

1 **AN ECONOMETRIC MODEL OF FLIGHT EN ROUTE INEFFICIENCY**

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1 **ABSTRACT**

2 The Federal Aviation Administration (FAA) and Eurocontrol publish metrics to evaluate flight  
3 horizontal en route inefficiency (HIE), which measures the excess distance flown with respect to  
4 the theoretical shortest distance route. Knowledge of the factors that drive variation in en route  
5 efficiency is, however, limited. This paper proposes an approach to relate HIE with convective  
6 weather, wind, Miles-In-Trail restrictions (MIT), Airspace Flow Programs (AFP), Monitor Alerts  
7 (MA), and Special Activity Airspace (SAA). Furthermore, we develop econometric models to  
8 quantify how these factors affect HIE based on a historical dataset with flights among 97 major  
9 US airport pairs in 2013. Our analysis is based on the concept of a synthetic nominal route, in our  
10 case a great circle route, whose features are time-dependent, and are assumed to affect HIE of a  
11 given flight even though its trajectory does not follow the great circle. In the models, we also  
12 consider the effects of airspace route structure by inclusion of airport-pair fixed effects, and a  
13 measure of flight distance that is sensitive to the efficient placement of terminal entry and exit  
14 points. The estimation results suggest that long-haul flights are in general more efficient than short-  
15 haul flights, and inefficient terminal entry and exit points lead to greater HIE. The estimates  
16 confirm that inefficiency is greater when synthetic great circle routes have greater exposure to  
17 convective weather, unfavorable winds, MITs, SAAs, and long-delay AFPs. Finally, we find that  
18 MAs do not appear to have much direct impact on en route inefficiency.

19

20 *Keywords:* En route inefficiency, convective weather, wind, Miles-In-Trail, Airspace Flow  
21 Program, Special Activity Airspace, Monitor Alert; Fixed effects model

22

## 1 1. INTRODUCTION

2 In recent years, flight en route performance has received more attentions in the literature. In both  
 3 US and Europe, it is evaluated by a simple metric termed as “horizontal en route inefficiency”  
 4 (HIE), which is calculated based on the actual distance traveled and a benchmark distance between  
 5 a 40 nautical-mile circular boundary around the departure airport (D40) and a 100 nautical-mile  
 6 circular boundary around the arrival airport (A100). Equation 1 formulates the HIE, where A is the  
 7 actual flown distance, and H is the benchmark distance termed as the “achieved distance” (1).  
 8 While the achieved distance is highly correlated with the D40A100 great circle distance, it captures  
 9 the effects of terminal exit and entry points and varies from flight to flight.

10

$$11 \quad HIE = \frac{A-H}{H} \quad (1)$$

12

13 Simple as it is, flight en route inefficiency is core to many fuel efficiency benefit assessments.  
 14 Therefore, both the Federal Aviation Administration (FAA) and Eurocontrol employ the metric and  
 15 publish joint annual report to compare and evaluate the overall performance in both regions. Ref.  
 16 (2) reports that in 2013, the HIE was 2.91% and 2.71% for Europe and the US, respectively. With  
 17 the implementation of free route airspace (FRA), Europe experienced continuous improvement of  
 18 HIE between 2011 and 2014, however, this trend reversed in 2015. US HIE improved from 2008  
 19 to 2012, but has been worsened since then. This has been linked to airports with increased traffic  
 20 levels (LAX, SEA, DAL) (2). However, work on linking inefficiencies to specific causal reasons,  
 21 a necessary step in developing strategies to improved performance, is limited. Accordingly, in this  
 22 study, we will identify potential causal factors and the mechanisms by which they may contribute  
 23 to HIE, propose metrics that quantify the exposure of individual flights to these factors, and, lastly,  
 24 build econometric models to quantify the effects of different factors on HIE.

25

26 The rest of the paper is organized as follows. In section 2, we first review literature that is related  
 27 to en route inefficiency analysis, and then introduce the datasets used in the study. Section 3  
 28 describes the methodology and algorithms of the paper. Section 4 presents the results and our  
 29 analysis, and section 5 offers the conclusions.

30

## 31 2. PRELIMINARIES

### 32 2.1 Literature Review

33 There is some previous literature analyzing correlations between different causal factors and flight  
 34 en route inefficiency. Liu et al. (2017) examine the causal effects of weather, wind and Miles-In-  
 35 Trail (MIT) restrictions on en route inefficiency using the concept of nominal routes (3). In the  
 36 paper, the authors select six airport pairs and build airport-pair specific models to quantify the  
 37 contributions of different factors. The results vary across pairs but in general convective weather  
 38 has the greatest contribution, followed by wind and miles-in-trail restrictions. However, the factors  
 39 considered in that study together account for a small fraction of the total en route efficiency. In  
 40 part, this is because the study considers factors that vary from flight to flight for a given airport  
 41 pair. Therefore, the present study adopts a different approach: we estimate pooled cross-sectional  
 42 models that are informed by HIE variation both within and between different airport pairs. This  
 43 allows us to investigate factors whose variation is substantially between pairs rather than between  
 44 flights within a pair, such as special activity airspace (SAA) and airspace flow programs. Moreover,

1 the methodology adopted here is more readily “scalable” so that much larger number of airport  
2 pairs can be incorporated into the analysis.

3  
4 One set of factors that affect HIE pertains to weather – including convective weather and winds.  
5 There is extensive literature on modeling flight trajectories in avoidance of convective weather.  
6 For example, McNally et al. (2012) and McNally et al. (2013) developed tools to automatically  
7 reroute flights to find more efficient routes around convective weather, which they termed  
8 “dynamic weather routes” (4), (5). Flights almost will always go around hazardous weather zones  
9 (see SWAP from (6)) and therefore increase their HIE. Additionally, a large body of literature  
10 focuses on optimizing trajectories with respect to wind – i.e. finding the wind optimal route (7),  
11 (8), (9). In many cases, a flight taking the great circle trajectory, which is the shortest path, will  
12 not be optimal when winds are taken into account. Therefore, a flight that is “inefficient” in terms  
13 of HIE flight may actually be more “efficient” in terms of fuel/flight time.

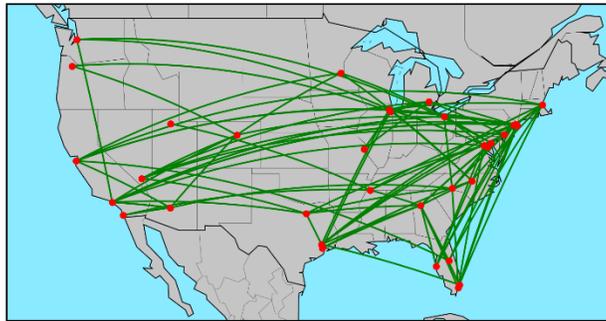
14  
15 Another important group of potential factors contributing to HIE is traffic management initiatives  
16 (TMIs), particularly those related to airspace. They have received far less attention in the open  
17 literature. One such initiative is Miles-In-Trail restrictions (MIT), which specify the minimal  
18 distance required between two consecutive aircrafts over a fix, airport, sector or route (6). MITs  
19 are a common tool that FAA uses to maintain a manageable flow into busy airspace. Ref. (10)  
20 reports that MIT restrictions did not have significant effects on airborne delay, but their effect on  
21 HIE has only been studied recently. Liu et al. (2017) reports that MITs have a statistically  
22 significant impact for certain pairs such as JFK to FLL (3). However, how and to what degree MIT  
23 may affect the traffic flow and flight inefficiency in a broader range of airport pairs need further  
24 exploration. A second example is Airspace Flow Programs (AFP), which identify constrained areas  
25 in the airspace and assign expected departure clearance times (EDCT) to flights entering the area.  
26 Flights can choose either stay in the AFP and accept the EDCT and its attendant ground delay, or  
27 reroute the flight out of AFP to get a longer route, or reroute to another AFP with lower expected  
28 delays. Tereshchenko and Hansen (2018) studied the airline decision making in response to the  
29 AFP with emphasis of relative trajectory costs. Though the authors conclude that flights usually  
30 avoid rerouting out of AFP, but such reroutes are common enough so that AFPs could affect en  
31 route inefficiency (11). Thirdly, Special Activity Airspace (SAA) defines 3D geometries in the  
32 NAS wherein limitations are imposed on aircraft operations at certain times, when the SAA is said  
33 to be “active.” SAAs include Special Use Airspace (SUA) such as Military Operational Areas  
34 (MOA), Restricted Areas (RA) and Air Traffic Control Assigned Areas (ATCAA). SAA activation  
35 and de-activation involves communication and negotiation between FAA and DoD, but lacks  
36 flexibility and automation (12). Krozel et al. (2008) designed tools to balance the usage of SAA  
37 between military and civilian operations. The authors point out that up to the publication date, the  
38 dispatchers must assume that aircraft will have to fly around all known SUAs regardless the active  
39 status and must be fueled to do so (13). Therefore, a system by which the military can activate  
40 SUAs based on its needs and civilian airspace users can use unused SUAs would be of great benefit.  
41 The data used in our study confirm that most flight trajectories deliberately avoid the SUA areas,  
42 even if they are not activated. Lastly, Monitor Alert (MA) is a tool that alerts sector personnel  
43 when the forecast flight demand exceeds Monitor Alert Parameter (MAP) value, which is an  
44 indicator of sector capacity. When the forecast demand, which is based on the number of flights  
45 that have already departed in a given time interval, exceeds the MAP value, MA will be triggered  
46 as “red” alert; otherwise, it will be triggered as “yellow” alert.. Sector personnel receiving the alert

1 must evaluate the impact and take appropriate actions (14). Actions include but not limited to  
 2 accepting traffic, splitting the sector, and requesting TMIs such as MIT and AFP. While not a TMI  
 3 per se, MA's may also affect HIE if flights are rerouted to avoid the red or yellow regions.  
 4

## 5 2.2 Data Sources and Summary Statistics

6 In this study, we combined eight historical datasets from different sources. The flight event dataset,  
 7 which comes from the Traffic Flow Management System (TFMS) of the FAA, contain the flight  
 8 level en route performance statistics including D40 – A100 actual flown distance and D40 – A100  
 9 achieved distance. We obtained the data for the calendar year (CY) 2013 and derived the flight en  
 10 route inefficiency. The full dataset includes around 6.5 million records, 87% of which are domestic  
 11 flights. In this study, we limit our scope to flights among the US main 34 airports listed in the 2013  
 12 US-Europe operational performance report, which accounts for around 47% of the total traffic with  
 13 an average en route inefficiency of 3.41%.  
 14

15 The flight tracks dataset, which also comes from the FAA TFMS, contains the 4D position –  
 16 longitude (in degrees), latitude (in degrees), altitude (in 100 feet), and time (in seconds) – for each  
 17 flight throughout its trip. The time resolution of the flight tracks is typically 1 minute. In this study,  
 18 we first sampled 97 airport pairs based on the traffic volume in the flight event dataset and then  
 19 queried into the TFMS to obtain all flight tracks among the selected pairs in CY2013. Figure 1  
 20 shows the selected airport pairs. The red markers are selected airports, and the green curves are  
 21 great circle routes connecting any two airports. After preprocessing all the flight tracks, we ended  
 22 up with 436,830 flights in 2013.  
 23



24  
 25 Figure 1 Selected airport pairs (direction not specified in the figure)

26 We derived the convective weather data from the Quality Controlled Local Climatological Data  
 27 (QCLCD). The dataset includes hourly summaries for different weather instances, such as  
 28 thunderstorm, rain, hail, etc., at around 2,500 ground stations in the US. Each record is a vector of  
 29 binary variables indicating whether there was a certain type of weather instance occurring at a  
 30 specific time and location. We collected the weather data in CY2013.  
 31

32 The wind dataset, which comes from the National Center for Atmospheric Research (NCAR),  
 33 contains raster of southerly and westerly wind speeds at specific hours and grid points. To be more  
 34 specific, the dataset records the wind speed four times a time – 00:00, 06:00, 12:00, 18:00 UTC –  
 35 and each grid point is described as a tuple of (longitude, latitude, pressure altitude). The horizontal  
 36 grid resolution is  $2.5^\circ \times 2.5^\circ$ , and there are 17 pressure levels ranging from 10 mbar (around

1 85,000 ft) to 1000 mbar (around 350 ft). For CY2013, we ended up with 1,460 raster files.

2  
3 The Miles-In-Trail (MIT), Airspace Flow Program (AFP), and Monitor Alert (MA) datasets all  
4 come from the National Traffic Management Log (NTML). The MIT data describe where, when,  
5 why and how the MIT restrictions were implemented. Fields of interest include: requesting facility  
6 (center), providing facility (center), NAS element (where the MIT was initiated), time and spacing  
7 parameters. The AFP dataset records, similar to MIT, when and where the AFP was initiated, and  
8 what the assigned flight delay and acceptance rate were. Interested readers may also refer to the  
9 AFP visualizer web tool developed by Estes (15). Since both MITs and AFPs are often modified,  
10 extended or cancelled after initiation, we excluded those MITs or AFPs that were cancelled before  
11 initiation, and merged those that were extended or modified from the initial plan. The monitor alert,  
12 while is a tool that reflects the projected demand in different sectors, was recorded in the MA  
13 dataset by the alert time, alert type and the corresponding actions. We collected all the three  
14 datasets for CY2013.

15  
16 Finally, the Special Activity Airspace (SAA) dataset comes from NASA Sherlock data warehouse.  
17 It contains the start/ stop time, facility, type and altitude restrictions of each activity. We merged  
18 the SAA dataset with the facility geometry file provided by FAA National Flight Data Center  
19 (NFDC) and excluded those SAAs with unknown geometries.

### 21 3. METHODOLOGY

22 Using the data sources described above, we create a pooled, cross-sectional data set of flights  
23 across 97 airport pairs that took place in the year 2013. Following (3), we characterize each flight  
24 by considering a nominal route rather than the actual flown trajectory. This is because one of the  
25 main sources of the flight inefficiency comes from reroute or detours to avoid adverse conditions.  
26 For example, a flight from LAX to JFK may take a long route crossing the Great Lakes because  
27 of unfavorable wind and weather conditions on the great circle route. In other words, it is the  
28 meteorological/ TMI condition on the most efficient route that “causes” the actual flight route. In  
29 this paper, we consider a single nominal route for each airport pair. The routes used in this paper  
30 are synthetic 4D great circle trajectory (GCT), which is theoretically the “most” efficient route, in  
31 terms of HIE<sup>1</sup>, for each flight. As will be shown, by matching the synthetic GCT with features such  
32 as weather and MIT, we relate the flight HIE with different causal factors and provide an approach  
33 to quantifying how those factors impact HIE.

#### 35 3.1 Generating Synthetic 4D Great Circle Trajectories

36 Generating 2D (longitude and latitude) great circle trajectory can be achieved by using spherical  
37 trigonometry and assuming the earth is an oblate ellipsoid. A realistic 4D great circle path, however,  
38 needs to satisfy the following two conditions: (a) it must have a reasonable altitude profile; (b) the  
39 time profile should not violate the basic law of kinematics. In this study, therefore, we first use  
40 WGS-84 ellipsoid and generate equally spaced waypoints. Then for each waypoint, we calculate  
41 the distances away from the origin and destination airports. Lastly, we use the historical flight  
42 trajectory dataset to approximate the altitude and time along the GCT by finding k-nearest  
43 neighbors based on the two distances. The full algorithm *GCT-Generator* is shown below.

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<sup>1</sup> This is true without considering the exit/ entry points of the terminal.

1  
2

TABLE 1 GCT-Generator Algorithm

<p><b>Algorithm 1. GCT-Generator</b></p> <p><u>Inputs:</u></p> <p>a. Historical flight track dataset: Track point: <math>TP_t^i = (lon_t^i, lat_t^i, alt_t^i, spd_t^i)</math>, with subscript <math>t</math> are time and superscript <math>i</math> as the <math>i^{th}</math> flight. Trajectory dataset with M flights: <math>FT = \{[TP_1^1, \dots, TP_{T_1}^1], \dots, [TP_1^M, \dots, TP_{T_M}^M]\}</math>.</p> <p>b. Coordinates of departure airport and arrival airport: <math>(lon_{dep}, lat_{dep}), (lon_{arr}, lat_{arr})</math>.</p> <p><u>Parameters:</u></p> <p>a. Space interval for the synthetic great circle trajectory (default 10 nautical miles): <math>d</math>.</p> <p>b. Number of nearest neighbors (default 50): <math>K</math>.</p> <p><u>Outputs:</u></p> <p>The synthetic 4D great circle trajectory.</p> <hr/> <p><b>Step 0:</b> Random sample 75% of the total flights from <math>FT</math>. Get <math>FT_s</math></p> <p><b>Step 1:</b> Augment each <math>TP_t^i</math> in <math>FT_s</math> by calculating the great circle distance away from the origin airport and destination airport, respectively. Get <math>TP_t^i = (lon_t^i, lat_t^i, alt_t^i, spd_t^i, gcd_{ori,t}^i, gcd_{des,t}^i)</math>.</p> <p><b>Step 2:</b> Build a 2D <i>kd-tree</i> based on <math>[(gcd_{ori,t}^i, gcd_{des,t}^i)]</math> for <math>\forall i, t</math>. Get <math>tree_{GC}</math>.</p> <p><b>Step 3:</b> Generate a 2D great circle trajectory given <math>(lon_{dep}, lat_{dep}), (lon_{arr}, lat_{arr})</math> and <math>d</math>. Calculate <math>gcd_{ori,t}</math> and <math>gcd_{des,t}</math> for every waypoint. Get <math>GCT_{2D} = \{WP_i = (lon_i, lat_i, gcd_{ori,i}, gcd_{des,i}), \forall i\}</math>.</p> <p><b>Step 5:</b> Query the <math>tree_{GC}</math> with the two distance measures from <math>GCT_{2D}</math> and return <math>K</math> nearest points for every waypoint along <math>GCT_{2D}</math>. Get <math>QNP = \{QP_i = (TP_i^1, TP_i^2, \dots, TP_i^{50}), \forall i\}</math>.</p> <p><b>Step 6:</b> For a waypoint <math>WP_i</math> in <math>GCT_{2D}</math>, weighted average the <i>altitudes</i> and <i>speeds</i> among the 50 queried points in <math>QP_i</math>, where the weights are linearly inverse proportional to the distance. Get <math>GCT_{2D} = \{WP_i = (lon_i, lat_i, gcd_{ori,i}, gcd_{des,i}, alt_i, spd_i), \forall i\}</math>.</p> <p><b>Step 7:</b> For each <math>WP_i</math>, use <math>(lon_i, lat_i, spd_i)</math> and <math>(lon_{i-1}, lat_{i-1}, spd_{i-1})</math> to calculate the time interval <math>t_i</math>. Return <math>GCT_{4D} = \{WP_i = (lon_i, lat_i, alt_i, t_i), \forall i \in [1, T]\}</math>.</p>
--

3

4 **3.2 Matching**

5 To understand how weather, wind, TMIs and SAA affect flight en route inefficiency, we need to  
6 construct representative metrics for each flight based on the appropriate nominal route, which is  
7 the synthetic 4D great circle route described in Algorithm 1, but with the actual flight departure  
8 time. In other words, we want to characterize the conditions a given flight would have encountered  
9 if it had flown the nominal route. The detailed matching algorithms are introduced in the sections  
10 below.

11 **3.2.1 Matching with convective weather and wind**

12 Though convective weather and wind data come from different sources, their data structure is  
13 similar. Both can be stored in a fixed-dimension array, where the rows and columns are  
14 respectively the temporal and spatial indices, and planes are the fields of the dataset. To be more  
15 specific, the temporal indices for the weather dataset can be represented as the number of hours

1 elapsed from a base time, e.g., 01/01/2013 01:00 will have the temporal index of 1 with respect to  
 2 the base time 01/01/2013 00:00, therefore, we have  $365 \times 24 = 8,760$  rows in the weather array  
 3 for the year 2013. Similarly, the wind array has 1,460 rows since wind data are stored every 6  
 4 hours. The spatial indices are the location of the “reference” points, which are the fixed locations  
 5 in the airspace. For the weather data, they are ground stations; for the wind data, they are 3D grid  
 6 points. As a result, there are 1,763 and  $17 \times 435 = 7395$  columns in the weather and wind array,  
 7 respectively. Since the weather dataset has seven different weather types and the wind dataset has  
 8 two wind speeds (southerly and westerly), the number of planes is respectively 7 and 2. Lastly, the  
 9 elements in the array are the features we need to match with. As will be shown later, storing data  
 10 as fixed-dimension arrays greatly boosts the matching procedure by making tree-based search  
 11 possible.

12  
 13 Matching a trajectory with a numeric array can be achieved simply by greedily searching the rows  
 14 and columns and find the closest element(s) for every track point. Realizing that both the spatial  
 15 (columns) and temporal (rows) dimensions of the weather/ wind array are fixed, we can simply  
 16 build  $k-d$  trees to further structure the datasets, and batch query the trees to find the nearest  
 17 neighbors for different track points. The algorithms are described in TABLE 2.

18  
 19 **TABLE 2 Matching with Fixed-Dimension Array**

<b>Algorithm 2. Matching with fixed-dimension array</b>
<p><u>Inputs:</u>            a. Synthetic 4D great circle trajectories: <math>GCT_{4D} = \{WP_i = (lon_i, lat_i, alt_i, t_i), \forall i \in [1, T]\}</math>.            b. Flight event dataset: <math>FE = \{[DepTime_i, AchDist_i, Inefficiency_i], \forall i \in [1, N]\}</math>.            c. Fixed-dimension array with features: <math>FDT</math>.</p> <p><u>Parameters:</u>            a. Base time (default 01/01/2013 00:00:00 UTC): <math>baseT</math>.</p> <p><u>Outputs:</u>            Matched feature vectors.</p>
<p><b>Step 0:</b>            Convert all geographic coordinates from <math>(lon, lat, alt)</math> to Earth-centered rotational coordinates <math>(x, y, z)</math>.</p> <p><b>Step 1:</b>            Construct great circle trajectories for all flights in the <math>FE</math> data by adding to the temporal dimension the difference between departure time <math>DepTime</math> and base time <math>baseT</math>, while keeping the spatial dimension fixed. Get <math>FGCT = \{[WP_i^1, \forall i], \dots, [WP_j^N, \forall j]\}</math>, where <math>WP_i^k = (x_i^k, y_i^k, z_i^k, elapT_i^k)</math> is the <math>i^{th}</math> waypoint of the <math>k^{th}</math> flight.</p> <p><b>Step 2:</b>            Construct two <math>kd</math>-trees for spatial (<math>s\_tree</math>) and temporal (<math>t\_tree</math>) dimensions, respectively. The spatial tree is built based on the location of the reference points <math>(x, y, z)</math>, and the temporal tree is built based on the elapsed time from a base time <math>baseT</math>.</p> <p><b>Step 3:</b>            Query<sup>1</sup> <math>s\_tree</math> with the converted coordinates <math>(x, y, z)</math> from <math>FGCT</math>, and <math>t\_tree</math> with the elapsed time <math>elapT</math> from <math>FGCT</math>. Get the tuple of the nearest spatial-temporal indices and return the corresponding elements from the feature array <math>FDT</math>.</p> <p><b>Step 4:</b>            If <math>FDT</math> is the wind array, then for each waypoint <math>WP_t^k</math> on flight <math>k</math>, we used the azimuth <math>\theta</math> and matched southerly wind speed <math>u_t^k</math> and westerly wind speed <math>v_t^k</math> to calculate the headwind/ tailwind speed by <math>HTW_t^k = u_t^k \cos\theta + v_t^k \sin\theta</math>. Calculate the average <math>HTW_t^k</math> along the flight.            For flight <math>k</math>, use the ground speed <math>spd_t^k</math> and <math>HTW_t^k</math> to calculate the airspeed, then calculate the distance</p>

traveled with respect to the air (equivalent still air distance)  $WD^k$ .

**Step 5:**

If  $FDT$  is the weather array, then for each waypoint  $WP_t^k$  on flight  $k$ , we get a list of matched weather variables  $MI_{t,m}^k$ , where  $m$  represents one of the weather phenomenon, and a list of distances away from matched weather stations ( $MSD_t^k$ ) to  $WP_t^k$ .

Compute the weighted average  $MI_{t,m}^k$  and get weather scalar  $MW_{t,m}^k$  for waypoint  $WP_t^k$ , where the weights are inversely linear proportional to the elements in  $MSD_t^k$ . Average  $MW_{t,m}^k$  along all waypoints for flight  $k$  and return this metric.

*Note:*

1. For wind array, we performed nearest neighbor query, i.e., only return indices with the nearest distance; for weather array, we performed radius query, i.e., return all indices within a circle with radius  $r$ .

### 3.2.2 Matching with TMIs and SAA

MIT, AFP, MA and SAA all have similar structures, including a start time, a stop time, a location, and how it would affect the traffic. To be more specific, a typical MIT is recorded as  $[st, et, reqfac, provfac, nas\_elem, alt, value]$ , which can be interpreted as facility  $reqfac$  (e.g., ZLA) requests a MIT to meter traffic into that facility, while facility  $provfac$  (e.g., ZOA) implements a MIT restriction that is enforced at the NAS element (e.g., BTY) with value  $value$  (e.g., 15 miles) and altitude range specified by  $alt$  from time  $st$  to time  $et$ . AFP, MA and SAA, similarly, can be represented as  $[st, et, facility, alt, value]$ , where  $value$  for AFP includes average assigned delay and average acceptance rate;  $value$  for MA is the alert type (red or yellow); and  $value$  for SAA is the SUA type. To match with a TMI or SAA, a flight trajectory must satisfy the following condition: (a) it must cross the corresponding facilities in a correct order, for example, a flight could match a MIT if it first crosses  $provfac$ , and then  $reqfac$  and  $nas\_elem$ ; (b) the crossing time must within the period of  $st$  and  $et$ ; (c) the crossing altitude must satisfy  $alt$  restrictions. TABLE 3 summarize the general matching framework.

**TABLE 3 Matching with TMI/SAA**

**Algorithm 3. Matching with TMI/ SAA**

Inputs:

a. Synthetic 4D great circle trajectories:  $GCT_{4D} = \{WP_i = (lon_i, lat_i, alt_i, t_i), \forall i \in [1, T]\}$ .

b. Flight event dataset:  $FE = \{[DepTime_i, AchDist_i, Inefficiency_i], \forall i \in [1, N]\}$ .

c. TMI (SAA) dataset:  $TSD = \{[st_i, et_i, facility_i, alt_i, value_i]\}$

Parameters:

a. Buffer altitude (default 1000 ft):  $B_{alt}$ .

b. Buffer NAS element radius (only applicable for MIT, default  $0.5^\circ$ ):  $B_{nas}$ .

Outputs:

Matched feature vectors.

**Step 0:**

Construct great circle trajectories for all flights in the  $FE$  data by adding to the temporal dimension the difference between departure time  $DepTime$  and base time  $baseT$ , while keeping the spatial dimension fixed. Get  $FGCT = \{[WP_i^1, \forall i], \dots, [WP_j^N, \forall j]\}$ , where  $WP_i^k = (lon_i^k, lat_i^k, alt, elapT_i^k)$  is the  $i^{th}$  waypoint of the  $k^{th}$  flight.

**Step 1:**

Filter  $TSD$  whose  $et$  is before the departure time  $DepTime_i$  and  $st$  is after the arrival time of flight  $i$ . The remaining  $TSD_{filter}$  are retained as a candidate.

**Step 2:**

Intersect flight  $i$ 's great circle trajectory  $FGCT_i$  with every candidate  $TSD_{filter}$ .

If  $TSD$  is MIT, then if  $FGCT_i$  intersects the  $MIT_i$ 's influencing area<sup>2</sup>,  $reqfac_i$  and  $provfac_i$  in a correct order, and the time of intersecting with influencing area is within  $[st_i, et_i]$ , then go to Step 3, otherwise discards  $MIT_i$ .

Otherwise, if  $FGCT_i$  intersects the  $facility$ , and the time of intersecting is within  $[st_i, et_i]$ , then go to Step 3, otherwise discards  $TSD_i$ .

**Step 3:**  
If the altitude(s) of the intersecting waypoint(s) is within the altitude restriction  $alt \pm B_{alt}$ <sup>3</sup>, add the records  $TSD_i$  to the matching list, otherwise discards  $TSD_i$ .

**Step 4:**  
Count the number of matched TMIs/ SAA as  $Count$ .

If  $TSD$  is MIT, then calculate average and maximal of the matched MIT value, MIT duration and MIT stringencies<sup>1</sup>.

If  $TSD$  is AFP, then calculate average and maximal of the matched average AFP assigned delay, maximal AFP assigned delay, and average AFP acceptance rate<sup>4</sup>.

If  $TSD$  is MA or SAA, then calculate the average/max traverse time within the alert/SUA facility.

Return  $Count$  and other calculated statistics.

Note:

1. MIT stringency is defined as the product of MIT value and MIT duration
2. If the NAS element is a fix, then the influencing area is a circle of radius  $B_{nas}$  around the fix. If the NAS element is a jet route, then the influencing area is swath centered on the jet route with overall width of  $B_{nas}$ . If the NAS element is a center/TRACON, then the influencing area is the polygon itself.
3. If  $alt$  is already specified as a range (e.g., ceiling and floor), then we don't add the  $B_{alt}$  to  $alt$ .
4. If a flight does not cross any AFPs, we set the AFP acceptance rate to be 999/hr.

Through Algorithms 2 and 3, we construct a panel data set within which each flight has a list of explanatory variables in the form of  $X_{i,j} = [weather_i, wind_i, MIT_i, \dots, OD_{ij}]$ , where index  $i$  indicates the  $i^{th}$  flight, and index  $j$  indicates the  $j^{th}$  airport pair. The description of the full explanatory variables is listed in TABLE 4.

**TABLE 4 Summary Statistics of All Variables**

Notation	Description	Min	Max	Mean
<i>InEff</i>	Flight en route inefficiency (in percentage)	0.0021	402.74	3.22
<i>TS</i>	Thunderstorm exposure (in percentage)	0.00	7.40	0.40
<i>Rain</i>	Rain exposure (in percentage)	0.00	20.60	2.37
<i>Squall</i>	Squall exposure (in percentage)	0.00	2.34	0.0027
<i>Ice</i>	Ice exposure (in percentage)	0.00	2.44	0.0043
<i>Precipitation</i>	Precipitation exposure (in percentage)	0.00	2.30	0.0055
<i>Shower</i>	Shower exposure (in percentage)	0.00	1.28	0.0072
<i>Hail</i>	Hail exposure (in percentage)	0.00	0.82	0.00027
<i>AvgWindSpd</i>	Average wind speed (positive if tailwind and negative if headwind) along the great circle route (in 100 m/s)	-0.39	0.39	0.0095
<i>WindDist</i>	Distance traveled with respect to air (equivalent still air distance, in 1000 nmi)	-0.29	0.23	-0.0050
<i>NumMIT</i>	Number of MIT crossed	0	13	0.32
<i>MaxMITSTR</i>	Maximal MIT stringency among all crossed MITs (in 100 mile · hr)	0.00	9.83	0.18
<i>NumAFP</i>	Number of AFP crossed	0	2	0.02
<i>MaxAFPDly</i>	Maximal AFP assigned delay among all crossed AFP (in hours)	0	0.03	0.0002
<i>MaxAFParr</i>	Maximal AFP acceptance rate among all crossed AFP (in 100	0	1.76*	0.013*

	per hour)			
<i>NumSAA</i>	Number of SAA crossed	0	9	0.57
<i>MaxSAAT</i>	Maximal transverse time within crossed SAA (in hours)	0	0.46	0.025
<i>NumMAREd</i>	Number of red MA crossed	0	8	0.10
<i>NumMAYel</i>	Number of yellow MA crossed	0	5	0.013
<i>MaxMAT</i>	Maximal transverse time within crossed MA (in hours)	0	1.29	0.021
<i>AchDist</i>	Achieved distance (in 100 nmi)	0.56	26.64	6.91

Note: \* These are respectively the “true” maximal and average AFP acceptance rate after excluding all records with rate of 999/hr.

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2

### 3.3 Multiple Regression

3  
4 We estimate linear models to investigate how meteorological conditions, TMIs and SAA on the  
5 great circle route affect flight HIE. In the regression model, the dependent variable is the flight en  
6 route inefficiency, and there are five categories of explanatory variables. The first category  
7 includes weather-related variables, such as thunderstorm, rain, ice and squall. Although there are  
8 seven types of weather events in our dataset, most of these occur only at low altitude and thus are  
9 unlikely to affect the en route phase of a flight. Therefore, we only include thunderstorm and squall  
10 events in the model specification. Since a flight may need to adjust its route to avoid the convective  
11 weather, we expect these variables to have positive effects on en route inefficiency. The second  
12 category includes wind-related variables – average tailwind speed (negative if headwind) and  
13 equivalent still air distance. Since flights in general favor strong tailwind, we expect higher  
14 tailwind speed to decrease and greater equivalent still air distance to increase HIE. The third  
15 category includes airport pair fixed effects; we fit the model with airport-pair specific intercepts  
16 and expect flights between pairs that are more inefficient (e.g., short haul flights) will have larger  
17 positive effects. The fourth category contains the TMIs and SAA. Like weather, we expect they  
18 will have positive effects to inefficiency. Finally, we include the achieved distance of each flight.  
19 When airport pair fixed effects are controlled, this variable mainly captures the effect of inefficient  
20 terminal entry and exit points and we expect it to have a positive impact on HIE. The model  
21 specification can be written as Equation 2, where index  $i$  represents the  $i^{th}$  flight, and index  $j$   
22 represents the  $j^{th}$  airport pair.

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29

$$\begin{aligned}
100 \cdot InEff_{i,j} = & \beta_j + \beta_1 \cdot TS_i + \beta_2 \cdot Squall_i + \beta_3 \cdot AvgWindSpd_i + \beta_4 \cdot WindDist_i + \beta_5 \\
& \cdot NumMIT_i + \beta_6 \cdot MaxMITSTR_i + \beta_7 \cdot NumAFP_i + \beta_8 \cdot MaxAFPdly_i + \beta_9 \\
& \cdot MaxAFParr_i + \beta_{10} \cdot NumSAA_i + \beta_{11} \cdot MaxSAAT_i + \beta_{12} \cdot NumMAREd_i \\
& + \beta_{13} \cdot NumMAYel_i + \beta_{14} \cdot MaxMAT_i + \beta_{15} \cdot AchDist_i
\end{aligned}
\tag{2}$$

30 To appropriately estimate the model, we must take into account the heteroskedasticity across  
31 different airport pairs. To verify such effect, we use Breusch-Pagan test and the results reject the  
32 null hypothesis of homoskedasticity against the alternative that the residual variances depend on  
33 the explanatory variables. Moreover, we expect autocorrelation for flights departing at similar  
34 times between the same airport pairs, since they may experience similar meteorological conditions  
35 or TMIs throughout the flights. We use the Wooldridge test and the results reject the null that there  
36 is no autocorrelation. Therefore, we estimate the final model using ordinary least squares (OLS)  
37 with Newey-West standard errors with a maximal lag of 2.

38

## 1 4. Results

2 To save space, TABLE 5 only reports the estimates of factors that interest us the most – weather,  
 3 wind, TMIs and SAA – for four linear models. Model I, which we term “full model”, includes all  
 4 variables of interest and airport-pair fixed effects and is presented in the first column of TABLE 5.  
 5 Model II, in which variables (except fixed effect variables) that are not significant at the 10% level  
 6 are omitted, is presented in the second column. Model III, which eliminates the achieved distance  
 7 effect, and Model IV, which eliminates the airport-pair fixed effects but includes a generic intercept  
 8 and achieved distance, are presented in the last two columns of TABLE 5.

9  
 10 The vast majority of the estimates for the three reduced models (model II – model IV) are  
 11 significant with expected signs. First of all, the estimates of thunderstorm confirm that convective  
 12 weather along the great circle route increases the en route inefficiency. However, Model II and III  
 13 have far smaller magnitude comparing with Model IV due to the inclusion of the airport-pair fixed  
 14 effects – some direct routes inherently have more convective weather activities and therefore,  
 15 much of the weather effects are absorbed by the airport-pair fixed effects. Secondly, tailwind speed  
 16 on the great circle route seems to reduce inefficiency. When the airport-pair fixed effects are  
 17 controlled, the negative estimates of average wind speed and positive estimates of equivalent still  
 18 air distance imply that favorable tailwind conditions on the great circle route reduce flight  
 19 inefficiency. This can be explained by the fact that flights prefer routes with higher tailwind speed,  
 20 and therefore, if the great circle route has strong tailwind, flights gravitate toward routes close to  
 21 the great circle, decreasing en route inefficiency. However, models in this study do not explicitly  
 22 represent the mechanism of how winds affect the route choice; interested readers may refer to (3)  
 23 and (16) for more discussions on winds and flight route choice. Thirdly, the estimates of MIT, AFP  
 24 and SAA indicate that flights whose great circle routes have stronger MIT restrictions, AFP delays,  
 25 and traverse time in the SUA areas are more inefficient than the others. We also notice that the  
 26 estimates for all Monitor Alert associated variables are not significant. This is likely because an  
 27 MA does not, per se, affect air traffic; rather it may result in a TMI such as an MIT or AFP, the  
 28 effects of which are already incorporated in the model. Lastly, the estimates for achieved distance  
 29 vary drastically depending on whether airport-pair fixed effects are included in the model. When  
 30 airport-pair fixed effects are included (as in Model II), the estimate of achieved distance mainly  
 31 derives from variation among flights within the same airport pairs; however, when there are no  
 32 airport-pair fixed effects (as in Model IV), the estimate mostly captures the cross-sectional  
 33 variation in achieved distance. Accordingly, the negative coefficient in Model IV indicates that  
 34 long-haul flights tend to be more efficient; while the positive estimate in Model II indicates that  
 35 for any particular airport pair, flights with longer achieved distance are more inefficient. Variation  
 36 in achieved distance within a particular airport pair reflects variation in the efficiency of the entry  
 37 and exit points; a higher achieved distance means these points are less efficient. The results in  
 38 Models I and II therefore imply that flights with less efficient entry and exit points are also less  
 39 efficient in the en route phase of flight. Figure 3, which further confirms the cross-sectional effects,  
 40 presents the relationships between achieved distance and actual en route inefficiency, where scatter  
 41 points with the same color represent flights between the same airport pair.

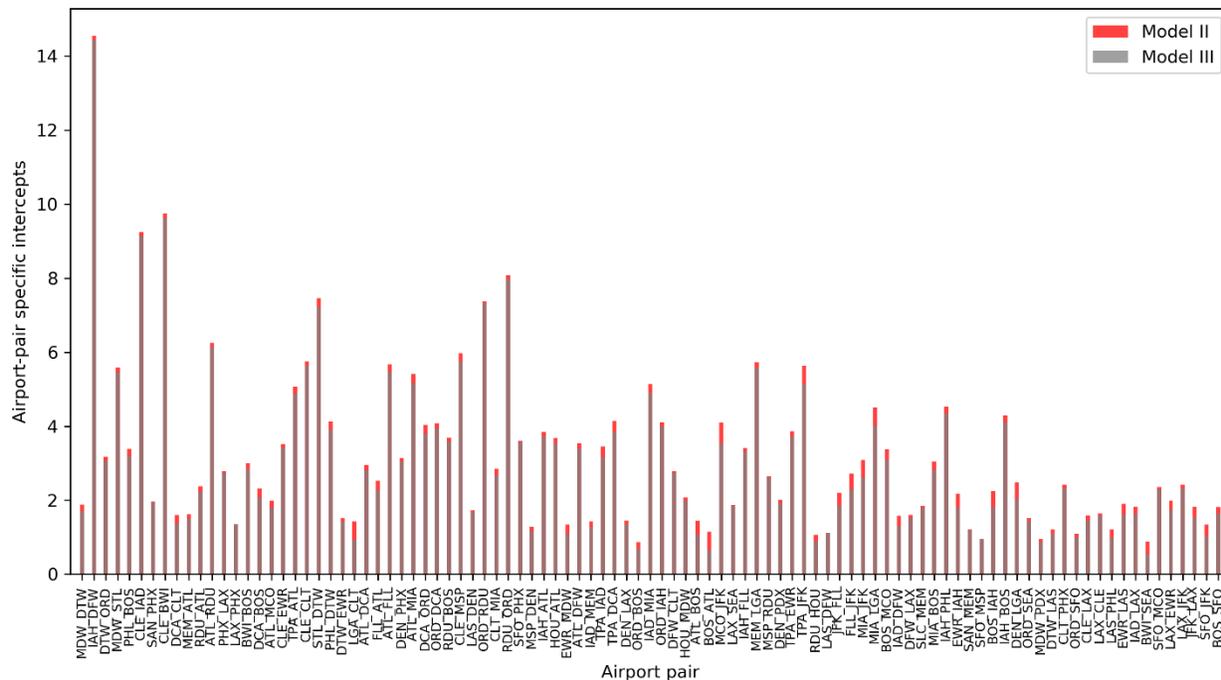
42  
 43 Figure 2 shows the airport-pair specific intercepts for Model II (red bars) and Model III (grey bars),  
 44 where the x-axis shows the airport pairs ordered by the average achieved distance (left is shorter).  
 45 Notice that Model II includes the variable *AchDist*, which varies marginally across flights  
 46 between the same airport pair but differs drastically across different airport pairs. Therefore, in

1 Figure 2, we adjust Model II's airport-pair fixed effects by adding the product of coefficients  
 2 before *AchDist* and the average achieved distance for each airport pair. The estimates for both  
 3 models are largely consistent with a decreasing trend to the right-hand side of the x-axis, indicating  
 4 long-haul flights such as BOS to SFO are in general more efficient.

6 **TABLE 5 Estimation Results**

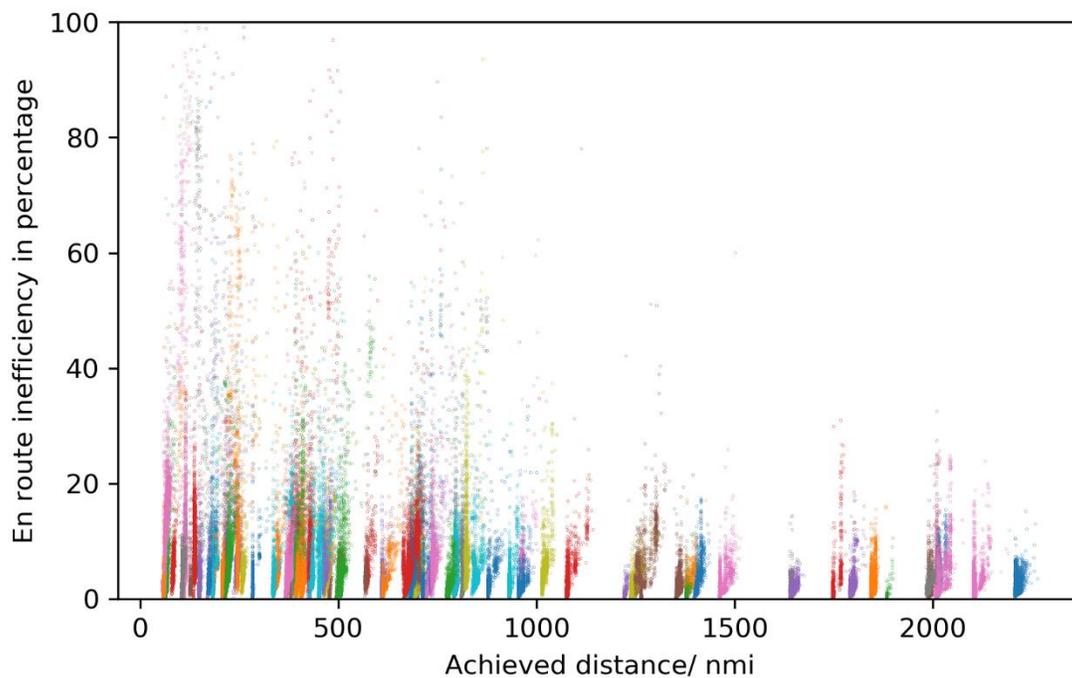
Variable	Models Est. / (Std.)			
	Model I	Model II	Model III	Model IV
<i>constant</i>	-	-	-	3.410*** (0.027)
<i>TS</i>	0.103*** (0.023)	0.109*** (0.021)	0.253*** (0.030)	0.819*** (0.030)
<i>Squall</i>	1.823 (1.377)	-	-	-
<i>AvgWindSpd</i>	-1.877*** (0.441)	-1.880*** (0.433)	-1.945*** (0.596)	-0.168 (0.113)
<i>WindDist</i>	6.775*** (1.415)	6.817*** (1.390)	6.247*** (1.872)	1.195*** (0.170)
<i>NumMIT</i>	0.148*** (0.016)	0.148*** (0.016)	0.314*** (0.027)	0.185*** (0.026)
<i>MaxMITSTR</i>	0.110*** (0.024)	0.110*** (0.024)	0.239*** (0.038)	0.244*** (0.040)
<i>NumAFP</i>	0.232 (2.004)	0.394*** (0.112)	1.078*** (0.224)	1.121*** (0.230)
<i>MaxAFPDly</i>	9.60 (14.393)	-	103.620*** (17.778)	112.215*** (18.050)
<i>MaxAFParr</i>	-0.005 (0.212)	-	-	-
<i>NumSAA</i>	-0.003 (0.010)	-	-	-
<i>MaxSAAT</i>	2.666*** (0.271)	2.587*** (0.183)	2.816*** (0.242)	2.981*** (0.134)
<i>NumMAREd</i>	-0.025 (0.018)	-	-	-
<i>NumMAYel</i>	-0.022 (0.028)	-	-	-
<i>MaxMAT</i>	0.086 (0.091)	-	-	-
<i>AchDist</i>	53.9478*** (1.871)	53.955*** (1.830)	-	-0.109*** (0.002)
<i>Airport-pair fixed effect</i>	...	...	...	-
<i>Obs.</i>	436,830	436,830	436,830	436,830
<i>Adjusted R<sup>2</sup></i>	0.654	0.654	0.445	0.040

Note: \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$



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Figure 2 Airport-Pair Fixed Effects Estimation



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Figure 3 Achieved Distance vs HIE (HIE is truncated to 100)

6 **5. Conclusions**

7 As an extension to (3) and (17), this study proposes econometric models to analyze flight en route

1 inefficiency, with emphasis on convective weather, wind, MIT, AFP, SAA and MA. We employ  
2 trajectory synthesis methods to generate hypothetical great circle trajectories for historical flights  
3 among 97 US airport pairs, and a trajectory matching framework to match those synthetic great  
4 circle routes with different factors (e.g., wind). Lastly, we develop metrics for the matched factors,  
5 and use multiple regression models with correction for heteroskedasticity and autocorrelation to  
6 quantitatively understand how they affect the flight en route inefficiency.

7  
8 The proposed methods relate en route performance with different “causal” factors. Great circle  
9 routes are the “most” efficient routes by definition, and the meteorological and traffic conditions  
10 throughout the routes can be treated as proxies to how attractive the great circle trajectories would  
11 be. In the worst case where there is strong headwind, lots of convective weather, traffic  
12 management initiatives and SAAs, flights deviate from the great circle, and this increases  
13 inefficiency.

14  
15 The estimation results, while confirm our conjectures, suggest that route structure is an important  
16 factor to en route inefficiency. Long haul flights, such as BOS to SFO, are in general more efficient  
17 than short haul flights. However, some airport pairs, even though they have similar distances, differ  
18 greatly in en route inefficiency. Examples include MDW to DTW (north) vs IAH to DFW (south),  
19 and SAN to PHX (west) vs CLE to BWI (east). Moreover, when airport-pair fixed effects are  
20 controlled, the achieved distance shows significant positive effect, indicating that inefficient  
21 terminal procedures will induce less efficient en route operations. The estimates for other  
22 covariates suggest that thunderstorm, MIT, SAA and AFP with longer assigned delays will increase  
23 the en route inefficiency, while strong tailwind on the great circle routes will reduce the inefficiency.  
24 Finally, the Monitor Alert does not appear to have much impact to en route inefficiency, which can  
25 be explained by the fact that the effect of MAs is mediated by TMI actions that are already  
26 incorporated in the model.

27  
28 These models have several applications. First they can help target strategies to reduce HIE by  
29 predicting how changes the different factors that are subject to human control, such as TMIs and  
30 SAAs, would affect HIE. Second, it can be used to normalize comparisons between HIE in  
31 different times, regions, or airport pairs. As a specific example, from the fixed effects estimated in  
32 the model one can identify which airport pairs are the most and least HIE, all else equal. Pairs in  
33 the former group could then be further examined to improve their HIE.

34  
35

1 **Author Contribution Statement**

2 The authors confirm contribution to the paper as follows: study conception and design: Yulin Liu,  
3 Mark Hansen; data collection: Mark Hansen, Yulin Liu; analysis and interpretation of results: Yulin  
4 Liu, Mark Hansen; draft manuscript preparation: Yulin Liu, Mark Hansen. All authors reviewed  
5 the results and approved the final version of the manuscript.

6  
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