# CONTACT TRACING TO MAINTAIN MOBILITY AT THE BORDER DURING A PANDEMIC

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# EXECUTIVE SUMMARY

COVID-19 is the infectious disease caused by the most recently discovered coronavirus (SARS-CoV-2). Although most of the people who have COVID-19 have mild symptoms, it can also cause severe illness and even death. The United States is the most affected country based on the total number of cases and fatalities. To slow down the speed of spread, most countries applied travel restrictions, school closures, shutdowns, and stay-at-home orders. A fiscal year 2020 Center for International Intelligent Transportation Research study, Cross-Border Transportation as a Disease Vector in COVID-19, found that in both countries, the U.S. and Mexico border crossing has a significant effect on the speed of spread. The El Paso–Juarez region is one of the places hit hard by the virus spread. This was Phase I of the COVID and border studies done by the researchers. (The report is available at http://tti.tamu.edu/documents/185920-00015.pdf.)

As a follow-up, in Phase II, researchers wanted to focus on a commonly used practice to slow down the spread with a focus on the same region. Contact tracing is an approach to track down anyone that was in close contact with a person who has been diagnosed with the illness. It is considered one of the key practices to slow the spread for all infectious diseases. The traditional way is accomplished through manual interview of the infected individuals. The main challenge with this practice is that people may not accurately recall each person they have been in contact with and cannot identify the people if they do not personally know them. Considering the limitations, researchers started focusing on emerging technology solutions to automate the contact-tracing process. During the COVID-19 pandemic, many smartphone contact-tracing apps have been proposed and deployed. However, the number of downloads and active users remained low worldwide. In the United States, states initiated their programs and have been developing contact-tracing apps, and so far, only half of the states have a contact-tracing app for their residents. The apps rely on the users' willingness to participate, and the privacy concerns are still a major obstacle against wide use. Although the effectiveness of contact-tracing apps is questionable, taking advantage of mobile technology is expected to help in transitioning back to daily life while managing the risk of future outbreaks.

One objective of this study is to explore the destinations of the trips in the United States that originated in Mexico and crossed the border in the El Paso–Juarez region. The changes before and after border restrictions are documented and illustrated by using mapping techniques. The results are documented in two categories: number of trips and number of contacts. The total number of trips decreased 63 percent, and the highest decrease was experienced at schools and churches with a 79 and 90 percent decrease, respectively. The follow-up study showed that the highest decrease in the number of contacts was also experienced at schools and churches. These are followed by commercial land uses with a 79 percent decrease in the number of contacts. Total daily contacts decreased 61 percent for the residential land uses. The lowest decrease was experienced at industrial land uses, which was 42 percent.

In this study, researchers developed a mathematical model based on a simple susceptible, infected, and recovered (SIR) model coupled with mobility trends and linear regression expressions to understand the outbreak spreading. Linear regression analyses were generated and embedded into the SIR model to estimate the consequences of the different what-if scenarios in the region. Using the cumulative number of cases, researchers could evaluate the border restrictions and contact-tracing practices for four different scenarios:

- Scenario 1 was developed to explore the effects of the increasing border mobility.
- Scenario 2 was developed to understand the effectiveness of a mandatory border-crossing contact-tracing program.
- Scenario 3 was developed to see the potential benefits of substituting the conventional contact-tracing efforts with a contact-tracing app.
- Scenario 4 was developed to show the impact of a comprehensive contact-tracing system that includes traditional contact-tracing efforts and the use of a contact-tracing app.

The model was run for each scenario, and the results of the cumulative number of cases were compared with the base scenario. Scenario 1 findings are telling; if northbound mobility was 50 percent higher than the actual (with border restrictions in place), there would be a 14 percent increase in cases in El Paso. With the same conditions but if there was a mandatory contact-tracing program just for travelers from Mexico, there would be a 9 percent increase in cases. However, if 50 percent of the entire El Paso population participated in a contact-tracing program without any other conventional contact-tracing practice, there would be 15 percent or fewer cases. Finally, the best-case scenario was Scenario 4, which keeps the existing contact-tracing efforts and has 25 percent of the community use a contact-tracing app. This would result in up to a 22 percent reduction in the number of cases in El Paso County.

In February and March 2021, researchers reached out to various stakeholder groups in the El Paso region and presented the findings at several virtual meetings attended by close to 100 individuals. Stakeholders are all aware of the importance of contact tracing and agree that if the region had a more comprehensive contact-tracing program with increased use of a contact-tracing app, the number of cases and deaths would be fewer. Health officials also advised researchers to improve the study by including the vaccination efforts and total number of immunized people. Researchers will conduct a follow-up study as Phase III of the overall COVID and border studies.

# CHAPTER 1: INTRODUCTION

## 1.1 BACKGROUND

COVID-19 is the infectious disease caused by the most recently discovered coronavirus (SARS-CoV-2). It was first identified in December 2019 in Wuhan, China, and spread to all countries in the world. As of February 10, 2021, more than 107 million confirmed cases and over 2.3 million deaths have been reported globally (*1*). The United States is the most affected country based on the total number of cases and fatalities. To slow down the speed of spread, most countries applied travel restrictions, school closures, shutdowns, and stay-at-home orders, which caused millions of people to lose their jobs and global economic uncertainties.

Although some measures and restrictions were introduced locally, the El Paso–Juarez region is one of the places hit hard by the virus spread. Currently, El Paso County has more than 117,000 cases (14 percent of the population) and over 2,000 deaths (*2*). On the other side of the border, Ciudad Juarez has over 21,000 confirmed cases and around 2,600 deaths (*3*). Juarez accounts for 50 percent of the cases and 53 percent of the disease-related deaths in the state of Chihuahua (*3*).

A Center for International Intelligent Transportation Research (CIITR) project conducted by the authors in 2020 and titled Cross-Border Transportation as a Disease Vector in COVID-19 focused on developing an understanding of the relationship among socioeconomic, transportation, and border-crossing-related parameters and the speed of spread of COVID-19. The study found that in both countries, the U.S. and Mexico border crossing has a significant effect on the speed of spread. The United States and Mexico has had an agreement to restrict border crossings on nonessential travel since March 2020, but as the economies started to reopen, border crossings increased significantly during the summer months of 2020.

Contact tracing is an approach to track down anyone that was in close contact with a person who has been diagnosed with the illness. As a result, those contacts can quarantine themselves, preventing further spread. To be successful in the fight against widespread outbreak, the use of contact tracing is required and commonly used by nearly all countries throughout the world. An effective contact-tracing program tailored to the unique characteristics of the U.S.–Mexico border communities may allow border agencies and other stakeholders to develop approaches that are equally effective in maintaining public health while minimizing the negative impacts on cross-border mobility.

## 1.2 OBJECTIVE

The objectives of this study are to:

- Conduct extensive literature research on contact tracing.
- Measure the trip changes and mobility at the border with border restrictions.
- Explore the impacts of border restrictions and measures and contact-tracing practices by developing an epidemiological simulation model.

This project allows researchers to understand the impact of border restrictions on the spread of the disease and answer what-if questions from stakeholders regarding contact-tracing implementation in the border communities.

## 1.3 OUTLINE OF REPORT

The remaining chapters of this report include the following:

- Chapter 2: Literature Review—This chapter reviews existing literature and reputable U.S. and Mexican news sources to provide background information about the COVID-19 pandemic. Literature documenting the use of different means of contact-tracing approaches are also explored.
- Chapter 3: Border Restrictions and Destination Shifts—This chapter explores the impacts of the border restrictions on border mobility and illustrates the changes of the destinations of border-crossing travelers by comparing before and after border restrictions.
- Chapter 4: Model Development—This chapter presents the data, the development of the epidemiological model, and the details of the simulation.
- Chapter 5: Scenarios and Model Results—This chapter introduces the scenarios and shares the findings from the model deployment with a focus on El Paso County.
- Chapter 6: Findings and Conclusions—This chapter presents the main findings and conclusions drawn from the study and discusses the potential for further studies.

# CHAPTER 2: LITERATURE REVIEW

This chapter summarizes pandemics with a focus on COVID-19, border crossings, and contact-tracing practices based on the literature reviewed. The purpose of this chapter is to provide background on the operations of contact-tracing use, its issues, potential solutions, and research gaps. From these reviews, five sections were identified:

- Pandemics and COVID-19.
- Transportation and COVID-19.
- Borders in the time of COVID-19.
- Contact tracing.
- El Paso–Juarez binational region.

This chapter concludes with a final summary section, which highlights the review findings.

## 2.1 PANDEMICS AND COVID-19

A *pandemic* is defined as the worldwide spread of a new disease (*4*). Throughout history, as people have moved, infectious diseases have spread across the world, and millions of people have died because of pandemics (the Black Death, smallpox, the Spanish flu, HIV, SARS, MERS, etc.). The World Health Organization (WHO) officially declared COVID-19 a pandemic on March 11, 2020 (*5*), and as of February 10, 2021, the number of cases is more than 107 million globally with more than 2.3 million deaths (*1*).

COVID-19 first arrived in the United States early in 2020, and the first case was officially reported on January 20, 2020. Afterward, the virus started to spread at an increasing pace. Currently, the United States is one of the worst affected countries and is still facing an increased incidence with more than 27 million COVID-19 positive cases and over 470,000 deaths (*1*). In the United States, the worst affected states are California, Texas, Florida, New York, and Illinois. They all recorded more than 1 million positive cases by March 2021. The death rates across these states have increased alarmingly and are still surging.

Based on epidemiological research, COVID-19 has distinct features and significantly differs from recent outbreaks (SARS, MERS, and Ebola). The virus has a comparatively longer incubation period with high variance (*6*). Other studies also showed that people infect others before showing symptoms (*7, 8*). Moreover, a significant percentage of asymptomatic carriers (estimated between 6 percent and 41 percent) never develop symptoms but still significantly contribute to epidemic dynamics (*9*). One other specific feature of COVID-19 is the difference in symptom development for different age groups. Children and young adults generally have milder symptoms and easily carry and transmit the disease. However, seniors are more likely to exhibit serious symptoms.

First reactions with the focus on social distancing aimed to compensate for clinical unpreparedness and to control the load on the health care systems by flattening the infection curve. Countries first put into place international travel restrictions, followed by school closures and limits or bans on all other gatherings including at bars, restaurants, churches, and entertainment venues.

Although strict measures and closures seemed to help reduce the infectivity rate, economic and social needs started putting pressure to consider reopening strategies. Still, researchers are trying to explore the contribution of isolation, social distancing, and hygiene to keeping the disease contained at some level. Over a year of experience and research on COVID-19 led to a better understanding of both virus-related and social dynamics including classifying destinations by the risk of infectivity. The use of face masks is considered the most crucial aspect along with keeping a minimum distance of 6 feet especially in enclosed spaces (*10*).

## 2.2 TRANSPORTATION AND COVID-19

In response to the rapid spread of COVID-19, countries worldwide applied widespread measures to attempt to flatten the curve. One of the major measures taken is to limit people's mobility. With fast and more accessible transportation systems, people are getting more interconnected, which leads to quicker spread of infectious disease outbreaks, which then turns into a global pandemic. COVID-19 was the latest example of this phenomenon. After WHO declared a pandemic, countries started to take strict measures, and the first reaction was to limit people's mobility. Shutdowns of borders and airlines were announced to restrict the movement of people to slow the spread. Ninety percent of the commercial passenger flights were grounded, and nearly all countries have introduced some form of transportation- and mobility-related measures including screening, quarantine, and/or restrictions for people traveling from high-risk areas.

Askitas et al. (*11*) collected data related to COVID-19 and population mobility patterns across 135 countries. Canceling public events and banning private gatherings were found to be the most effective strategies followed by school closures, workplace mobility restrictions, and stay-at-home orders. Bonardi et al. (*12*) collected data from 184 countries and checked the effects of lockdowns on the number of cases and deaths. Movement within countries increases the cases, and limiting people's mobility reduces the spread of disease. Xiang et al. (*13*) reviewed over 50 COVID-19 mathematical models with focus on different measures taken by the countries. The most significant effect was travel restrictions.

## 2.3 BORDERS IN THE TIME OF COVID-19

Infectious disease outbreaks can cause serious damage to the human population if effective measures are not taken. To slow down the spread, one of the first reactions made by governments was to implement travel bans or travel restrictions. However, restricting travel has social and economic consequences. Travel bans can be implementation of visa bans based on nationality, bans on direct flights from origin countries, or complete bans on anyone (regardless of nationality) entering a country (*14*). On the other hand, the majority of countries allowed essential travelers, citizens, and people who have permanent residencies.

Severe acute respiratory syndrome (SARS) was an outbreak experienced in 2003. International travel was treated as one of the main reasons for the rapid spread. SARS never reached the level of a pandemic and stayed at a local level. Still, the outbreak reaction and consequences taught lessons to researchers and decision makers. During SARS, Singapore took measures at airports, seaports, and land ports of entry including travel restrictions and visual and temperature screenings. However, no infected travelers were detected after the implementation of these screening methods. Only 0.03 percent of the incoming passengers were sent to a hospital for a secondary check, and none were diagnosed with SARS. In summary, existing screening technologies at entry points are costly in time and money and did not show expected results (*15*). During the Ebola outbreak in 2016 in West Africa, the Centers for Disease Control and Prevention (CDC) implemented travel and border health measures to prevent the international spread of the disease. Staff was located in Ebola-experiencing countries and provided technical assistance for exit screening. Cohen (*16*) believed that although it is difficult to assess, border health measures might have helped control the Ebola outbreak before it turned into a pandemic. In another study, Gold et al. (*17*) found that exit screening is more effective than entry screening to capture the sick person before entering the country. On the other hand, in their study, Mouchtouri et al. (*18*) reported that based on SARS and Ebola experiences, entry or exit screenings were not significant in identifying cases. Mouchtouri et al. also reported that there might be several hidden effects of border screening that are very difficult to assess including discouraging travel of sick people, raising awareness, and educating people.

Since many newly reported cases of COVID-19 during early phases of the pandemic had been associated with travel history from the epidemic region, the majority of the countries took measures with a focus on border crossings. Moreover, the authors' previous study, which covers the early months of the disease spread, found border crossing is a significant parameter in spreading the virus (*19*). In other words, cities or counties having a border crossing are more likely to have more COVID-19 cases than others. However, secondary cases, known as community spread, continued to increase and be transmitted to locals who had no travel history. Different studies assessed the impacts of border control and quarantine. Eckardt et al. (*20*) conducted a study in the Schengen area of Europe that covered COVID-19 cases until the end of April 2020 and found that border controls had a significant effect to limit the pandemic. Hossain et al. (*21*) evaluated border control measures with different infectivity rates and found that the border restrictions were not very effective when the infectivity rate was high, which is the case with COVID-19 in the early days of the outbreak. Similarly, using the actual data of COVID-19, Askitas et al. (*11*) found that international travel controls and restrictions on movements across cities and regions are not significant in reducing the daily incidence of disease spread.

## 2.4 CONTACT TRACING

Contact tracing is considered one of the key practices to slow disease spread for all infectious diseases. Contact tracing has been widely used during the COVID-19 pandemic all over the world. The aim of contact tracing is to let people know that they may have been exposed to the virus and should monitor themselves for signs and symptoms. Therefore, all potentially sick people can be self-quarantined and tested. If tested positive, they are asked to self-isolate. Ultimately, these practices reduce the community spread in a region.

One of the challenges with the COVID-19 outbreak is the high rate of asymptomatic cases. This increases the necessity of contact tracing to identify all individuals who had close contact with a positive carrier. CDC defines close contact as someone who was within 6 feet of an infected person for a cumulative total of 15 minutes or more over a 24-hour period starting from 2 days before illness onset until the time the patient is isolated (*22*). Countries worldwide have implemented contact tracing by using different methods with the aim of reaching all close contacts of each positive case. The most common and traditional way is accomplished through manual interview of the infected individuals. The main challenge with this practice is that people may not accurately recall each person they have met and cannot identify people if they do not personally know them. A secondary challenge may be the requirements of the considerable workforce necessary to conduct interviews.

Considering these limitations, researchers started focusing on emerging technology solutions to automate the contact tracing process. High use of smart devices with location tracking technology and built-in Bluetooth® technology allowing location and proximity detection makes them reliable solutions for contact-tracing efforts. During the COVID-19 pandemic, many smartphone contact-tracing apps have been proposed and deployed. In September 2020, Google and Apple, two major companies whose operating systems run nearly all smart devices, jointly created the Exposure Notification System, which allows public health authorities to build apps by using the system to support their contact-tracing efforts. This system does not collect or use the location of the user. The system only uses Bluetooth® technology to detect and store the information of the other devices with defined proximity and time of exposure (*23*).

Ahmed et al. (*24*) classified and grouped the system architectures considering how the server is used and what data are stored in it. The three system architectures commonly used in developing the contact-tracing apps are as follows:

- The centralized approach requires users to pre-register with a central server. Users' devices store their locations and/or contacted people's anonymized IDs and upload all messages to the central server when tested positive.
- The decentralized approach moves the functionalities to the users' devices. The users' devices keep real user identities and process the exposure notifications on individual devices instead of a central server.
- The hybrid approach keeps the anonymized ID generation and management decentralized on the users' devices, and the analysis and notifications are done by a central server.

A contact-tracing app basically stores close contacts and immediately notifies users if they have contacted infected individuals. Technologically, the concept of location and proximity are embodied in two standard smart device components: global positioning system (GPS) receivers and Bluetooth® transceivers. GPS-derived location data capture makes it easy to map and analyze the movements of all individuals who use the app. Bluetooth® communication allow the capture of all individuals that have been within 6 feet for at least 15 minutes and will notify the user if the contacted person is infected and will share his/her data. In the United States, nearly 80 percent of the population have smart devices with these technologies. In order to capture the remaining population, one way recently developed in Singapore is using smart tokens. Some countries like New Zealand use quick response (QR) code technology and ask all businesses, workplaces, and public transit services to display a QR code for each location. Therefore, anyone entering the building or transit service should scan his/her device, and all the people using the services are recorded with respect to time.

During the development of the apps, researchers have worked on the apps' effectiveness to slow the spread of disease. Braithwaite et al. (*25*) reported that there was no evidence of the effectiveness of contact-tracing apps on the reduction of transmission. More than half of the modeling studies suggested that to control COVID-19, a high rate of public use (market penetration), from 50 percent to 90 percent, is required alongside other control measures. However, a recent study found that even if 15 percent of the population used a contact-tracing app alongside the conventional practice, the spread of the virus may be slowed by around 5 to 10 percent (*26*).

Despite the early expectations for the comprehensiveness of contact-tracing app use, the number of downloads and active users remained low worldwide. In Germany, it is around 25 percent, and in Japan it is only 15 percent of the adult population. Very few countries, Ireland, Iceland, and New Zealand, have higher download rates to date, all above 50 percent. None of the countries reached 60 percent of their adult population that uses a contact-tracing app (*27*). In the United States, states initiated their programs and have been developing contact-tracing apps. There is still no national contact-tracing program. The Google and Apple systems allow different apps developed by different states to communicate and share information. Therefore, interstate travelers can be tracked. With the deployment of the apps, concerns have arisen regarding the users' privacy issues, and these concerns are the main factor that influences their adoption (*28*). An analysis in December 2020 by the Associated Press found that in the states providing contact-tracing apps, only 7 percent of the population have used the technology (*29*). Figure 1 illustrates the states that signed an agreement with Google and Apple and developed an app using the Exposure Notification System. Some other states are conducting pilot programs and are expected to expand to state level soon (Oregon and South Carolina). Some other states developed their own contact-tracing apps without using the Google and Apple systems (South Dakota and Rhode Island).

The system relies on the users' willingness to participate. One limitation is that people want to load the app so that they can be notified if someone else was positive, in a self-serving way, but if they are positive, they do not have the motivation to share the information and take the time. Some studies showed that the number of downloads does not represent the number of uses. In summary, the apps have not been used enough to slow the spread of disease. The technical shortcomings and privacy concerns are still the major obstacles against the wide use of the apps in contact tracing.

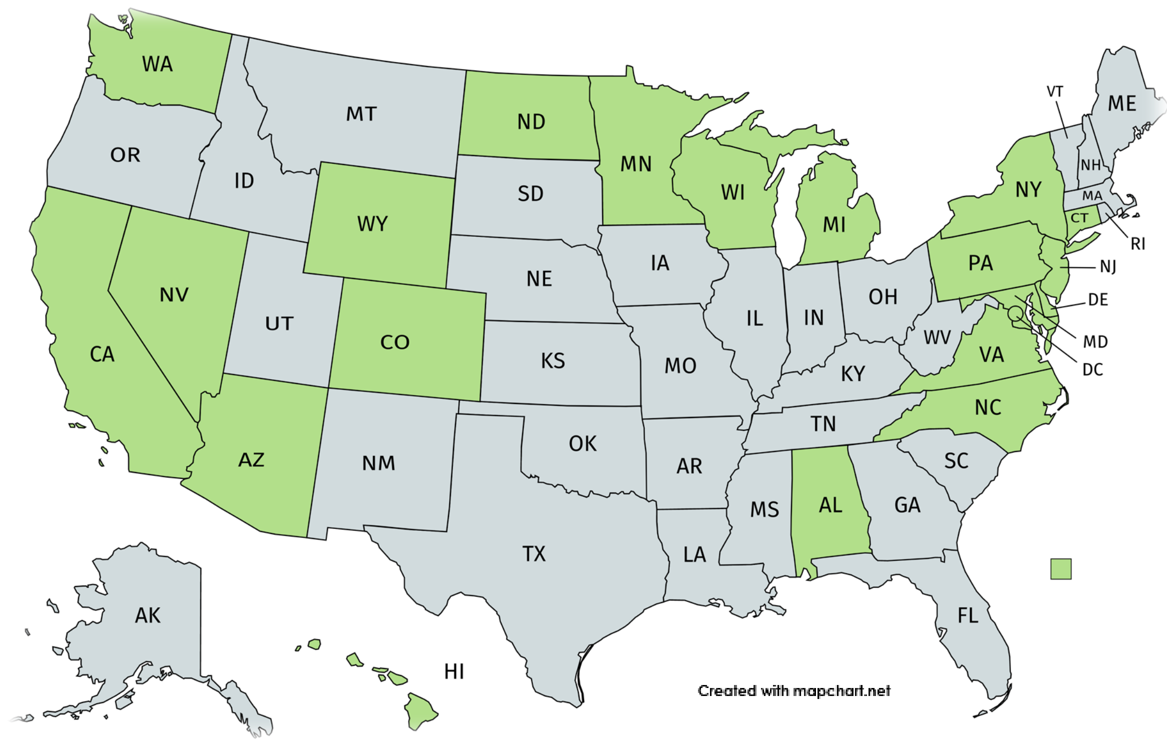



**Figure 1. Google and Apple System Use for Contact-tracing Apps in the United States.**

## 2.5 EL PASO–JUAREZ BINATIONAL REGION

The El Paso–Juarez region has more than 2 million residents, which induces significant cross-border passenger travel. The El Paso–Juarez corridor is the busiest border crossing in Texas, with its unique location encompassing a binational conurbation of two large cities, one on each side of the border. This corridor supports major binational manufacturing, warehousing, and transportation industry. Both cities on each side of the border were hit hard by the COVID-19 pandemic. As of mid-February 2021, although vaccination efforts have started, the disease still has not been controlled.

To limit the further spread of disease, the United States has reached agreements with both Canada and Mexico to limit travel across borders (*30*). The United States does not allow non-essential travelers to enter the country, excluding citizens and permanent residents, but has not taken any other special measures at the borders.

The City of El Paso provides daily information regarding the city and El Paso County on its website (El Paso Strong) (*31*). Daily and cumulative cases and deaths are given with some other epidemiological parameters including infectivity rate, positivity rate, identified contact rate, case fatality rate, etc. Currently, contact tracing in El Paso is done by public health officials who reach all the identified contacts and ask the questions listed in the case investigation form about the patient and his/her previous contacts. There is not a smart device application or an automatic contact-tracing program in use. According to El Paso Strong (*31*), public health officials can reach 86 percent of the contacts and manage to notify them within 48 hours. This number is being updated daily and was below 10 percent in July and in November for a time (Figure 2). El Paso Strong also reports the infection source of the individuals and reports that only 40 percent of the infections in El Paso were spread through close contacts (Figure 3). In other words, more than half of the patients got the infection from other sources including community transmission or travel sources, which are very hard to track with conventional contact-tracing efforts.

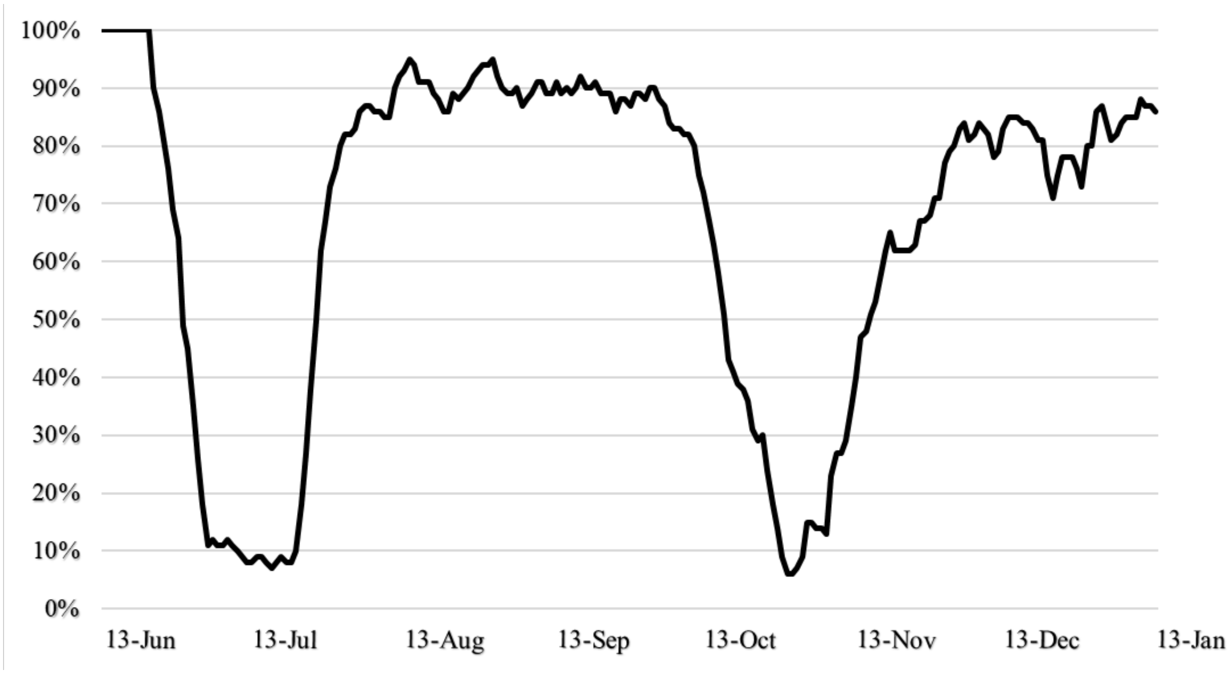



**Figure 2. Identified Contacts Notified within 48 Hours.**

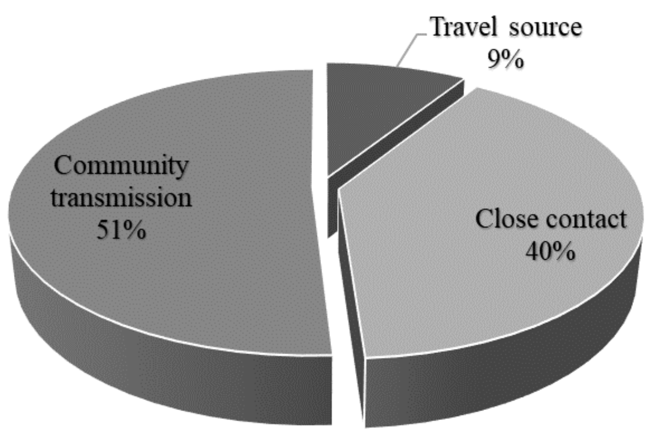



**Figure 3. El Paso Infection Source.**

## 2.6 CHAPTER SUMMARY

Transportation is considered a vector for infectious diseases. The COVID-19 pandemic showed once more how vital transportation is in spreading the disease as well as providing goods and services for people. After WHO officially declared COVID-19 a pandemic in March 2020, countries started taking measures focusing on social isolation and border restrictions. Most governments have only allowed essential travelers to enter their countries since then. Alongside the stay-at-home orders and closure of businesses and schools, border restrictions have impacted the economies a great deal.

Contact tracing has been considered one of the key practices to slow the spread of all infectious diseases. A growing number of countries are implementing technology-based practices to check the movement and proximity of their citizens. Using technology to supplement the contact-tracing efforts was first used with the COVID-19 pandemic. One of the main objectives of this study is to understand the potential benefits of increasing the comprehensiveness of contact tracing by using technology-based contact-tracing programs. Researchers aim to explore the different levels of adoption of the contact-tracing programs and see the impacts on reducing the number of cases and deaths.

# CHAPTER 3: BORDER RESTRICTIONS AND DESTINATION SHIFTS

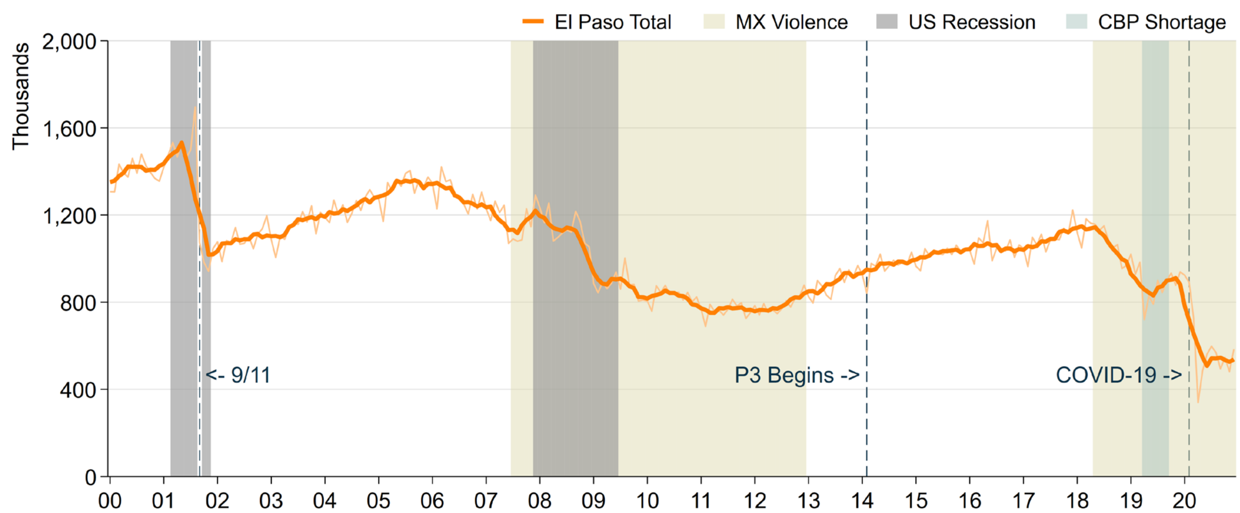
This chapter focuses on exploring the trip destination changes of border-crossing travelers. Different sources of trip data were used and aggregated to detect the destinations of the trips crossing borders in the northbound direction. Researchers used state-of-the-art mobility analysis to detect changes in mobility patterns. The changes before and after border restrictions are documented and illustrated using mapping techniques.

## 3.1 BORDER RESTRICTIONS AND MOBILITY

Soon after the WHO declared COVID-19 a pandemic, most countries started taking measures, especially at their borders. Researchers have different views on this concept; some promote the restrictions and believe that they may help at least delay the spread. Others think that the effects are negligible.

The United States and border countries Mexico and Canada have reached an agreement to limit all non-essential travel across their borders. Non-essential travel includes travel that is considered tourism or recreation oriented. U.S. citizens and lawful permanent residents are exempt from this action and are allowed to enter the country. The measures were first implemented on March 21, 2020, and were in place for 30 days. Several further monthly extensions were made, and the latest is in place until February 20, 2021. The number of cases and higher community spread are still a concern in the region; therefore, it is expected that there will be more extensions before the spread is under control.

In the El Paso–Juarez region, border restrictions alongside the stay-at-home orders and other social isolation restrictions impacted border mobility significantly. Border mobility in the El Paso–Juarez region has experienced ups and downs over the last 20 years. Figure 4 demonstrates the number of privately owned vehicles' (POVs') northbound crossings with the different milestones in the last 20 years (*32*) including the 9/11 attacks, Mexico violence, U.S. recession, and staff shortage of U.S. Customs and Border Protection. However, the most dramatic change in border mobility was experienced with the COVID-19 pandemic. To understand better, a simple border mobility index (BMI) was defined. The monthly average of the last 5 years of border crossings was assigned as the base BMI with a value of 100. The BMI stayed within 80 to 120 until the border restrictions and went down below 40 immediately after the border restrictions. Afterward, the BMI recovered a little and went back to 60 but still needs some increase to reach the values that it used to have (Figure 5).




Source: PDNUno

**Figure 4. Northbound Privately Owned Vehicle Crossings.**

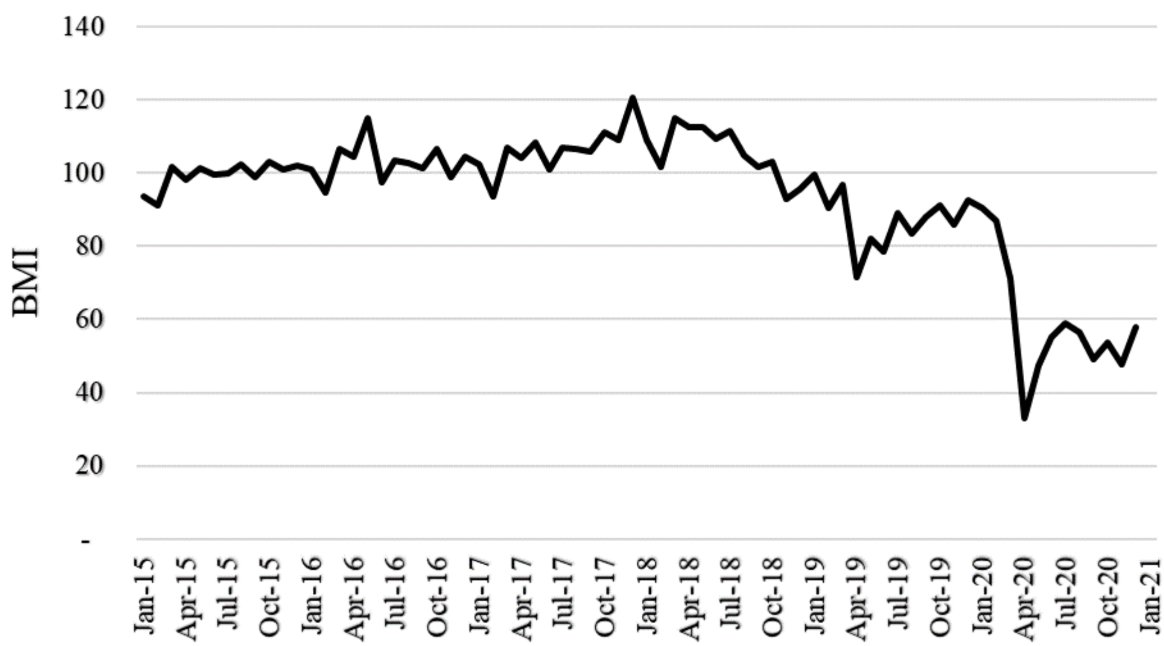



**Figure 5. Border Mobility Index for Northbound Personal Vehicle Crossings.**

## 3.2 DESTINATION CHANGES OF CROSS-BORDER COMMUTERS

One objective of this study is to explore the destinations of the trips in the United States that originated in Mexico and crossed the border in the El Paso–Juarez region. Different sources of trip and trajectory data were aggregated to detect the destinations. The changes before and after border restrictions are documented and illustrated by using mapping techniques.

### 3.2.1 Data Sources

This project used two main data sources to explore cross-border travelers' behavior and potential interaction with other people in El Paso County. CIITR obtained 3 months of vehicle location-based cross-border trip data with the focus on five ports of entry (Zaragoza, Santa Teresa, Paso del Norte, Stanton, and Bridge of Americas) from INRIX.[1] The data timeline starts on January 20, 2020, and ends on April 20, 2020. All the data for the selected regions were delivered in comma-separated value (CSV) format. Researchers used two datasets (Trips and Trajectories). The Trips dataset contains the following information:

- TripID: A trip's unique identifier.
- DeviceID: A device's unique identifier. Set to the TripID for restricted data providers.
- ProviderID: A provider's unique identifier.
- Mode: The mode of travel (walk, vehicles, or unknown).
- StartDate: The trip's start date and time in Coordinated Universal Time (UTC).
- StartWDay: The trip's start weekday in local time.
- EndDate: The trip's end date and time in UTC.
- EndWDay: The trip's end weekday in local time.
- StartLocLat: The latitude of the centroid of the trip's start quad key in decimal degrees.
- EndLocLat: The latitude of the centroid of the trip's end quad key in decimal degrees.
- EndLocLon: The longitude of the centroid of the trip's end quad key in decimal degrees.
- GeospatialType: Describes the trip's geospatial intersection with the requested zones:
    - Internal-to-Internal (II): Trips that start and end within any zone.
    - Internal-to-External (IE): Trips that start within any zone and end outside any zone.
    - External-to-Internal (EI): Trips that start outside any zone and end within any zone.
    - External-to-External (EE): Trips that start and end outside any zones but are selected because of an intersection with one or more zones.
- ProviderType: A numeral representing the provider type (consumer, fleet, or mobile).
- VehicleWeightClass: A numeral representing the vehicle weight class.
- TripMeanSpeedKph: The mean speed of the trip in kilometers per hour (kph).
- TripMaxSpeedKph: The maximum speed of the trip in kph.
- TripDistanceM: The trip distance in meters.
- OriginCensusBlockGroup: The census block group of the origin (United States only).
- DestinationCensusBlockGroup: The census block group of the destination (United States only).

The Trips dataset covers each captured trip by focusing on the locations of the origin and destinations of the trips with exact timestamps. The Trajectories dataset, however, records all

[1] INRIX is a private company that provides location-based data and analytics and delivers real-time traffic and parking information. More information is available at https://inrix.com/about/.

trips with the information of route (Trajectory). Therefore, Trajectory data have more datapoints with the following information:

- TripID: A trip's unique identifier.
- DeviceID: A device's unique identifier.
- ProviderID: The provider's unique identifier.
- TimeZone: The trip's start time zone.
- TrajIdx: The index of a trajectory for this trip.
- TrajRawDistanceM: The cumulative distance of raw points in meters relative to the start of the trajectory.
- TrajRawDurationMillis: The cumulative duration of raw points in milliseconds relative to the start of the trajectory.
- SegmentId: The segment ID of the road section on the map. For the open street map, the segment ID includes a minus sign to indicate directionality.
- SegmentIdx: An index of a segment within a trajectory.
- LengthM: The length of the segment in meters.
- CrossingStartOffsetM: The start offset in meters relative to the start of the segment where a device enters this segment.
- CrossingEndOffsetM: The end offset in meters relative to the start of the segment where a device leaves this segment.
- CrossingStartDateUtc: The start date in ISO 8601 format when a device enters this segment.
- CrossingEndDateUtc: The end date in ISO 8601 format when a device leaves this segment.
- CrossingSpeedKph: The segment crossing speed in kph.
- ErrorCodes: The list of error codes associated with this segment.

Although the Trips and Trajectory datasets are very comprehensive and deliver insightful values, to understand local or border-crossing travelers' mobility patterns, these datasets do not provide the number of potential contacts. In order to address this shortcoming, researchers used another resource called SafeGraph that provides traffic data from cell phone records (*33*). SafeGraph data contain aggregated, anonymized, high-frequency geolocation data collected across thousands of cellular devices that have opted in to location-sharing services. Several researchers have used these data extensively to measure various effects of the COVID-19 pandemic. For this project, the Patterns dataset is used and provides information on hourly visitors based on the locations of all points of interest in a region. This dataset is delivered in a CSV data format with the following information:

- Placekey: The unique ID tied to the point of interest.
- Location_name: The name of the place.
- Street_address: The street address of the place.
- Brands: If this point of interest is an instance of a larger brand that is identified.
- Date_range_start: The start time for the measurement period.
- Date_range_end: The end time for the measurement period.
- Visits_by_day: The number of visits to the place each day over the covered period.
- Poi_cbg: The census block group in which the place is located.

- Visitor_home_cbgs: A mapping of census block groups to the number of visitors to the place.
- Distance_from_home: The median distance from home traveled by visitors.
- Median_dwell: The median minimum dwell time in minutes.
- Popularity_by_hour: A mapping of the hour of the day to the number of visits in each hour over the course of the date range in local time.

Due to the availability of the data, researchers succeeded in gathering the SafeGraph data for El Paso County between January 1, 2020, and November 1, 2020. As of the writing of this report, SafeGraph does not provide similar data for the Mexican side of the border.

### 3.2.2 Findings

Having information on the exact location of each trip, researchers first mapped the points of border-originated trips. Table 1 lists the number of trips captured in the dataset. The trips ending in the United States overlap with the parcel-level maps gathered by El Paso County in Texas and Dona Ana and Otero Counties in New Mexico to illustrate in which land use the trip ended. Researchers also filtered the POVs to see the sampling success of the INRIX dataset at the border crossings. The INRIX dataset provided over 4.3 million data points, and among them, nearly 3.2 million points were POVs that had destinations located in the United States. Using both the Trips and Trajectory datasets, researchers filtered the trips that originated in Mexico and finished in the United States. In total, 128,500 trips were captured, and 108,054 (84 percent) of them were dated between January 20, 2020, and March 20, 2020; the rest were dated between March 21, 2020, and April 20, 2020. Also, 89.8 percent of the trips ended in one of the selected counties (El Paso, Otero, and Dona Ana).

**Table 1. INRIX Dataset Number of Data Points.**

| Port of Entry | Total | POV—U.S. Destination | All Northbound Traffic | Before Restrictions | After Restrictions |
|---|---|---|---|---|---|
| Zaragoza | 820,451 | 622,390 | 32,560 | 27,217 | 5,343 |
| Santa Teresa | 31,499 | 11,513 | 4,548 | 4,419 | 849 |
| Paso del Norte (PDN)–Stanton | 1,703,974 | 1,263,014 | 43,692 | 37,642 | 6,050 |
| BOTA | 1,763,081 | 1,279,359 | 47,700 | 38,776 | 8,924 |
| Total | 4,319,005 | 3,176,276 | 128,500 | 108,054 | 21,166 |

The daily number of crossings provided by the INRIX dataset was aggregated and compared to the reported monthly number of northbound crossings provided by the City of El Paso International Bridges Department (PDNUno) (*32*). Since the INRIX dataset only has two full months (February and March 2020) of data, researchers compared only those months (see Table 2). The sampling rate of the INRIX data was found between 3.8 percent and 7.1 percent for different ports of entry, and the overall sampling rate was 5.6 percent for both months.

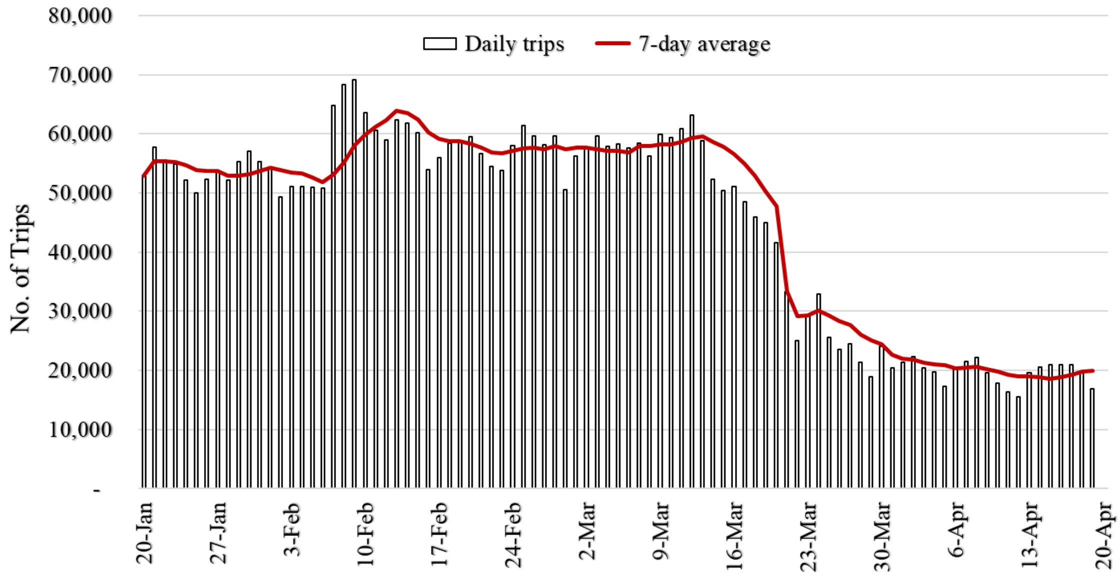
**Table 2. INRIX Sampling Rate for Northbound Border Crossing Travelers.**

| Port of Entry | All Northbound INRIX | February 2020 | | March 2020 | |
|---|---|---|---|---|---|
| | | INRIX | PDNUno (Sampling) | INRIX | PDNUno (Sampling) |
| Zaragoza | 32,560 | 13,227 | 314,023 (4.2%) | 10,966 | 248,433 (4.4%) |
| Santa Teresa | 4,548 | 1,817 | 40,983 (4.4%) | 1,267 | 33,718 (3.8%) |
| PDN–Stanton | 43,692 | 18,906 | 314,228 (6.0%) | 14,352 | 250,018 (5.7%) |
| BOTA | 47,700 | 18,518 | 263,086 (7.0%) | 16,386 | 229,429 (7.1%) |
| Total | 128,500 | 52,468 | 932,320 (5.6%) | 42,971 | 761,058 (5.6%) |

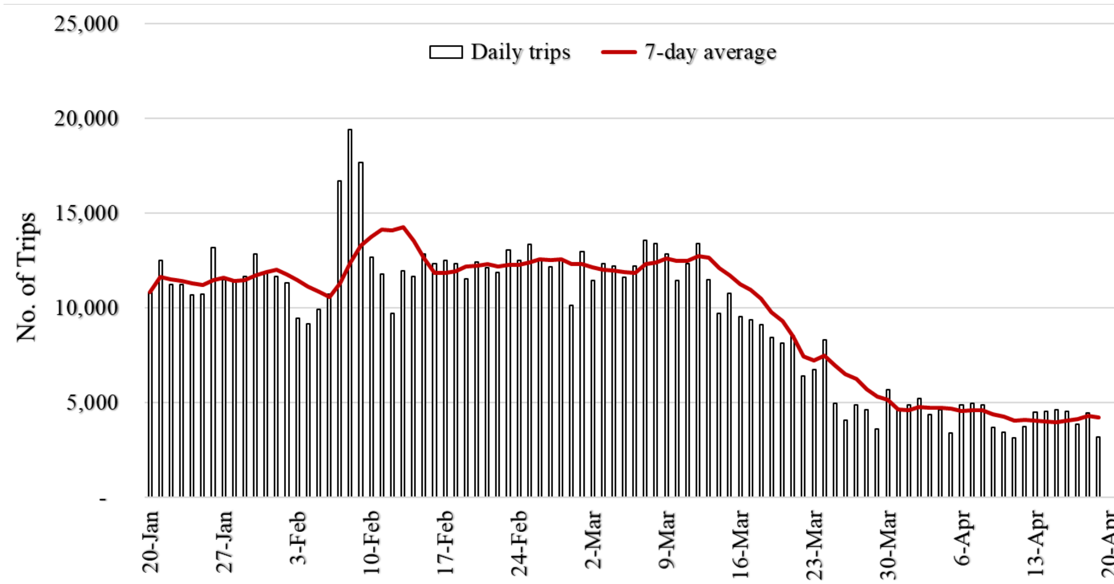
After finding the average sampling rate of the INRIX data for the border-crossing commuters, researchers estimated the number of daily trips by extrapolating the trips in the dataset. The land uses of the parcels from El Paso, Otero, and Dona Ana Counties were grouped under seven categories:

- Residential.
- Commercial.
- Agricultural.
- Industrial.
- Church.
- School.

Based on the destination choices' estimated total daily trips, Figure 6 plots all seven categories with their 7-day averages.

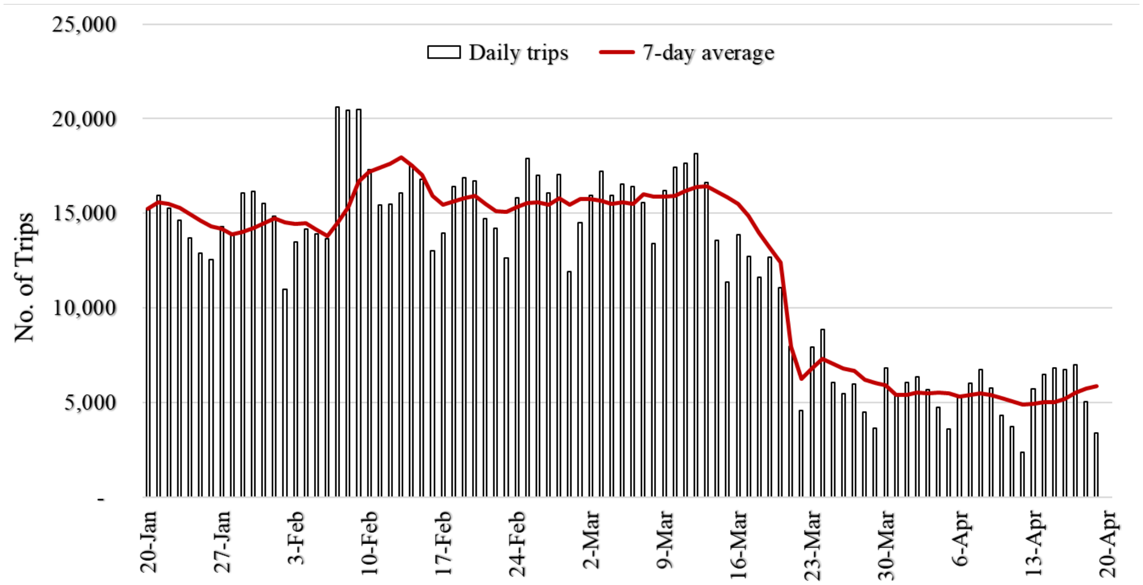



(a) Total Trips

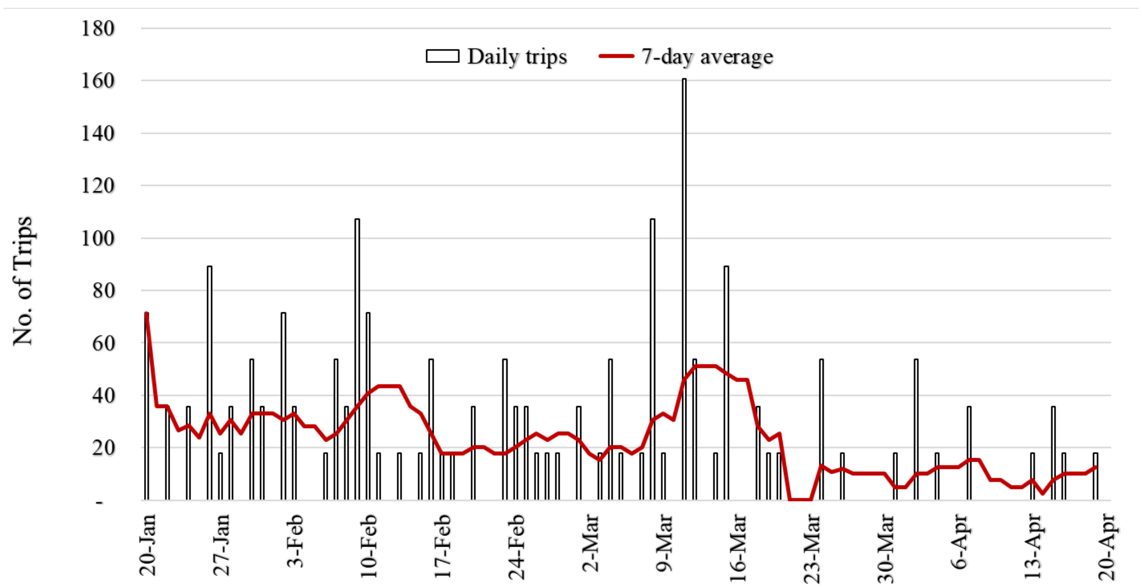



(b) Residential Trips

**Figure 6. Estimated Number of Northbound Daily Trips.**

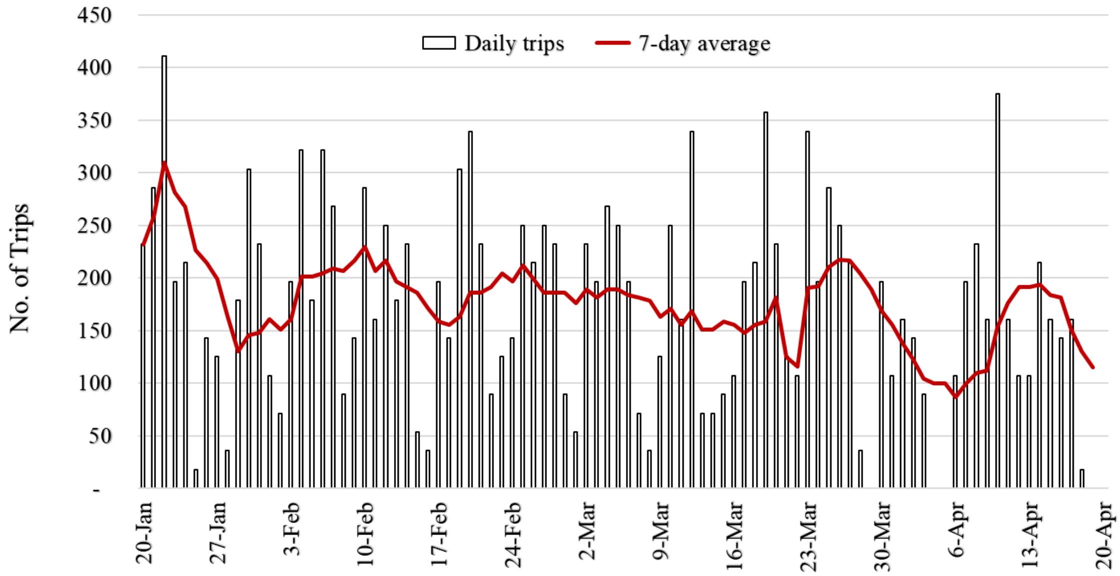



(c) Commercial Trips

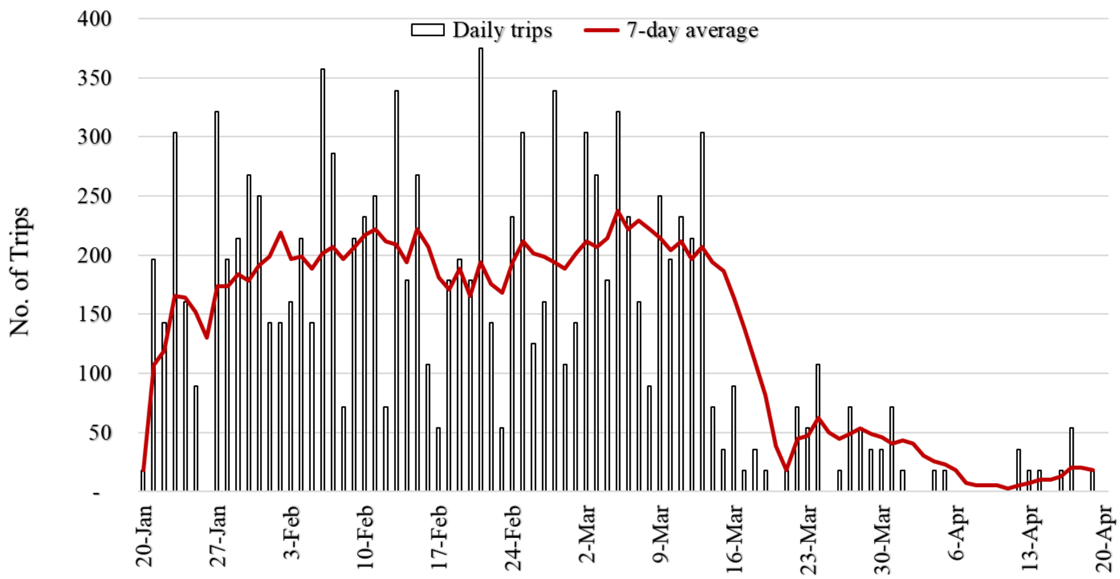



(d) Agricultural Trips

**Figure 6. Estimated Number of Northbound Daily Trips. (Continued)**

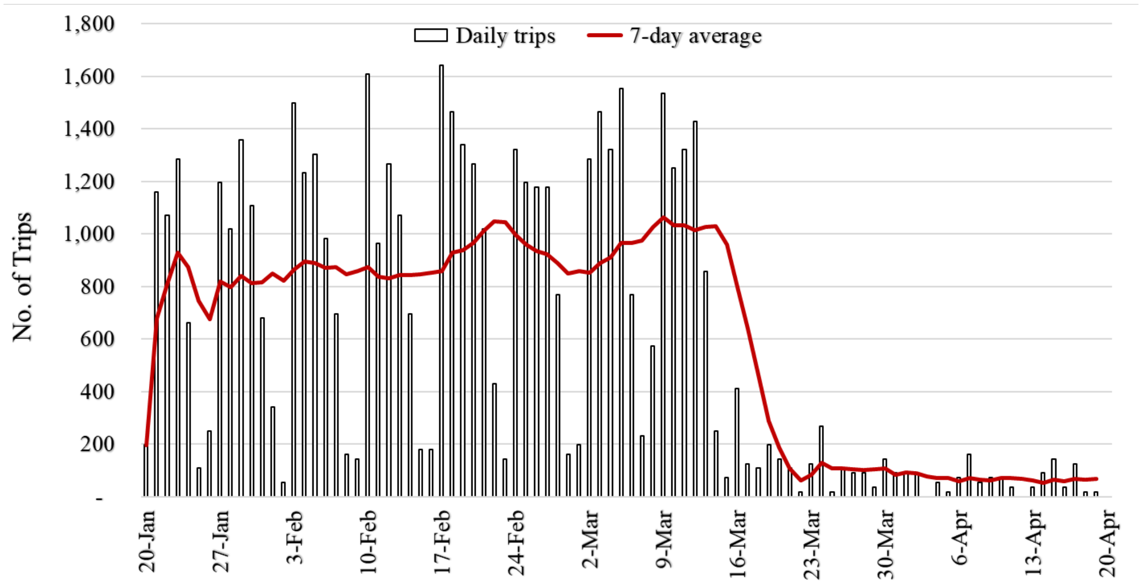



(e) Industrial Trips




(f) Church Trips

**Figure 6. Estimated Number of Northbound Daily Trips. (Continued)**



(g) School Trips

**Figure 6. Estimated Number of Northbound Daily Trips. (Continued)**

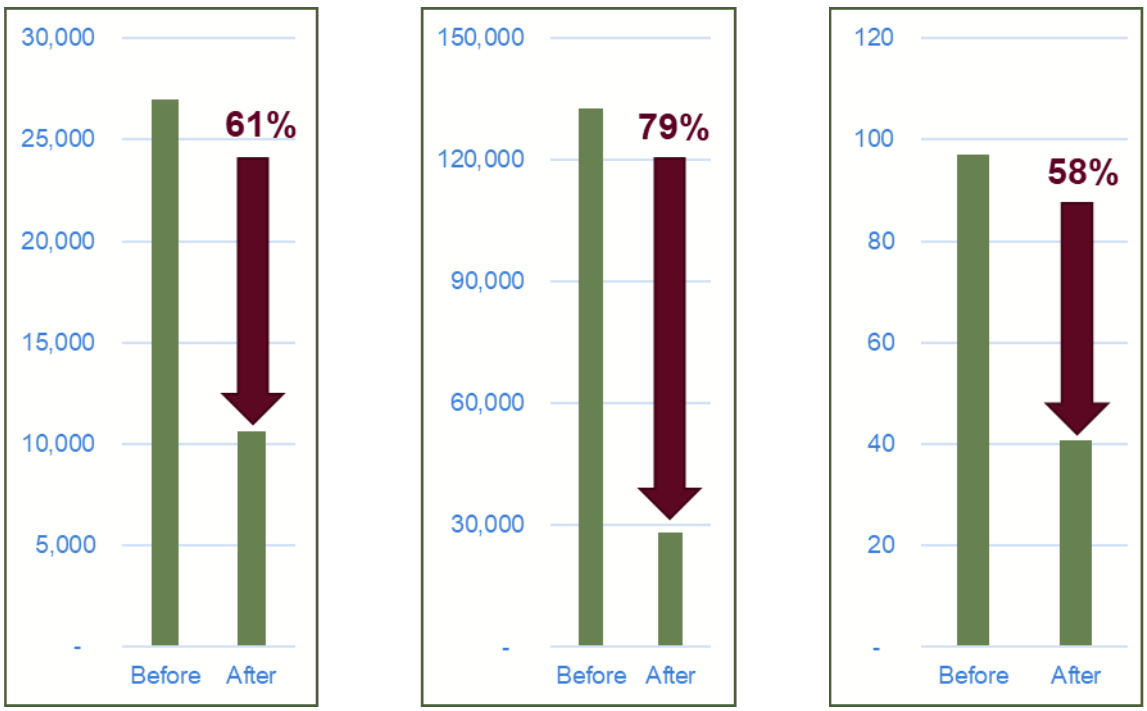
Table 3 lists the land uses and provides information about the number of trips that ended on each land use. The dataset covers 2 months before restrictions and 1 month after restrictions; thus, the number of trips before and after restrictions only has the information of the number of data points captured for the study. For comparison purposes, researchers extrapolated the numbers for each land use and found the estimated average daily trips.

**Table 3. Trip Destinations Based on Land Uses.**

| Land Use | Total Trips | | Average Daily Trips | | |
|---|---|---|---|---|---|
| | Before Restrictions | After Restrictions | Before Restrictions | After Restrictions | Change (%) |
| Residential | 40,517 | 7,989 | 11,311 | 4,449 | −61% |
| Commercial | 52,076 | 9,460 | 14,139 | 5,120 | −64% |
| Agricultural | 100 | 16 | 169 | 135 | −20% |
| Industrial | 638 | 246 | 43 | 25 | −41% |
| Church | 613 | 42 | 827 | 82 | −90% |
| School | 2,837 | 127 | 184 | 39 | −79% |
| Total | 96,781 | 17,880 | 26,673 | 9,850 | −63% |

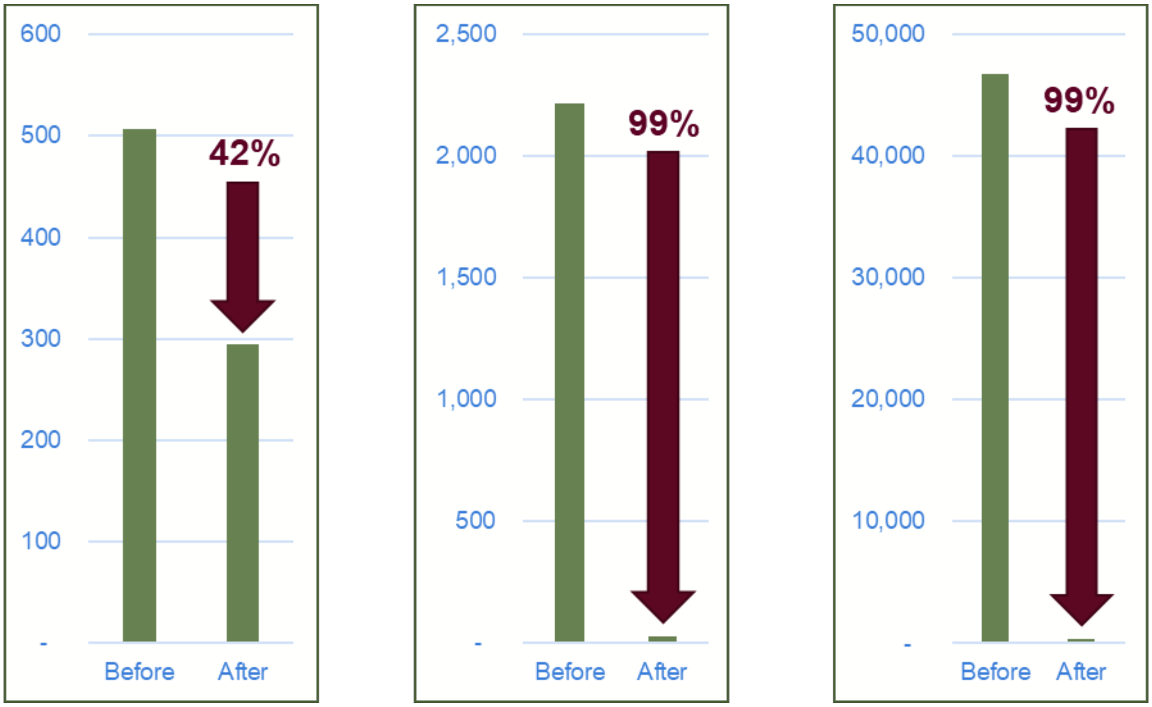
Using the INRIX data, researchers managed to locate the destination of trips. To find the number of contacts, a second study was conducted using the SafeGraph data. The number of potential contacts was found for each border-crossing trip by linking the number of other visits reported by the SafeGraph data. Like the INRIX data, SafeGraph does not provide information for the entire population. The sampling rate is calculated for each region based on the active users of data resources and published by the developers. The El Paso County sampling rate was reported as 16.3 percent (*34*). After extrapolating the number of visits for each place, researchers matched the border-crossing travelers with the number of visits at the same place. One limitation was the uncertainty of the proximity of the people. The datasets do not provide information about how close the individuals are at the same place at the same time. Because the study followed the same methodology for each person and location, the consistency could be kept in the model development.

The results showed that the highest decrease in the number of contacts was experienced at schools and churches. These are followed by commercial land uses with a 79 percent decrease in the number of contacts. Total daily contacts decreased 61 percent for the residential land uses. The lowest decrease was experienced at industrial land uses, which was 42 percent (Figure 7).




(a) Residential (b) Commercial (c) Agricultural

**Figure 7. Number of Daily Contacts of Border Crossing Travelers at Different Land Uses.**




(d) Industrial (e) Church (f) School

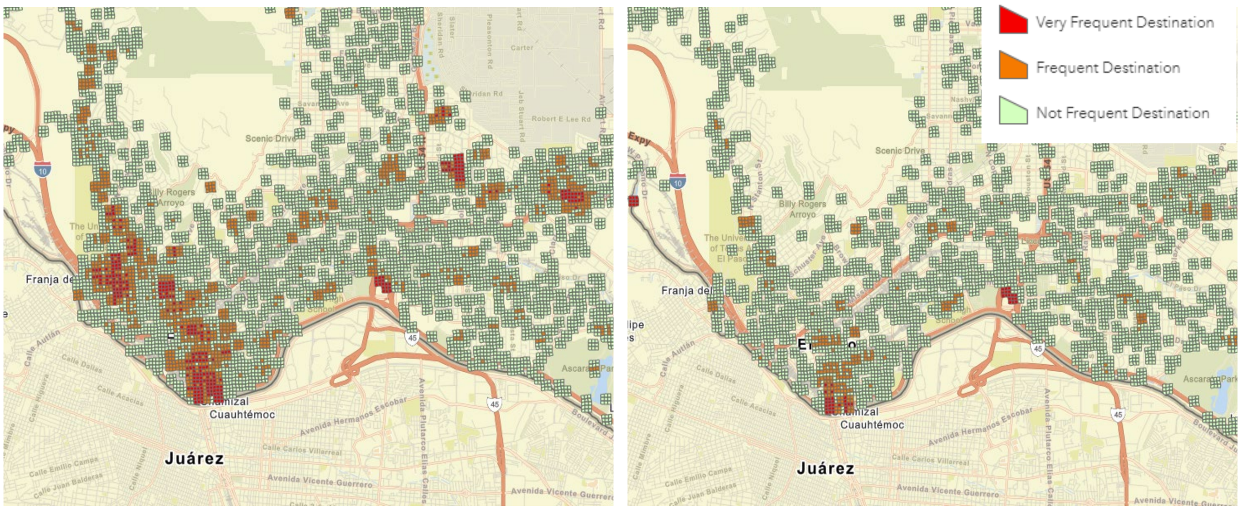
**Figure 7. Number of Daily Contacts of Border Crossing Travelers at Different Land Uses. (Continued)**

### 3.2.3 Maps

The researchers developed a set of online maps to present the changes on mobility patterns of cross-border commuters 4 weeks before (February 21, 2020–March 20, 2020) and after (March 21, 2020–April 18, 2020) border restrictions were implemented. Specifically, the researchers developed four maps for trip density, contact density, trip change in block group, and contact change in block group. A user manual about how to use the online maps is presented in the appendix of this document. The following provides a brief description of each map along with their access links:

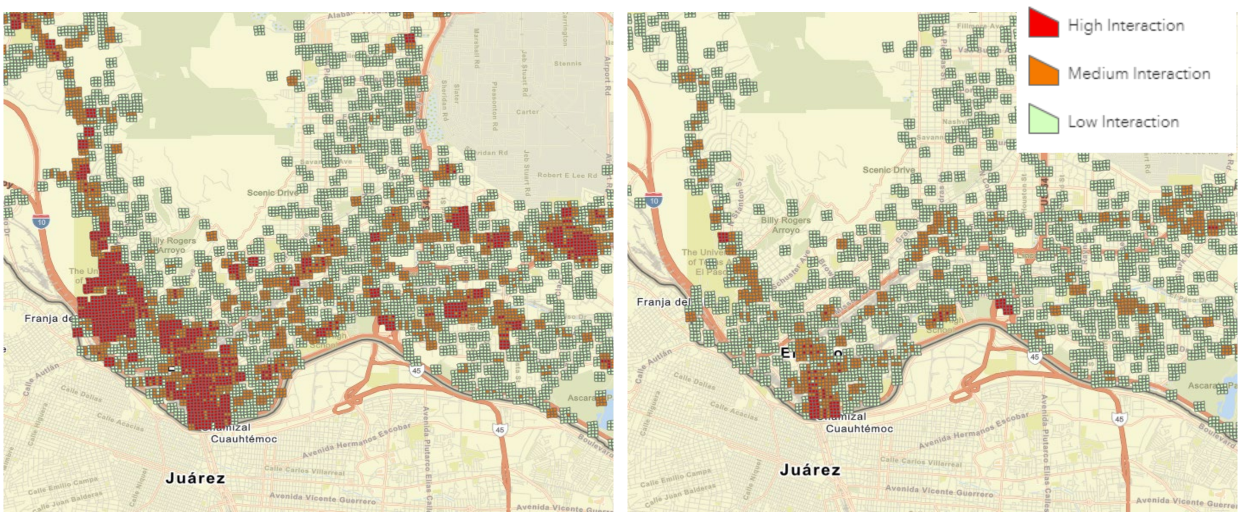
- Trip density—This map presents the frequent destinations of cross-border commuters before and after border restrictions were implemented. Trip density is expressed in the number of cross-border commuter trip destinations per acre. Figure 8 presents a screenshot of the online map that can be accessed at https://arcg.is/1uLOqP1. Very frequent destinations (red areas) were diminished after border restrictions were implemented.
- Contact density—This map presents the average number of close contacts encountered by cross-border commuters before and after the implementation of cross-border restrictions. Contact density is expressed in the number of close contacts per acre. Figure 9 presents a screenshot of the online map that can be accessed at https://arcg.is/1ziDy. High close contact interaction areas (red areas) were diminished after border restrictions were implemented.

- Trip change block group—This map presents the change in trip destinations of cross-border commuters. Trip change is expressed as the difference of the number of destinations within each block group before and after border restrictions were implemented. Figure 10 presents a screenshot of the online map that can be accessed at https://arcg.is/1Gmunz. Most of block groups suffered a decrease in trip destinations.
- Contact change block group—This map presents the difference in the average number of close contacts encountered by cross-border commuters before and after the implementation of cross-border restrictions. Figure 11 presents a screenshot of the online map that can be accessed at https://arcg.is/1nar4i. Most of block groups suffered a decrease in close contact interaction events.




(a) Before Restrictions (b) After Restrictions

**Figure 8. Trip Density Map.**




(a) Before Restrictions (b) After Restrictions

**Figure 9. Contact Density Map.**

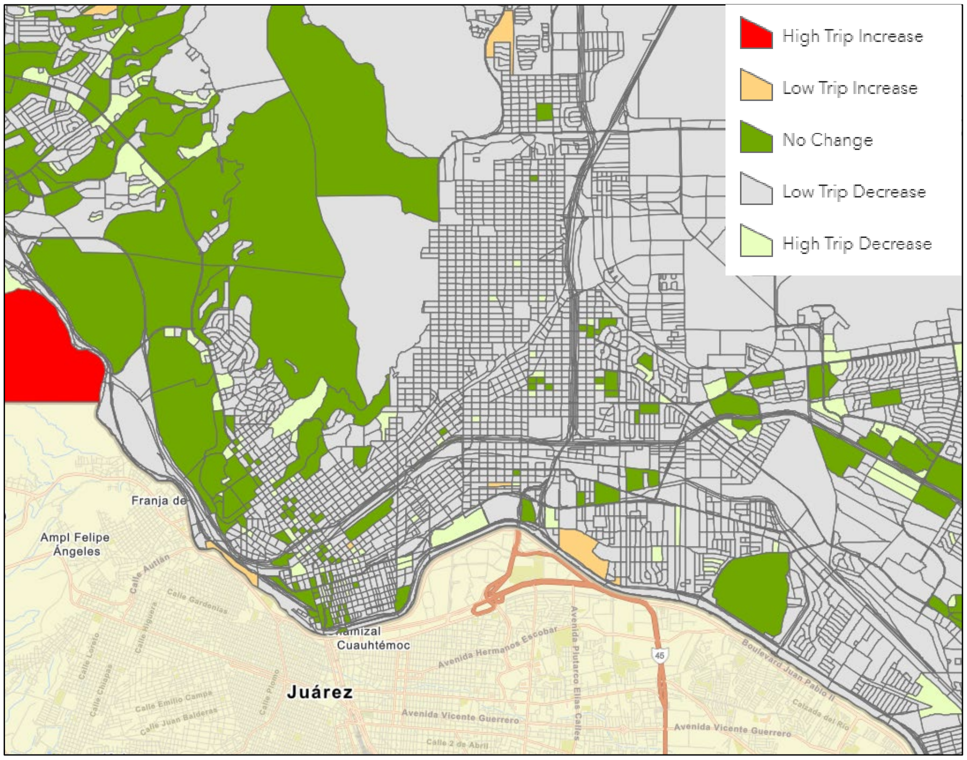



**Figure 10. Trip Change Block Group Map.**

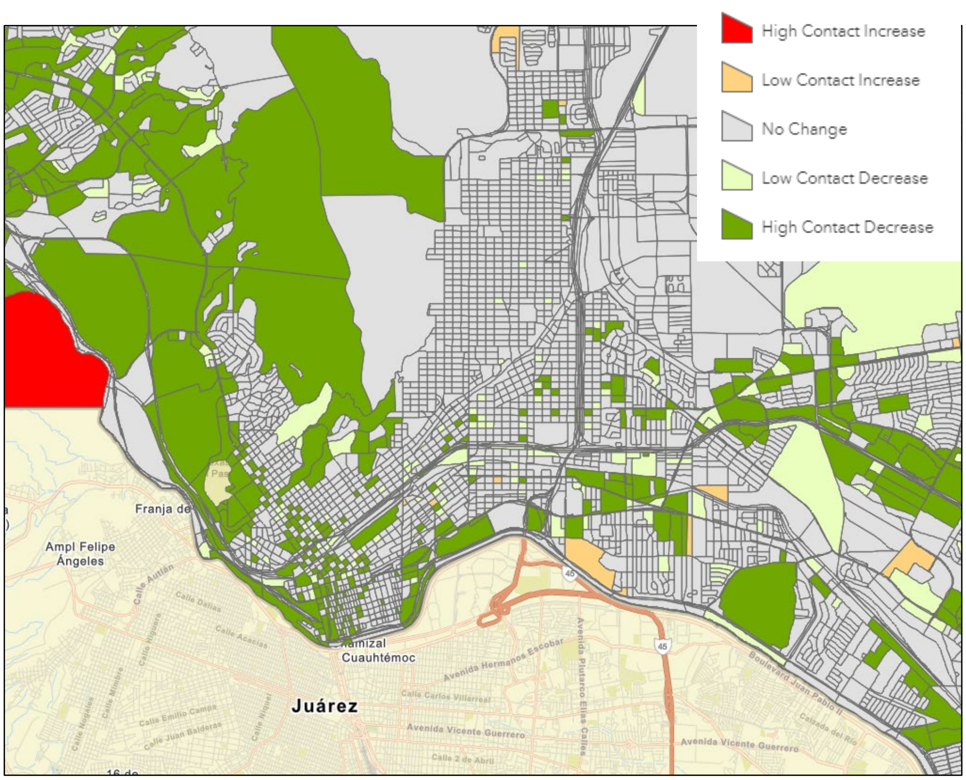



**Figure 11. Contact Change Block Group Map.**

# CHAPTER 4: MODEL DEVELOPMENT

This chapter introduces the Border Crossing Epidemiology Model (BCEM) that uses various data sources to estimate the number of cases and number of deaths due to the COVID-19 disease in El Paso County. Data with the sources are given, and the model development is explained in detail with the comparison of the reported numbers.

## 4.1 DATA

Two groups of data sources were used to develop the model:

- Epidemiological facts about coronavirus.
- Infectivity rate, contact tracing, and mobility features at the local level.

With the former group, researchers had a chance to have a general idea of the length of the incubation period and the timeline a sick person remained infectious. The latter group provides specific information for the El Paso region. The parameters used in model development are:

- Number of cases: The number of reported cases in El Paso County (*35*).
- Number of deaths: The number of reported deaths in El Paso County (*35*).
- Incubation period: The incubation period for COVID-19 (between 2 to 14 days with a median time of 5 days) (*36*).
- Infectivity rate: The infectivity rate of COVID-19, the number of people one person can infect. The value for El Paso is reported weekly (*31*).
- Population: The population of El Paso County (*37*).
- Average duration being infectious: The time people remain infectious. People with mild to moderate COVID-19 remain infectious up to 10 days after the symptoms began. Those with more severe illness remain infectious up to 20 days after their symptoms began (*38*).
- Case fatality rate: The rate of infected people that died. The rate for El Paso is updated daily and has stayed between 1 and 3 percent between April 2020 and February 2021 (*31*).
- Notified identified contact rate: The number of identified contacts notified within 48 hours by public health officials (*31*) (see Figure 2).
- Number of daily contacts: Total number of daily contacts calculated in El Paso County. These values are gathered from SafeGraph data and extrapolated for the entire county.

## 4.2 BORDER CROSSING EPIDEMIOLOGY MODEL

Researchers all around the world have focused on predicting the trend of COVID-19 spread scientifically using mathematical models. Timely mathematical models play a key role in the decision-making process of health policy makers. The models start with the statistical analysis of epidemiological data to describe, quantify, and summarize the transmission of disease in susceptible populations. With the community spread, public health authorities were also interested in obtaining reliable estimates of the pandemic transmission and the potential impact of policy interventions.

One of the key parameters introduced in an epidemiological model is the infectivity rate or basic reproductive number ($R_0$). It refers to the average number of secondarily infected persons infected by one primary infected patient during the infectious period. The $R_0$ is mainly a function of three factors: contact rate, infectivity rate, and rate of susceptible people in the population. If the population is denser, it is more likely to have a greater number of contacts and more people in susceptible groups. Most probably, the infectivity of the virus will be higher. All measures and restrictions by governments aim to reduce the infectivity rate. A study by Xiang et al. (*13*) revealed that $R_0$ for COVID-19 was found between 2 and 4 before any measures were taken. The goal is to reduce the $R_0$ value below 1, which indicates that the infection will spread slowly and will eventually die out.

Few studies focus on the effects of contact tracing on the spread of COVID-19. Hellewell et al. (*39*) developed models with different $R_0$ values to check for the thresholds of required contact-tracing use in the community. The authors found that scenarios with an $R_0$ of 1.5 were controllable with less than 50 percent of contacts successfully traced. Seventy percent of the contacts need to be traced for an $R_0$ value of 2.5. If $R_0$ increases to 3.5, more than 90 percent of the contacts are expected to be traced.

In this study, researchers have developed a meta-population model based on a simple susceptible, infected, and recovered (SIR) model coupled with mobility trends and linear regression expressions to understand the outbreak spreading dynamics stratified by community spread at the El Paso–Juarez binational region. Linear regression analyses were generated and embedded into the SIR model to estimate the consequences of the different what-if scenarios in the region. Using the cumulative number of cases, researchers could evaluate the border restrictions and contact-tracing practices for different scenarios. Three major assumptions for the model development are:

- Deterministic—The results of the model do not include random effects, and eventually everyone in the population is believed to follow the process.
- Short term—Population is assumed to be constant, and there are no births or other deaths except caused by the disease.
- Constant rates—The recovery and infectivity rate are assumed to be constant throughout the study. The infectivity rate is allowed to be changed five times based on the significant changes experienced in the number of contacts.

In the SIR model (Figure 12), population is divided into five different groups:

- Susceptible—The group of people who have not yet contacted the disease and can potentially catch the disease.
- Exposures—The group of people who got infected in the pre-infectious period. This period can also be considered the incubation period.
- Infectious—The group of people who are infected and have the potential to spread the disease to others.

- Recovered—The group of people who recovered from the disease and have gained immunity. This group of people is expected not to be infected again during the study timeline.
- Death—The group of people who lost their lives because of the disease.

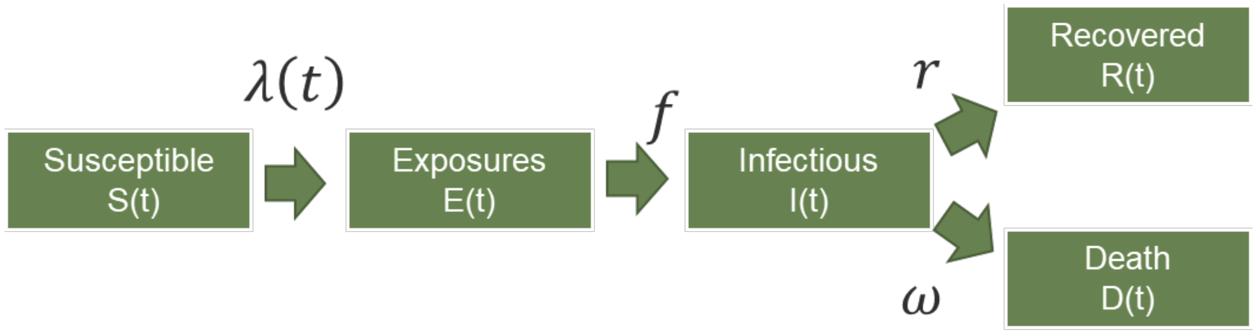



**Figure 12. SIR Model Methodology.**

The differential equations that link each group of people and that are used in the model development are:

$$\frac{dS(t)}{d(t)} = -\lambda(t)S(t) \tag{1}$$

$$\frac{dE(t)}{dt} = \lambda(t)S(t) - fE(t) \tag{2}$$

$$\frac{\mathrm{d}I(t)}{\mathrm{d}t} = fE(t) - rI(t) - \omega I(t) \tag{3}$$

$$\frac{\mathrm{d}R(t)}{\mathrm{d}(t)} = rI(t) \tag{4}$$

$$\frac{\mathrm{d}D(t)}{\mathrm{d}t} = \omega I(t) \tag{5}$$

The most important parameter that significantly affects Equation 1 is the infectivity rate. The value for El Paso is updated by public health officials based on the reported number of cases. To develop what-if scenarios, the model should consider interchangeable parameters instead of the infectivity rate. Therefore, researchers conducted a linear regression analysis to find the relationship between the infectivity rate and potential significant parameters including the number of contacts in El Paso. Researchers found that the number of contacts, number of susceptible, and rate of successful contact tracing (identified contacts notified within 48 hours) are all significant. This relationship allowed researchers to answer potential what-if questions and develop case and death estimations.

After researchers developed the model and input the required parameters, MATLAB software was used to run the simulation. First, the parameters were set based on the findings in the previous section. The model prediction and the reported numbers given by the Texas Department of State Health Services (DSHS) (*35*) for El Paso County were compared for validation purposes. Since the infectivity rate changes over time, researchers divided the total simulation into five time spans and updated the value for each period based on the infectivity rate calculated from the average number of contacts and number of susceptible. The simulation was run for 300 days starting from March 20, 2020, and ending on January 13, 2021.

Figure 13 shows the comparison of the reported cases and the simulation results. Actual cases had a slow trend until mid-October but experienced a large increase for a month until mid-November when the slope of the curve decreased again. The model prediction, on the other hand, had a much slower trend until August and then had a slowly increasing trend with upcoming days. On the last day of the simulation, the number of cases reported by Texas DSHS was 104,714, and the BCEM model predicted 103,681 cases.

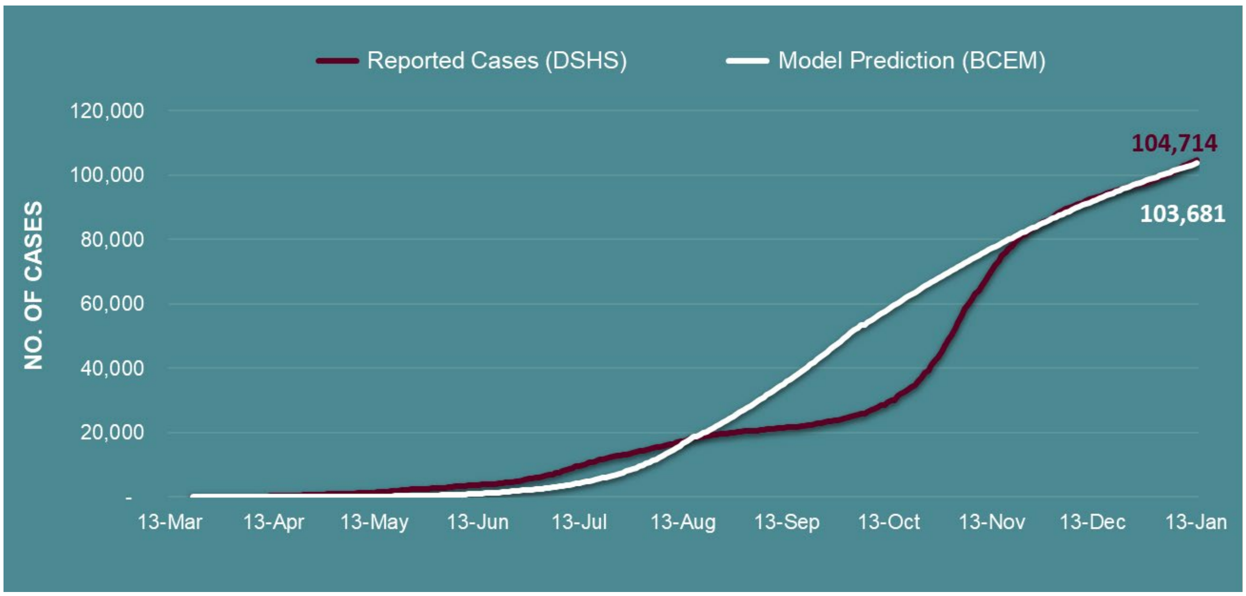



**Figure 13. Reported Cases and Simulation Results.**

Figure 14 compares the number of reported deaths with the simulation findings. The actual number of deaths had fluctuated a great deal, and as of January 13, 2021, El Paso County reported 1,869 deaths due to COVID-19. The BCEM model's prediction for the same time was 1,737. The prediction of the number of deaths was not as accurate as that of the number of cases but was still within the 7 percent range.

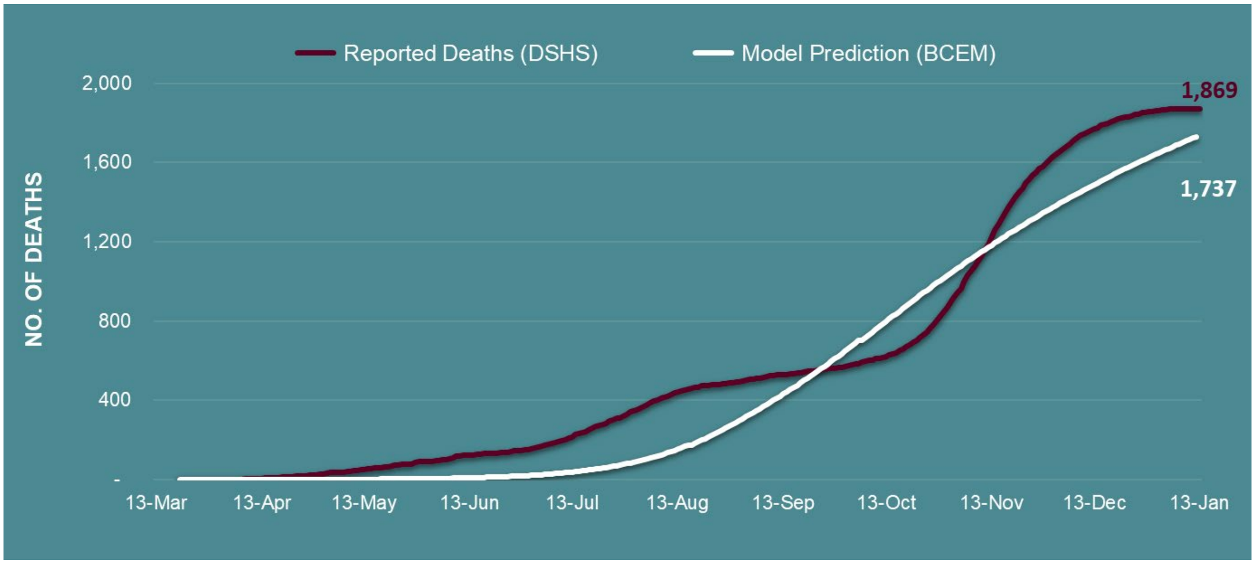



**Figure 14. Reported Deaths and Simulation Results.**

# CHAPTER 5: SCENARIOS AND MODEL RESULTS

After validation of the model in Chapter 4, the objective of Chapter 5 is to assess the impacts of border restrictions and potential contact-tracing implementation using different scenarios. Researchers developed several potential what-if questions regarding contact-tracing implementation in El Paso County and modeled the results. The results were presented at 5 virtual meetings to U.S. and Mexico public- and private-sector stakeholder groups in the El Paso–Ciudad Juarez region. This chapter also summarizes the stakeholder's input collected during those presentation. A final limitation section highlights the research and model limitations and addresses potential future research.

## 5.1 SCENARIO DEVELOPMENT

Researchers defined four scenarios, considering the existing conditions (border mobility restrictions to non-essential travelers) as the base scenario or no change. The other defined scenarios and their main considerations are:

- Scenario 1:
  - Northbound border crossing is 50 percent higher.
  - All other measures are in place (school closures, stay-at-home orders, etc.).
  - There is no change in contact-tracing efforts.
- Scenario 2:
  - Northbound border crossing is 50 percent higher.
  - All other measures are in place (school closures, stay-at-home orders, etc.).
  - Community contact tracing is as it currently is.
  - There is a mandatory contact-tracing program for northbound border-crossing travelers.
- Scenario 3:
  - Northbound border crossing is 50 percent higher.
  - All other measures are in place (school closures, stay-at-home orders, etc.).
  - There is no conventional contact tracing.
  - 50 percent of the El Paso population voluntarily participates in a contact-tracing program.
- Scenario 4:
  - Northbound border crossing is 50 percent higher.
  - All other measures are in place (school closures, stay-at-home orders, etc.).
  - Community contact tracing is currently as it is.
  - 25 percent of the El Paso population voluntarily participates in a contact-tracing program as a supplement to the conventional method.

In short, Scenario 1 was developed to explore the effects of the increasing border mobility. Scenario 2 was developed to understand the effectiveness of a mandatory border-crossing contact-tracing program. Scenario 3 was developed to see the potential benefits of substituting the conventional contact-tracing efforts with an automatic contact-tracing program. The last scenario was developed to show the impact of a comprehensive contact-tracing system that includes conventional contact-tracing efforts and an automatic detection technique.

## 5.2 RESULTS

The model was run for each scenario. The results of the cumulative number of cases are plotted in Figure 15 and compared with the base scenario (no change). Scenario 1 findings are telling; if the northbound mobility was 50 percent higher than the actual (with border restrictions in place), there would be 14 percent or more cases in El Paso. With the same conditions but if there was a mandatory contact-tracing program just for travelers from Mexico, still there would be a 9 percent or higher number of cases compared to the base scenario. However, if 50 percent of the entire El Paso population participated in a contact-tracing program without any other conventional contact-tracing practice, there would be 15 percent or fewer cases. Finally, the best-case scenario was found as Scenario 4. It keeps the existing contact-tracing efforts, and 25 percent of the community would use a contact-tracing program. This would result in up to a 22 percent reduction in the number of cases in El Paso County.

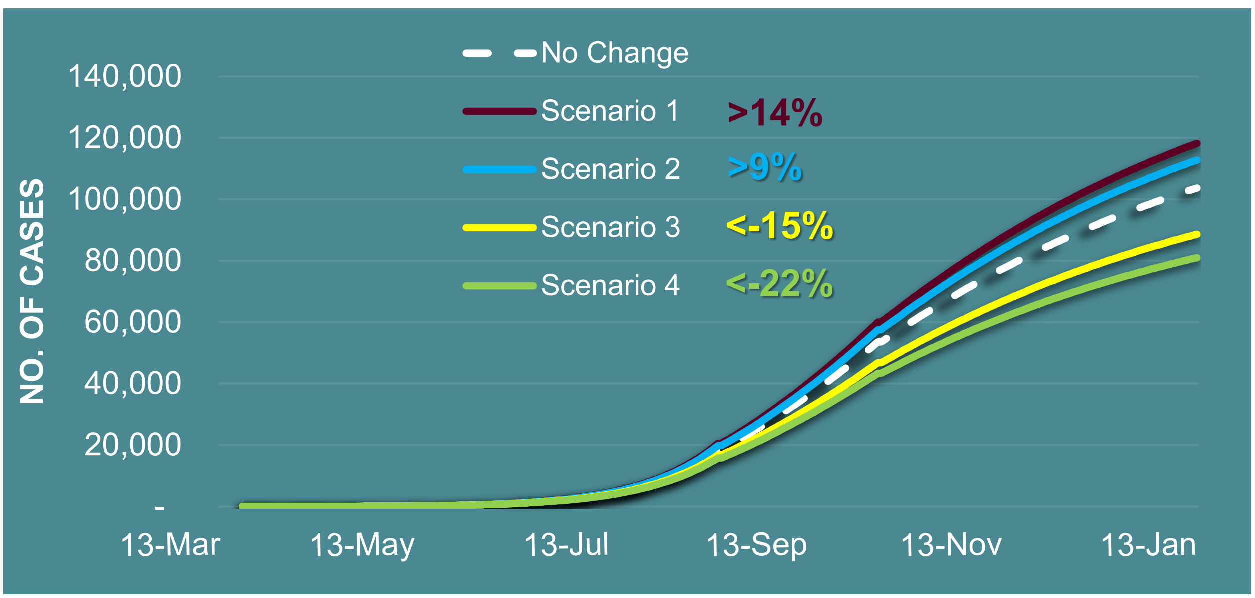



**Figure 15. Simulation Results for Scenarios (Number of Cases).**

Simulation results also provided information about the estimated number of deaths by day. Since the number of deaths has a linear relation with the number of cases, the trend was found similar with the same or very close percent changes from the base scenario. As Figure 16 represents, Scenario 4 was the best-case scenario with the lowest number of deaths.

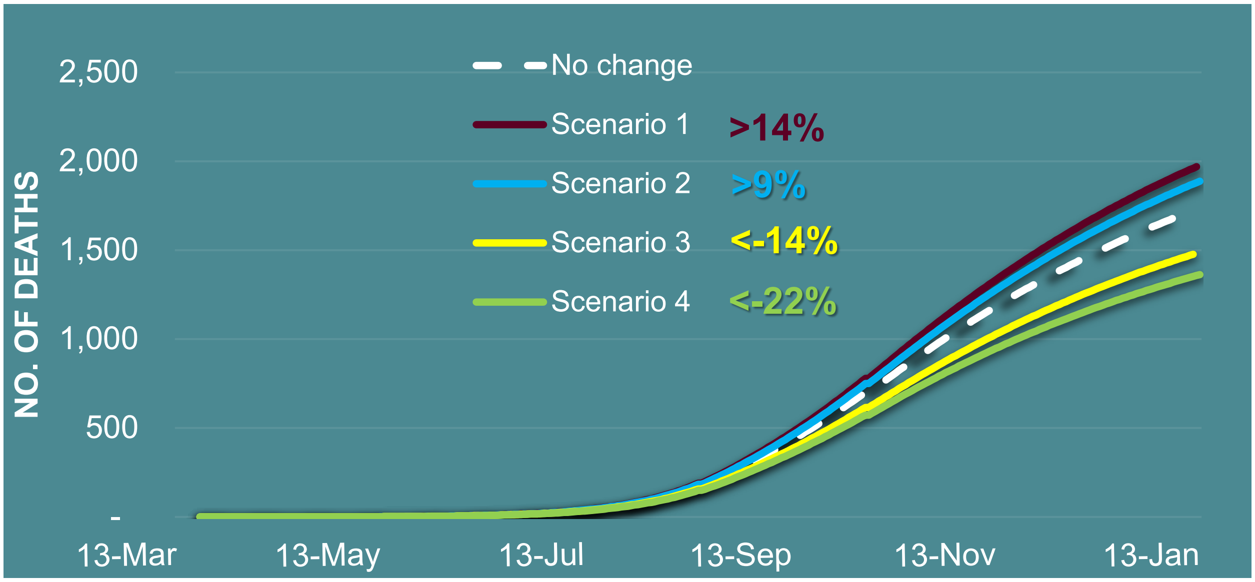



**Figure 16. Simulation Results for Scenarios (Number of Deaths).**

As of January 13, 2021, El Paso County experienced 104,714 cases and 1,869 deaths due to COVID-19. The model findings propose that if the border mobility was 50 percent higher than the actual crossings, there would be at least 14,600 more cases and 260 more deaths. On the other hand, this would be better with contact-tracing app use with a market penetration around 25 percent. This scenario would result in a reduction of the number of cases up to 23,000 and deaths up to 410.

## 5.3 STAKEHOLDER INPUT

One of the tasks of the project was to share the findings with interested stakeholders from El Paso County and Ciudad Juarez. In February 2021, researchers reached out to the City of El Paso International Bridges Department to present the draft presentation and gather their feedback. With their input, the presentation was updated and presented virtually to:

- Directora de Juárez Resiliente (February 3, 2021).
- The El Paso/Juarez COVID Communication and Support Group (February 4, 2021).
- COVID Community Partners (February 5, 2021).
- Border Crossing Steering Committee members (March 4, 2021).

Researchers had the chance to reach 95 participants in those meetings. Feedback obtained from these stakeholders is summarized as follows:

- Participants are aware of the importance of contact tracing, and all agree that if the region had a more comprehensive contact-tracing program, the number of cases and deaths would be fewer.
- Although this project evaluates border mobility and contact tracing and simulates different scenarios, participants are more interested in the contact-tracing efforts than the border mobility.

- Health officials and public health experts advised researchers to improve the study by including the vaccination rate and total number of immunized people. Researchers started working on a new project having a similar model and including the population of immunized people due to vaccinations.

## 5.4 LIMITATIONS

Border mobility, contact tracing, and disease spread are complex in nature and highly dependent on the human interactions and reactions to governmental measures. This research proposes relationships among them and answers potential what-if questions by developing different scenarios. Researchers used two datasets to estimate the number of border-crossing travelers and the number of contacts based on their trips. However, the Trips dataset can only capture one crop of the border-crossing travelers; subsequent trips are not in the dataset. Therefore, the models have been developed based on the consideration of one trip of the border-crossing travelers. This is the main limitation of this study. Considering this, researchers reported the findings with uncertainties. For example, simulation results gave a 14 percent increase for Scenario 1; however, since it is uncertain that border-crossing travelers have conducted more than one trip, it has been reported that the expected cases would be 14 percent or higher.

Researchers tried to cover every possible parameter that may affect the infectivity rate. Yet, there might still be some parameters like the rate of wearing a mask in the community that the model could not address. The model is developed just for the U.S. side of the border since researchers have ample data for model development. On the other hand, due to limited data for the Mexican side, researchers could not develop a specific model for south of the border. Similarities on both sides of the border community suggest that the Mexican side of the border would show similar behaviors regarding disease spread. In other words, the Juarez component would mirror these findings at least from a trend standpoint.

# CHAPTER 6: FINDINGS AND CONCLUSIONS

COVID-19 is a rapidly spreading infectious disease that was declared a pandemic by WHO on March 11, 2020 (*5*). As of February 10, 2021, more than 107 million confirmed cases and over 2.3 million deaths have been reported globally (*1*). The United States is the most affected country based on the total number of cases and fatalities. To slow down the speed of spread, most countries implemented travel restrictions, school closures, shutdowns, and stay-at-home orders, which caused millions of people to lose their jobs. From a transportation perspective, understanding the key parameters and effective policy implementations that help slow the spread of disease is vital for decision makers. There are different applications in the world in terms of border-crossing measures, and a growing number of countries are implementing technology-based practices to regulate the movement and tracking of citizens. Each practice has its advantages and limitations. Although border restrictions helped mitigate the speed of spread of COVID-19, they are having an adverse effect on the economy of border communities.

To understand the effects of border and other restrictions on the mobility and trip preferences of northbound border-crossing travelers, researchers used Trips and Trajectory data overlapping the county appraisal district data. The results showed that the number of trips decreased 63 percent on average, and the highest decrease was experienced in trips with school destinations. That was expected since schools were closed in the United States during the early days of the pandemic. The lowest decrease with 20 percent was seen in industrial land uses.

To explore the impacts of border restrictions and measures and contact-tracing practices, researchers developed an epidemiological model and analyzed different what-if scenarios to answer potential stakeholder questions. Current contact-tracing practices in El Paso are limited in that they rely on a list provided by the infected person and rely on his or her memory to reach all close contacts, limiting the comprehensiveness of the contact-tracing effort and decreasing its effectiveness. Improving the comprehensiveness of contact-tracing efforts for the entire community and keeping the conventional contact-tracing practice would reduce the number of cases and deaths by up to 20 percent, even with allowing 50 percent higher border mobility. However, enhancing contact-tracing programs only for individuals who cross the border would not significantly reduce the spread of disease. Considering worldwide app use and deployment, public outreach and binational coordination are needed to have a successful contact-tracing program in the El Paso–Juarez region.

This research has the potential to be expanded to examine some other mobility-related scenarios including the effects of closing schools and putting stay-at-home orders in place. Moreover, the model is flexible enough to add vaccination efforts as a new parameter. To do so, a similar approach can be followed with reliable vaccination data for both sides of the border.

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## ZOOM

To zoom in or out on the map, use the zoom keys in the bottom right corner of the screen (see the red rectangle in Figure 17). The home button in between the zoom keys allows you to go back to the original location where the map was when it was first opened. Another way to zoom is using the scroll function of your mouse.

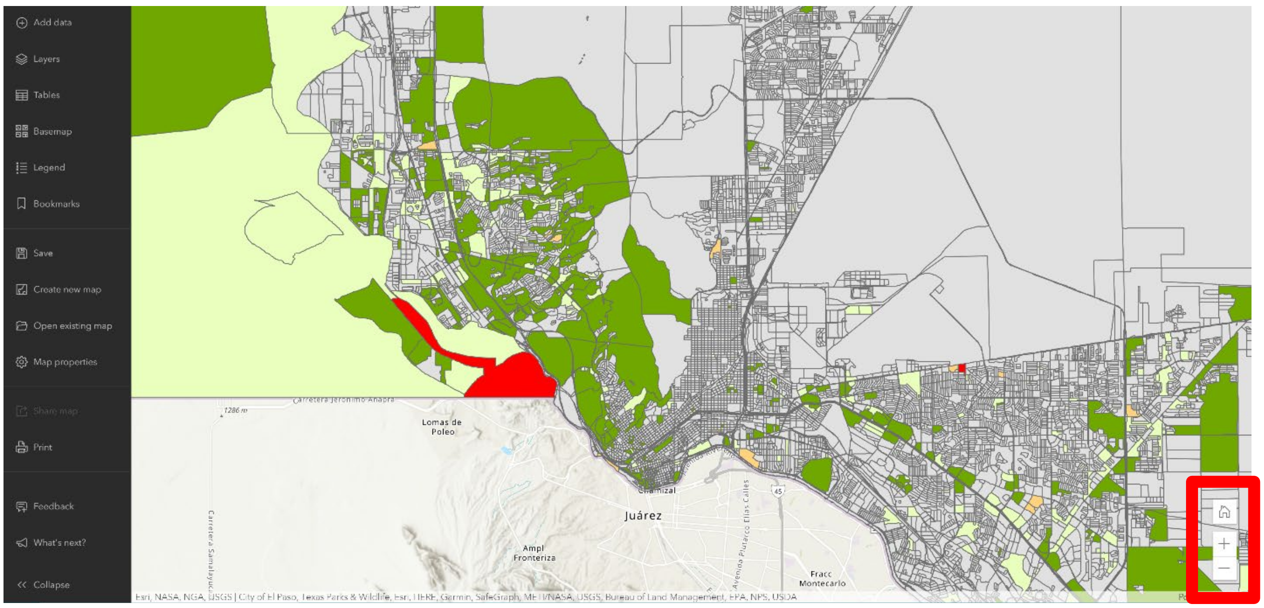


**Figure 17. Zoom Online Map Interface.**

## NAVIGATION

To move around the map, click and hold the left mouse button anywhere in the map and move your mouse pointer. To see the attributes of a parcel, left-click on any colored parcel, and a window with the attributes will pop up (see Figure 18). The blue outline highlights the selected parcel as shown in Figure 18. If you click on the square icon highlighted by the red box, the window is pushed to the side of the screen to get a better look at the map and the selected area.

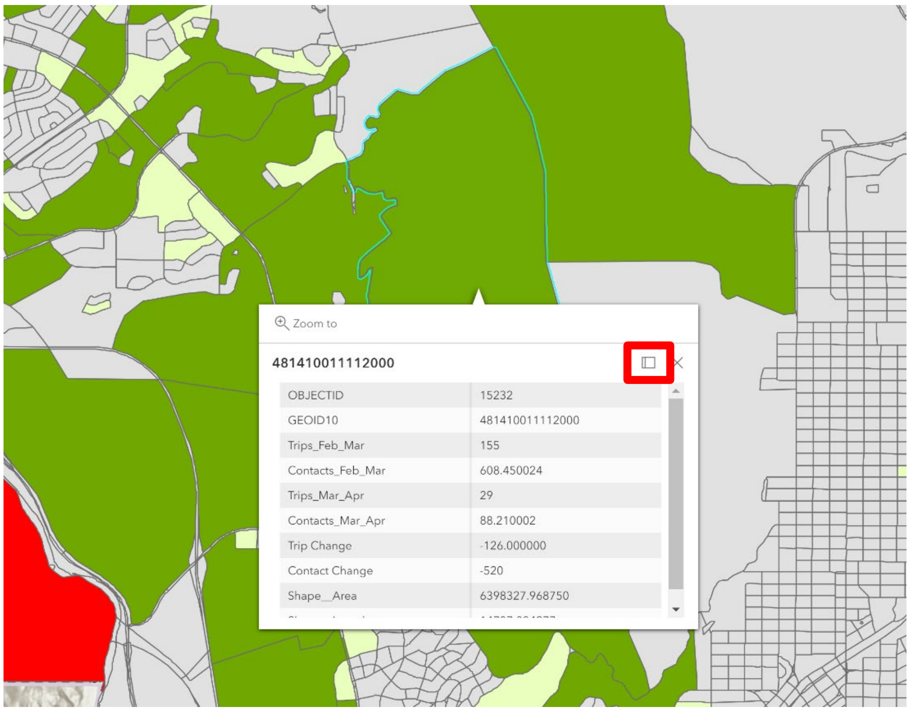


**Figure 18. Navigation Online Map Interface.**

## VISUALIZE ATTRIBUTE TABLE

To better visualize all layer features, you can open the attribute table of the layer. This shows all parcels along with their attributes. To do so:

1. Click on the "Layers" button on the left-hand side of the screen as shown in Figure 19.


**Figure 19. Layers Icon.**

2. After performing Step 1, a new window showing the name of the map is displayed. Click on the arrow shown in Figure 20 to expand the layers into view.

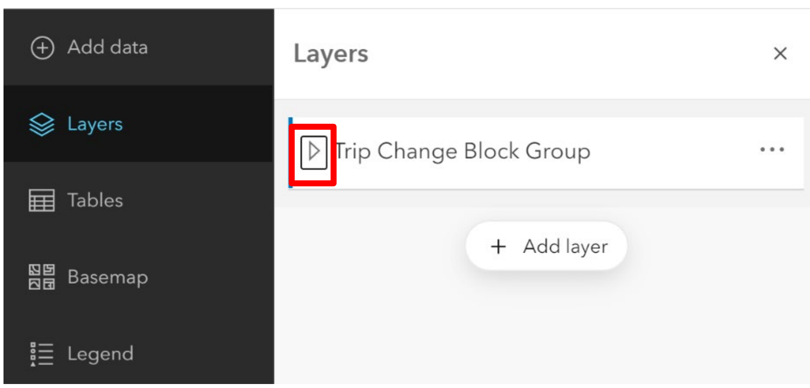


**Figure 20. Expand Layers.**

3. Once the layers are in view, click on the icon with three dots next to the layer name, as displayed by a red box in Figure 21.

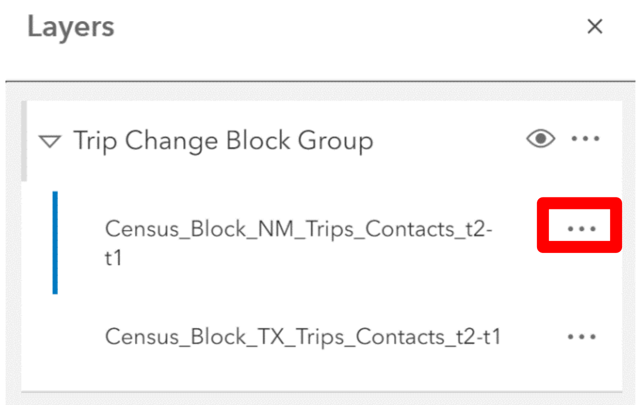


**Figure 21. Layer View.**

4. After completing Step 3, a new box with options for the selected layer appears. Click on the third option "Show table," as highlighted by a red box in Figure 22.

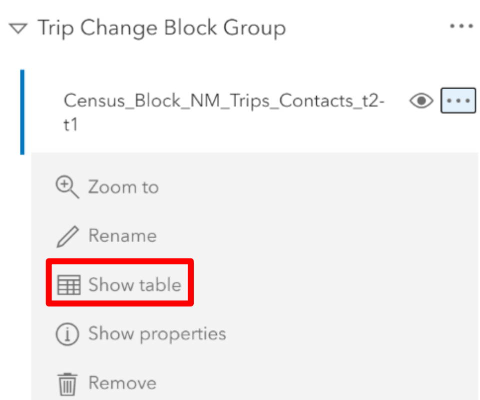


**Figure 22. Show Table.**

5. After completing Step 5, the attribute table comes into view as shown in Figure 23. You may close out the other windows to expand the table.

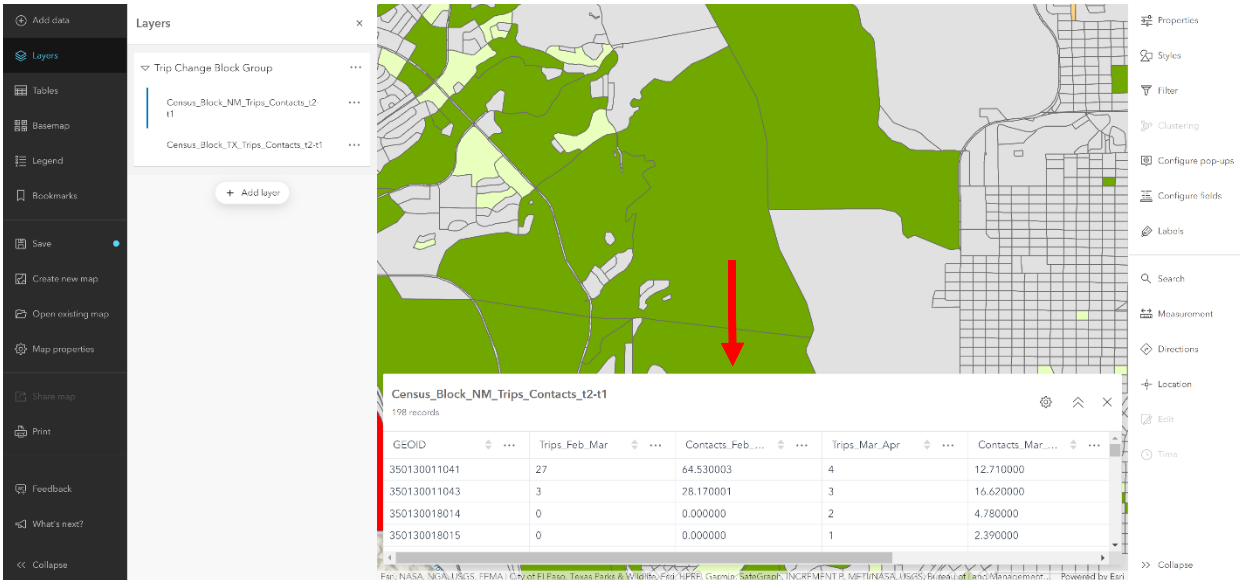

**Figure 23. Attribute Table Display.**

## CHANGE LAYER TRANSPARENCY

You may opt to increase the transparency of the colored-in parcels to get a better look at the map behind it. Transparency can be changed for each layer by following these steps:

1. Choose the layer you will be modifying. Repeat steps 1–3 from the previous section.
2. Click on the fourth option "Show properties" as highlighted by the red box in Figure 24.

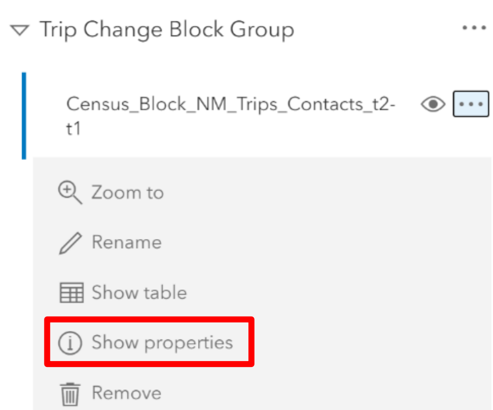

**Figure 24. Show Properties.**

3. After completing Step 2 a new window titled "Properties" is displayed on the right-hand side of the map, with four tabs to work with. Go to the third tab, "Transparency," as displayed by a red box in Figure 25. With this tool you can easily increase or reduce the transparency of the selected layer by moving the circle (see Figure 25) left or right, as desired.

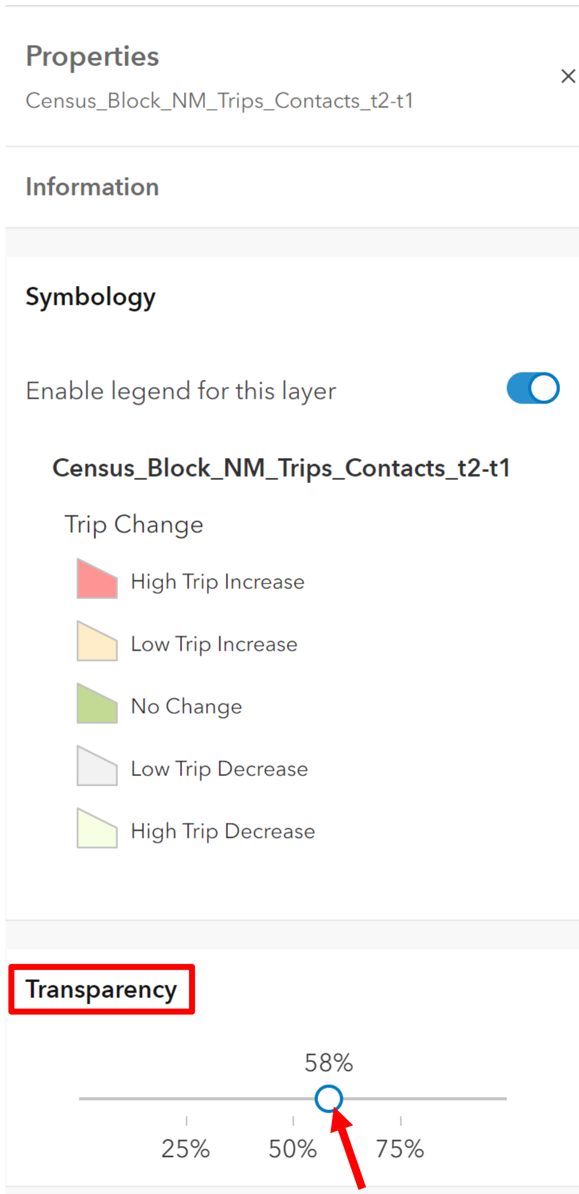


**Figure 25. Change Transparency.**