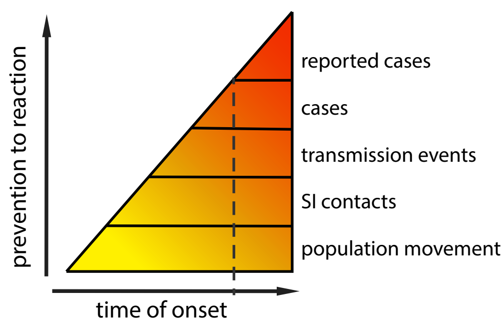

Figure 1: The relative time of onset of each population-level event. Population movement, contacts, transmission, and real cases significantly precede reported cases. The lower tiers of this triangle are all earlier indicators of risk than reported cases. Relying on delayed data sources shifts action from prevention to reaction, in red. The dashed vertical line shows the delay when relying on epidemic data.

Study design: Using near real time data acquisition, we will prospectively monitor activity levels starting in areas where the relaxation of BI presents an immediate risk of a subsequent wave of transmission (China, South Korea, Italy). Continuous satellite data collection and global coverage allow our methods to be rapidly scaled up as the number of locations affected increases. Annual LandScan and WorldPop products quantify gridded static population sizes, which we will use to calibrate the dynamic measures listed below. We will monitor:

1. Daily nighttime lights from NASA's Black Marble imagery, Open Access (*7, 8*).

2. Air pollution, including Nitrogen dioxide emissions and other known indicators of transportation from NASA's Aura Satellite Ozone Monitoring Instrument, European Satellite Agency's (ESA) Sentinel-5 satellite**,** Open Access (*9*).
3. Algorithm-based identification of vehicles for traffic estimates using Maxar's multispectral imagery short-wave infrared band (30 cm) (PSU contract, no charge, value $30,000/yr).
4. Density of radio frequency (RF) emissions, which measures amount, frequency, and location of communication device signals from Hawkeye 360's satellite product (privately owned).

Model For each location analyzed, we will fit a stochastic SIR model (equation 1) to estimate the relationship between behavior and incidence (equation 1) (*10*).

$$S_{t+1} = S_t - \beta_t S_t I_t$$
$$I_{t+1} = I_t + \beta_t S_t I_t - \gamma I_t$$
$$R_{t+1} = R_t + \gamma I_t \qquad \text{(Equation 1)}$$

$$\beta_t = f(x_t) \qquad \text{(Equation 2)}$$

For each location: S_t, I_t and R_t are the susceptible, infectious, and recovered individuals at time t, and γ approximates a gamma distributed duration of infection, fit to epidemiological data. At t=0, the susceptible class is discounted by previously reported COVID-19 cases. β_t is a time varying transmission parameter, which includes contact rates, and is informed by behavioral indicators, x_t (equation 2). The shape of this function will be fit to each indicator and location.

Expected outcomes: Pandemic decision-making requires actionable information and clear communication. We will produce the first visual representations displaying the dynamic contours of inhabited space, displaying population presence and absence across spatial scales (*11*). Our work will provide location-specific early warnings ahead of reported cases of COVID-19 (fig 1). These early indicators will guide surveillance and testing efforts and inform BIs to prevent resurgences (*8*). We will share code, data, model results, and all other findings with collaborators at humanitarian organizations, policy-makers, and researchers, as we have in the past (*12*). We will push frequent updates to GitHub, PSU's ScholarSphere, and PSU's unlimited Box storage.

Innovation: Multiple remotely sensed data streams on human behavior and activity levels are more representative and inclusive across ages, income levels, and population sizes than any single data source (*13*). This is important as different demographic categories present varying levels of risk and access to care during this outbreak. Data streams 3 and 4 have never been used for epidemiological predictions and we are adapting these techniques to a novel context. By monitoring behavior dynamics, our methods will detect changes in disease risk *before* cases are reported, providing valuable time to prevent an outbreak. By using remotely collected data, we can collect data and provide early warnings without sending epidemiologists into epidemics.

PI expertise: **Bharti** developed the methods to use remotely sensed behavioral indicators to inform epidemic prevention. She has expertise in disease modeling, spatial analysis, and human movement analysis. **Robinson** developed the visualization techniques to map the absence of activity in space. He has expertise in geospatial analysis, geovisualization, and cartography with focused applications in epidemiology and crisis management.
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Appendix A: References

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