Impact of Road Grade on the Risk Profile of Driver Behavior

Jeanne-Marie Gerber and Johan W. Joubert*

Centre for Transport Development, University of Pretoria, Pretoria, South Africa

***Corresponding author(s):** Johan W. Joubert, johan.joubert@up.ac.za

Abstract

Data generated from telemetry devices, such as acceleration and speed, are used in a variety of industries to determine the risk profile of a driver. This paper considers the addition of road gradient as a contextual variable to a driving behavior model to determine specifically if the risk of a driver is influenced by different road grades. This behavioral risk is demonstrated by comparing the performance of heavy vehicle drivers with and without the addition of road grade as a variable. This is done by using accelerometer data of 48 heavy goods vehicles over an entire month, and appending elevation data from digital elevation model (DEM) data, specifically that of the Shuttle Radar Topography Mission (SRTM), to the vehicles' GPS traces. The elevation values are used to calculate road grade values which are then categorized in five grade levels. The results show that there is a clear influence of gradient on the behavior of the drivers studied. There is also evidence that steeper sections on a road can cause a change in an individual's performance when compared with the group.

Keywords: data and data science, artificial intelligence and advanced computing applications, data analytics, freight transportation data, global positioning systems (GPS) and electronic logging devices (ELD), truck GPS data, geographic information science, GPS data, pedestrians, bicycles, human factors, human factors of vehicles, driver behavior, driver performance

The insurance sector has two main approaches to assess and mitigate the risk associated with a driver's behavior. The first, "pay as you drive," focuses on traveling over distances, for example, which roads the driver uses and how often. The second, referred to as "pay how you drive," bases the analysis more on a driver's dynamic personal behavior, looking at aspects such as speeding, harsh braking, and acceleration (*1*). While telematics data is becoming more ubiquitous and more accurate through an increase in market penetration of in-vehicle data recorders (IVDRs), these measures remain a mere proxy for the insured client's safety.

Telematic data can be profuse, requiring the decision-maker to reduce observations to (only) arguably *valuable* ones. A common approach in the literature is to apply thresholds. For example, some sources use acceleration thresholds to filter records and only identify extreme events like harsh braking, swerving, and hitting speed bumps (or potholes) at excessive speeds.

In previous work, Joubert et al. (*2*) introduced a discretization model for a vehicle's acceleration. The purpose of their tessellation of a multi-dimensional risk space is to reduce the massive volume of telemetry data generated by cars in a way that succinctly represents the main factors affecting driver behavior. The tessellation of the risk space has several advantages over static thresholds. Firstly, all records are retained instead of only focusing on extreme values. Consequently, an insurer can reward a driver who behaves well most of the time for driving frequently but not generating extreme events. Secondly, discretization is a form of unsupervised machine learning. It can adapt over time as the risk space evolves because of, for example, a radical change in vehicle technology or a difference in the cohort of insured individuals.

Joubert et al. (*2*) also demonstrate that the tessellation model is sensitive to contextual variables like road type, speed limit, and specific individuals. The one contextual variable not covered is that of road grade. Glennon (*3*) shows that road grade affects accident rates and fuel consumption, the latter point supported by Zhou et al. (*4*).

This paper's first contribution is demonstrating the effect that road grade has on evaluating driver risk. The results show that, indeed, when one discriminates on road grade, there is a change in individuals' risk profile ranking. To achieve the discrimination, however, one needs to estimate road grade accurately, which turns out to be a fair challenge. The second contribution of this paper is methodological. The paper proposes and evaluates an approach to estimate road grade from publicly available, open-access Shuttle Radar Topology Mission (SRTM) data. The methodology is tested using a gold standard route measured with high-precision sensors fitted to a light vehicle.

The paper is structured as follows. The next section reviews the literature related to estimating driver behavior from telemetry data, arguing that road grade is a necessary variable to consider. The paper then examines the current literature on calculating road grade. The section titled "Models" introduces the proposed methodology to estimate road grade, along with its evaluation. Then, in "Results and Discussion," the model is applied to the telemetry data of a cohort of 48 heavy goods vehicles. The value of using heavy goods vehicles is that they are more sensitive to road grade, while the methodology remains equally applicable to light vehicles. Finally, the paper concludes with a research agenda for further risk estimate enhancements.

Literature Review

This section first reviews key developments in how driver risk is measured and the role that road grade plays. Since road grade is rarely available, however, the second part of the review looks at how the estimation of road grade is done.

Driver Behavior

The telematics that determine driving behavior are found in the horizontal movement of a vehicle. This behavior then determines the overall performance of a driver, but factors outside of pure vehicle movement that might also influence performance, for example, road geometry, are neglected. Studies such as that of Hamdar et al. (*5*) show how characteristics like horizontal alignment, road and shoulder width, and median barriers influence driver behavior. However, a road characteristic that is not discussed is the gradient of the road.

Glennon (*3*) studied accident rates and showed how the rates are higher with grade sections compared with level sections. Steep grades have higher accident rates when compared with mild grades, and downgrades have higher rates than upgrades. Road grade also has a major presence in fuel consumption models. The study by Zhou et al. (*4*) concluded that driver-related factors and road gradients have a definite impact on fuel consumption and cannot be ignored in consumption models. Wang et al. (*6*) state that fuel consumption is heavily influenced when combined with road grade, arguing that when a vehicle is traveling uphill, a driver will usually accelerate to keep a constant speed, consuming more fuel than normal. The authors also argue how a change in behavior would prevent a change in fuel consumption. For example, a driver could rather pick up speed before the uphill portion of the road and only accelerate lightly up the hill. Their study also shows how negative road grades (downhills) can cause heavy driver braking that will in turn consume more fuel because of the vehicle not keeping a constant speed.

The influence of road grade is, therefore, apparent in fuel economy and we can see that there is a link between driver behavior and road grade. As hybrid and electric vehicles become more popular, Xu et al. (*7*) consider the effect that road grade has on range of battery electric vehicles in a mixed vehicle scenario. To see if we can see any relationship trends between behavior and gradients, we need a behavioral model that allows for the addition of the variable of road grade. The risk model of Joubert et al. (*2*) allows for exactly that in the form of contextual variables. Their model can be run on different subsets of a contextual variable within the envelope of telematics data. The overall risk spaces of a population of drivers can be visualized, and individual drivers can receive scores indicating their driving performance against the other drivers.

Joubert et al. (*2*) use accelerometer data of vehicles to classify risk profiles of drivers on three levels: good, average, and bad performers. Their model does not predefine extreme events. Rather, the entire envelope of data is observed and the model adapts to the pool of vehicles. The input data is generated via an on-board accelerometer that generates the following valuable variables: GPS location, time stamp, speed, lateral acceleration, longitudinal and vertical (*z*-axis) acceleration. Using the movement data, their model defines extreme events differently than most of the literature. Instead of considering predefined thresholds that can be exceeded, a three-dimensional risk space is constructed with all the records and cases of dangerous driving behavior found at the extremities of the space. One can then decide what percentage of drivers fall within each risk classification to determine the performance of each driver.

Estimation of Road Grade

The performance of each driver can be determined on different road grades using the model of Joubert et al. (*2*), but the challenge is to find the road grade for an already-traveled road. Road grade is a difficult variable to estimate accurately, especially when it is not calculated live (*8*). With instantaneous estimations, accelerometers can be used, but interference with unrelated vehicle movement creates a profile that is very noisy (*9*). Another commonly used measurement tool is a GPS logger (*10*). However, the accuracy once again presents a limitation with low resolution. Although horizontal errors with GPS are low, vertical errors are much higher since buildings and trees interfere with signaling. Changes in satellite locations will also influence the accuracy and resolution of the elevation, therefore, GPS is most accurate when paired with other sensors and equipment. When a GPS logger is used with a barometric altimeter, only then is it deemed accurate enough (*11*). With the emergence of automated and connected vehicles, Zhao and Zhang (*12*) highlight the necessity for high definition maps. But the general availability of such maps is still limited to small test cases.

Since the risk estimation of a driver is usually not instantaneous but rather the data is processed in bulk afterwards, we can use other options that are independent of sensor data. Slope values can be found on original or revised road design drawings, but these are only available for large building projects like highways or bridges. The elevation profiles might also differ from the actual roads since the drawings sometimes only specify the original construction design and not all the changes that were made during construction (*8*).

The unreliability of consumer-grade instantaneous estimates and road designs leads us to the mathematically simplest method by finding the derivative of elevation and distance. By using an elevation profile of a driven road, we narrow down the reliability problem by only focusing on the accuracy of the elevation values. If we have the GPS locations of the traces left by a vehicle, a digital elevation model (DEM) can be used to estimate elevation and will, according to Liu et al. (*13*), provide the most accurate road profile. Various open-source elevation data sets are available for the usage of the public. Digital maps are segmented into degrees and block grids where the center point of the block represents the true elevation at that point. This elevation value is then given to the entire block. Spaceborne InSAR is the most popular method used to create DEMs and is the technology behind the SRTM, the biggest open-access global DEM. By 2015 the SRTMGL1 version covered Africa, Europe, North America, South America, Asia, and Australia in 1° × 1° tiles at 1 Arc second (about 30 × 30 m) resolution. To date, this is the most accurate DEM that covers South Africa and most of the Southern Africa area.

DEMs are not a perfect representation of topography and, like most measurement systems, they have a few errors. These errors can be grouped in categories of cause: deficient data, old data, or both; processing and numerical errors; and faulty measurement errors from faulty equipment or poor placement accuracy (*14*). Errors can have a ripple affect in the accuracy of slope and curvature of the surface, and need to be tracked when elevation values are used in calculations such as that of road grade. To combat the accuracy uncertainty, this paper attempts to filter out DEM errors as well as smooth out the spatial resolution errors of the 30 m SRTM that is a result of the block grids.

SRTM Elevation Values

To derive road grade, one needs elevation values that accurately represent the profile of a road. To find this accurate representation, the stepwise elevations extracted from the SRTM dataset need to be smoothed. The stepwise nature of the road profile can cause derivatives to have completely incorrect slope estimations, but a smoothing model that is fitted to the profile will remove these sudden spikes or drops.

Wood et al. (*15*) smooth elevations with a Savitzky–Golay (SG) filter. The method uses local regression instead of the popular moving average, and thereby flattens peaks less than a moving average filter would. The SG filter is also a low-pass filter and uses a local least-squares polynomial approximation (*16*). It is another way to reduce noise while keeping the shape and height of waveform peaks. SG filters are thereby known to properly preserve the shape of peaks and will, in turn, preserve a road profile's peak and not remove it.

Models

SRTM and Road Grade

As shown in Figure 1, a 28 km sample route was used to record a gold standard elevation profile that can be used to test the accuracy of the SG filter on SRTM data. Two elevation profiles were constructed: driving the route multiple times while recording height with a consumer-grade GPS device that measures barometric altitude, and driving the route once with a specialized measurement unit.

Figure 1. The 28 km sample route (Pretoria, South Africa) with elevations in a color scale. The map was produced using R (*17*). The location of the University of Pretoria at 22.2276 °E; 25.7527 °S is indicated near the top left of the figure with the symbol

Firstly, elevation values of 15 runs were recorded with a consumer-grade GPS device. By driving the same route multiple times and measuring elevation values along the way, the researchers could overlap all the runs and have a much larger set of elevation values for the route. The bigger set of combined data allowed for more accuracy in times when a single run might miss the recording of values during high(er) driving speeds. After combining the location and elevation data of all 15 runs, equidistant samples were extracted that are 10 m apart, creating an elevation profile for the route.

The second profile was executed with Racelogic's VBOX that records data at 100 Hz with a height accuracy of 6 m. The route was driven once and again sampled values were taken out of the dataset, with equidistant points of 10 m to create a similar elevation profile as with the 15 runs. This second technique proved to provide elevation values closest to the SRTM values of the sample route and was therefore chosen as the chosen gold standard elevation profile to work with.

With the gold standard elevation profile, an SG filter was introduced to the SRTM data added to the sample route to smooth the stepwise nature of the DEM. The SG filter has a few changeable parameters, but there is one that has a notable impact on the level of smoothing—the filter length. The filter length was set to about 101 points to produce a medium amount of smoothing. The points are sampled with equal distances of 10 m. These new filtered SRTM elevation values are shown on a snippet of the sample road in Figure 2 in red, where it is plotted against the measured VBOX elevations in black and the raw SRTM values in gray. This method produced a set of estimated elevation values for the road profile that are smooth enough for use to calculate slope values.

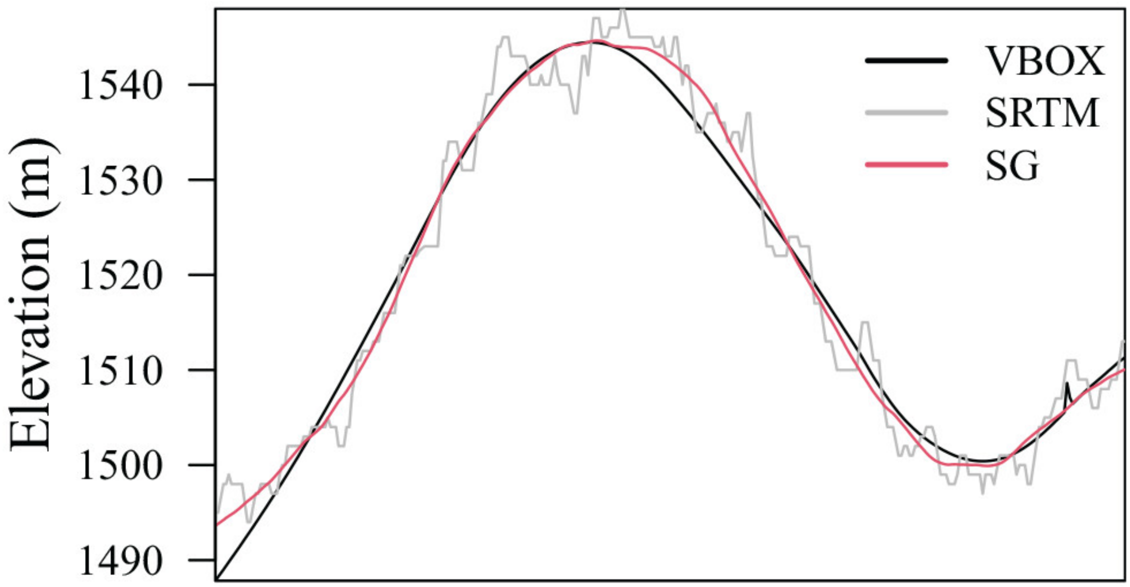

Figure 2. A sample of the road with elevation profiles of the VBOX, Shuttle Radar Topography Mission (SRTM), and filtered SRTM.

As previously discussed, road grade values can be calculated by deriving the elevation profile of the driven road. Dividing the difference of elevation by the distance between each point will, however, provide unrealistic gradient estimations that are too erratic to represent reality. This study rather uses a different type of derivative—linear regression.

More than one point can be used to fit a regression line and then draw the derivative off from that line for a road grade value. Here, a point is used with two points before and two points after, each 10 m apart. A regression expression is fitted to these five points and the coefficient (road grade) is extracted. This can be done for every equidistant point on the road.

To calculate road grade, six steps were followed, that started by determining the coordinate blocks of the GPS traces and extracting the SRTM 1-Arc DEM blocks to append each trace with an elevation value. The remaining steps are visualized in Figure 3. In Step 2, equidistant points of 10 m were sampled with elevation (y) and cumulative distance (x). Using these points, the elevation values of points where the elevation difference is more than 20% are removed and linearly interpolated in Step 3. Step 4 is added to filter the sampled points with an SG filter, and Step 5 uses the smooth(er) values to calculate road grade for each sampled point via linear regression using 40 m interval (five points). At the end, in Step 6, the original distance (x) values are used as the base to interpolate elevation and road grade to original GPS traces.

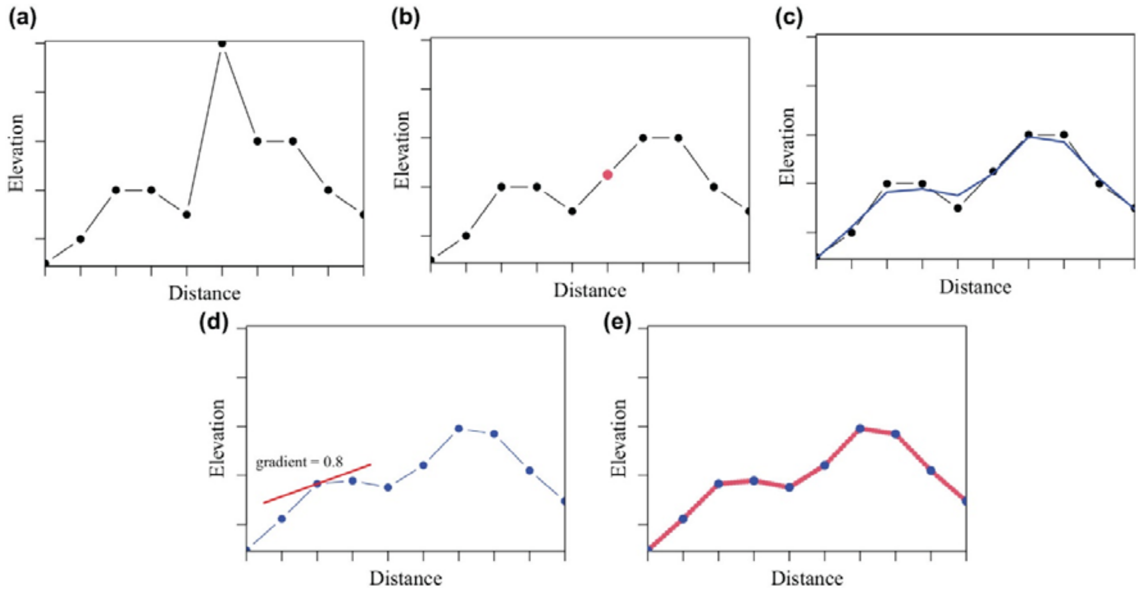

Figure 3. Steps to calculate road grade values: (*a*) Step 2: Sample equidistant points of original data, (*b*) Step 3: Remove unrealistic elevation values and linearly interpolate, (*c*) Step 4: Apply a Savitzky–Golay (SG) filter on the sampled points, (*d*) Step 5: Calculate road grade for each sampled point via linear regression, and (*e*) Step 6: Interpolate elevation and road grade values for all original points between sampled points.

To visualize how the final road grades pair with their respective elevations, the sample road's smoothed elevation profile is plotted in Figure 4. To inspect the accuracy, a quick glance at the zero-line of the road grade plot shows that downhill grades do indeed produce negative road grade values and the same the other way around. This road grade model can now be used with any set of data that contains consecutive lateral and longitudinal coordinates.

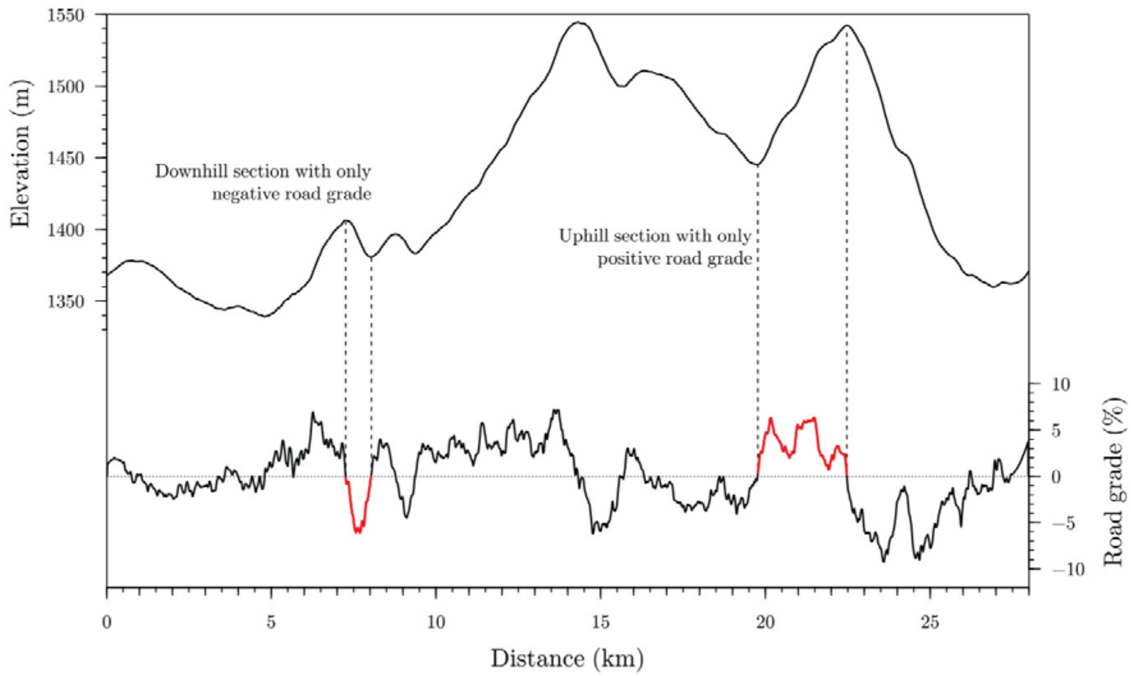

Figure 4. Final smoothed Shuttle Radar Topography Mission (SRTM) elevation profile and road grades of the sample road. The higher the absolute value of road grade, the steeper the incline/decline.

Dataset

The dataset used in this paper is the accelerometer records of 48 heavy-load vehicles (articulated trucks) over the course of one month. These trucks traveled across South Africa recording GPS information (at a rate of 1 Hz) such as longitude and latitude and three-axis accelerometer information, similar to the data used by Joubert et al. (*2*). Speed is determined by GPS movement and three-axis acceleration is found by an internal sensor (a type of IVDR).

Passenger Vehicles Versus Trucks

The mass of a vehicle will influence the forces needed when traveling on different inclines Kidambi et al. (*18*). Heavy vehicles will experience road gradients more significantly than lighter vehicles would, therefore, the authors chose to use trucks in this study. Before the impact of road grades can be visualized, first it is necessary to illustrate how the risk space of heavy vehicles compares with light vehicles.

The existing model of Joubert et al. (*2*) is run on the truck dataset and the risk space is visualized in Figure 5*b*. The risk space is an efficient, space filling, face-centered close-packed (FCC) three-dimensional arrangement where the three dimensions represent the longitudinal (x), lateral (y), and vertical (z) acceleration of the vehicle, respectively. The primitive cell of the FCC lattice is a rhombic dodecahedron. Each GPS record can then be associated with one of these cells based on its acceleration values. Once populated, the cells are sorted in descending order based on the number of GPS records associated with it. Fewer records associated with a cell suggest more extreme driving behavior.

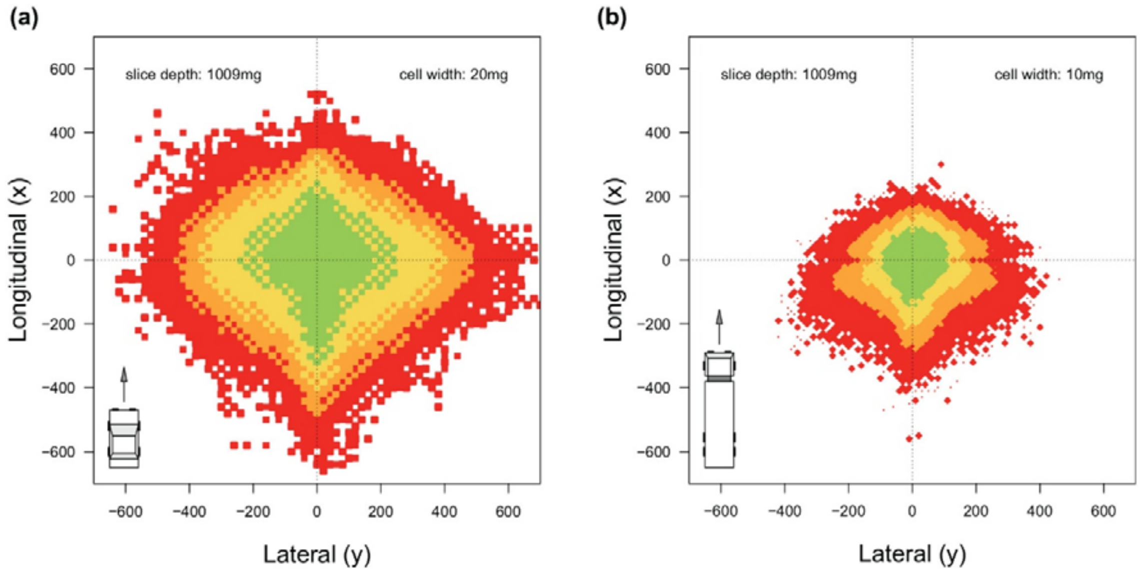

Figure 5. Risk spaces of light and heavy vehicles: (*a*) light vehicles, from Joubert et al. (*2*) and (*b*) heavy vehicles from this study's data.

In line with Joubert et al. (*2*), the sorted cells that account for 96% of all the records are considered *no risk* and colored green. The sorted cells that account for the next 3.4% of records are considered *low risk* and colored yellow. *Medium risk* cells are colored orange and account for the next 0.5% of the records. The remainder of the cells, which account for 0.1% being the most extreme acceleration observations are considered *high risk* and colored red. With the quantile coloring, one can slice the three-dimensional body in the xy -plane at a specific depth (z acceleration) to reveal and visualize the risk space.

When the new heavy vehicle risk space visualization is compared with the one in Figure 5*a*, one can see that the truck acceleration records are less spread out than that of light vehicles. The reason for this can be found in the size and weight of a truck. There is much less harsh movement on a heavier vehicle than one would with observe with a passenger vehicle. With more inertia present, more power is needed to slow down or speed up.

Another reason for a smaller extent of the risk space is the type of vehicles within the dataset. The vehicles are from the same logistics company, having similar size specifications and are more or less the same age. They might differ slightly in cargo weight, but we are observing an entire month's movement and tracking the behavior of varying cargo weights—spreading out the effect it might have. Recorded behavior would, therefore, be mostly affected by the drivers and not by the type of vehicle. A dataset of light passenger vehicles would yield many different types of vehicles, all with different capabilities of speed and acceleration.

The factors listed above can all affect the risk profile of a group of drivers, or truck drivers in this case. To find how much, if at all, road geometry affects driver behavior, one can add another variable to the dataset—road grade.

Results and Discussion

To add road grade as a contextual variable, this study set five categories, namely: steep downhill, medium steep downhill, flat, medium steep uphill, steep uphill. Thomason (*19*) states that anything between −8% and 8% can be considered as medium steep and between 8% and 15% can be considered as steep, on the negative side as well. However, because the dataset is based on the movement of heavy-load vehicles, these values should be reconsidered as the studied vehicles drove on highways for the most part. Instead, this study separated the variable at three standard deviations from the mean (which would be zero in this case). This method is known as the empirical rule or the 68-95-99.7 rule. Rounding the standard deviation of the dataset's road grade values to a useful decimal, a value of 0.02 is found to be sufficient in determining the different levels of steepness.

With five different levels (or categories) of steepness, we can analyze behavioral changes on a large scale looking at the entire envelope of drivers, or we can analyze individual behavioral performance changes, driving performance changes, or both. The sections below analyze and investigate both of these concepts by analyzing the impact road grade might have on a group of drivers, as well as the varying degree of influence it can have on individuals and their driving performance and risk.

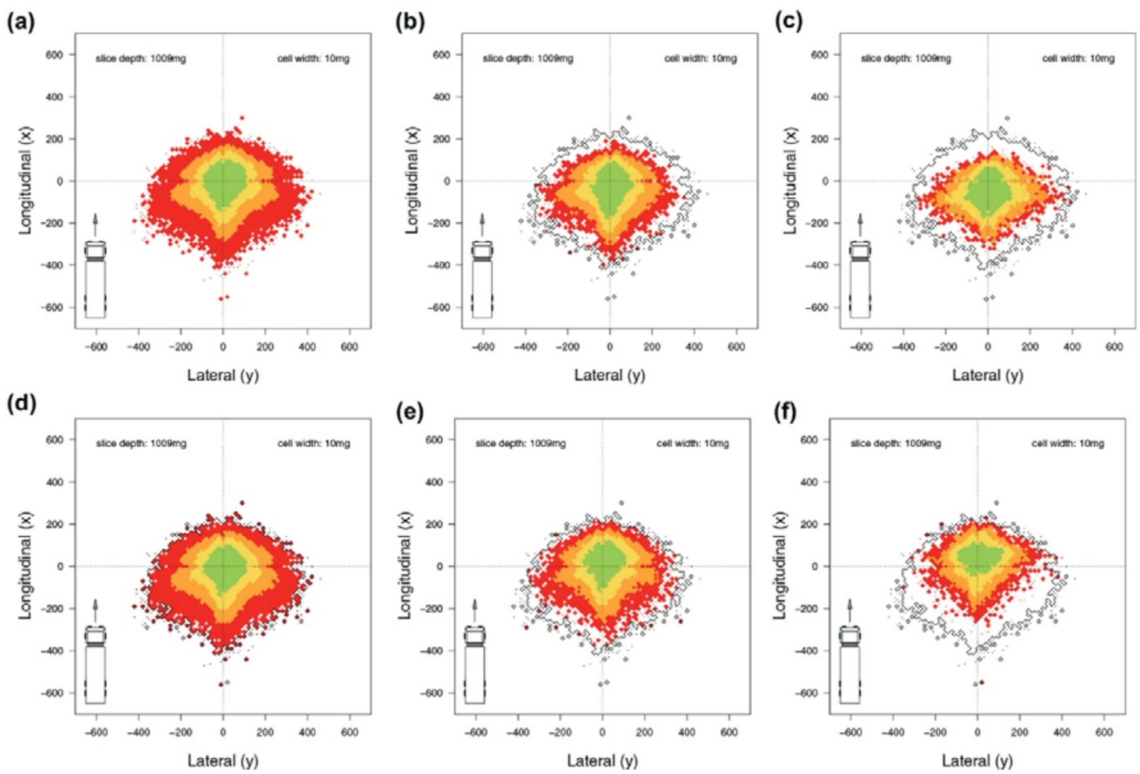

Figure 6. Risk profiles of drivers without road grade and profiles of different road grade categories. The outline in each of the parts (*b*) to (*f*) is a references to all records: (*a*) all records, (*b*) medium steep downhill, (*c*) steep downhill, (*d*) flat grades, (*e*) medium steep uphill, and (*f*) steep uphill

Behavior of the Population

In this section we use the five defined road grade categories within the risk model to analyse the risk space of each type of slope. The model filters records by only using the data points that fall within each of the grade categories and provides a risk space for each. Figure 6 illustrates the horizontal slices taken from the three-dimensional risk spaces of the model as-is and the five categories of road grades.

Figure 6 represents all the records, ignoring road grade. To compare the risk profile of specific road grade, each of Figure 6, *b* to *f*, has a black outline, which represents the risk space of Figure 6*a* where road grade is not accounted for.

Downhill Road Sections. The first two categories are of downhill sections (2.9% of the total records). A steep downhill is found beyond a road grade of −4%, that is, $\theta<-0.04$. A medium steep downhill road section has a road grade within a range of $-0.04<\theta<-0.02$.

From Figure 6, *c* and *b*, it can be seen that the majority of records have negative longitudinal acceleration, meaning that there are more records of decelerating/braking than records of forward acceleration. Anticipation is a basic aspect for any driver, especially the more experienced driver. Braking with a heavy vehicle traveling downhill is not only a wise anticipatory act, it is frequently a legal requirement and indicated through road signs. Reducing speed rather than trying to keep it constant might be an overcompensation, but it can be the safer option.

Many trucks, if not all these days, are fitted with an endurance braek, that is designed to keep the vehicle slow when going downhill over a longer period of time. This is to reduce “brake fade,” which is caused by manual foot-braking as brake fade can cause a driver to lose control when driving with a load downhill. Professional drivers also make use of engine braking, keeping the truck at a lower gear at high engine revolutions which also limits the speed. All of this compensates for the possible forward acceleration that can take place downhill, but does not provide a reason for so many records with negative acceleration.

The braking is most likely the result of overcompensation for the safety risks of driving downhill at high speeds with a heavy vehicle. A heavy load can cause the driver to brake earlier rather than to wait until the last moment and have less control of the vehicle—it is an easy solution to avoid the downhill acceleration of a heavy load.

For the lateral movement of the vehicles, there are a few high risk records scattered around the central “blob” and these records can be cases of drivers swerving sideways. They could have swerved around slower trucks to pass them while traveling downhill, but passing downhill can cause problematic instances such as speeding or overheating of the brakes. Both of these cases are unsafe with a large vehicle, especially if it has a heavy load, and could result in loss of control and an accident.

Flat Road Sections. Flat road sections in Figure 6*d* form the largest category and have a risk space that does not differ much from that of the entire population of records in the Figure 6*a*.The outer shapes of the two groups are seemingly identical. This is to be expected since 72.6% of all records are found in the flat category.

Uphill Road Sections. The last behavioral comparison that is studied is that of drivers on steep and medium steep uphill roads. The road grade values are found in the same manner as with downhill sections, but with positive values: $0.02<\theta<0.04$ and $0.04<\theta$ for medium steep and steep grades, respectively. Figure 6, *f* and *e*, illustrate the risk spaces of these two different types of uphill grades. It can be seen that both risk spaces have the majority of their records in the positive (forward) acceleration area, especially on steep uphills. This placement of records is even more visible than in the previous section of downhill grades.

The reason for the accumulation of records in the acceleration area of the risk space can again be found in the concept of anticipation, similar to that discussed in the previous section on downhill roads. Sometimes it is wise to depart from optimal fuel or speed ranges for a while to anticipate an event, to save fuel for an entire trip. For example, a driver can gather speed *before* an important peak on the hill they are currently making their way toward, saving the extra power that would have been used to go over the peak if they were driving at a constant speed.

When analyzing the lateral movement of all the heavy vehicle records, a small tail of observations to the right is found in Figure 6*f*. These records come from vehicles that were driving faster to the right and might be there because of them overtaking other vehicles, other trucks, or both. A lighter or more powerful truck can overtake an older, heavier, or less powerful truck. Passing on an uphill is much safer than on a downhill, so one would expect more records that look like swerving in this uphill section than those found on downhills.

Behavior and Performance of Individual Drivers

We found that overall driving behavior varies on different road gradients, but does it have an impact on an individual's driving *performance*? The risk model of Joubert et al. (*2*) allows for the scoring and ranking of individual drivers based on their performance. This is done by calculating an individual's proportion, p, of records within each risk category relative to the total population, P. The proportion of records for each individual are denoted by p^{none},p^{low},p^{med}, and p^{high}, where the weighting of each category is denoted by $w^{\text{none}}=0$,$w^{\text{low}}=1$,$w^{\text{med}}=2$, and $w^{\text{high}}=3$. Each person, i, then receives a score, s_i, that is calculated as follows.

$$s_i=3-(p^{\text{none}}w^{\text{none}}+p^{\text{low}}w^{\text{low}}+p^{\text{med}}w^{\text{med}}+p^{\text{high}}w^{\text{high}})\forall i\in P \quad (1)$$

Each driver's risk score is normalized to a range within [0,1] and thereafter sorted against all the scores of the population from best to worst, where the individual with the lowest score and worst performance receives a score of zero, and the individual with the highest score and best performance receives a score of one. The scores are then ranked from best to worst and each of the drivers is given a ranking number.

To investigate the impact of road grade on individual behavior, the change in an individual's ranking when different grade categories are considered is analyzed. Each person received a *base ranking* where all the records were used, but they also received a performance ranking for each grade category. This was achieved by filtering all the records on the five road grade categories (as done in Figure) to score and rank every person on each.

It is argued here that if road grade is relevant for a particular driver, then that person's ranking will change compared with the base case where road grade is ignored. The changes in a person's ranking relative to the ranking changes within the population can be quantified with a correlation coefficient (R) using the base model's ranking against each category's ranking respectively; that is, five lists of rank values are compared with the base list of rank values.

A high R value can be anything above 0.8 and would indicate a high correlation between the road grade category and the base model, suggesting that a driver's level of risk does not change much from the model when the respective road grade category is considered.

This study found that only one of the five categories had high R values and, overall, ranged between 0.48 and 0.92, indicating significant ranking changes. The most notable ranking changes were found when filtering on medium steep uphill sections (R=0.48) and steep downhill sections (R=0.52). To determine if this low correlation development is significant enough to conclude that the driving risk of some individuals changes on steep downgrades, we can visualize the ranking comparison.

The performance rankings of the drivers are plotted in Figure 7, where the base model rankings (denoted by the point's x -value) are plotted against the rankings of the same person when filtered on a specific road grade (denoted by the point's y -value).

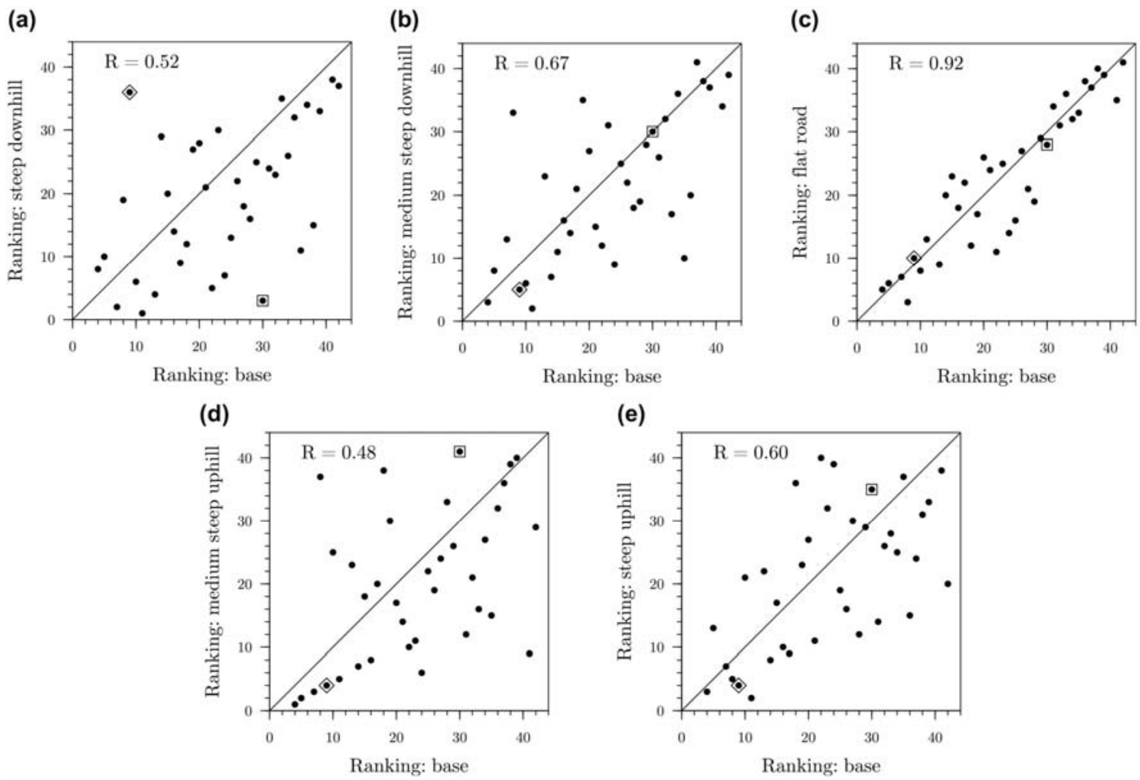

Figure 7. Rankings of individuals on different road grades versus when road grade is ignored (as the base model). In each part of the figure, two specific vehicles are highlighted, driver 21 (▭) and driver 39 (◇): (*a*) steep downhill, (*b*) medium steep downhill, (*c*) flat road, (*d*) medium steep uphill, and (*e*) steep uphill.

Points on the diagonal line are those individuals who have constant ranking positions. The points above the line represent those who have scored worse (a higher ranking number) when road grade is considered. The points below the line represent those who have improved their score (a lower ranking number) on the specific road grade.

With the low R value of steep downhill roads, we see that quite a lot of drivers do not line up on the diagonal. This shows us how some drivers have significant performance changes (compared with the population of drivers). Two individuals are highlighted in the figure for discussion: drivers 21 and 39.

On steep downhills (Figure 7*a*), driver 21 improved their ranking. They ranked 30th, in the base model, but performed much better (relative to the group) on steep downhill sections, ranking third. Conversely, driver 39's performance deteriorated when filtered on medium steep uphill road sections, from ninth down to 36th. This indicates that they drove much better than most of the drivers on medium steep downhill roads, information that is lost when only using the base model.

Conclusion

The motivation to investigate the impact of slopes on driver behavior comes from the understanding that road geometry can influence a vehicle and its performance. Existing literature does not show how much road grades can influence behavior, but it does show how it influences a vehicle's performance. This performance can be anything from higher emission rates to higher accident rates on inclines, leading to the question: how much, if at all, do inclines influence the behavior and risk of a driver?

Before this could be determined, it was first demonstrated how road grade can be added to an existing set of accelerometer data. Height values are extracted from a DEM to build an elevation profile that is then smoothed to filter out any unrealistic points. Five slope categories are defined from steep downhills to steep uphills, allowing for the addition of road grade as a contextual variable to an existing driver behavior model.

By analyzing behavior on different slope levels and the risk spaces resulting from the model, it was demonstrated that there is a clear overall relationship between the slope of the road and the behavior of heavy vehicle drivers. The grade categories with the most visual impact are those of steep slopes. It is also shown how individual driving performance differs on different grade levels, where the risk level of each driver's behavior is a measurement of performance. The type of slope that has a significant impact is that of steep downgrades while other gradients do not prove to have a notable influence on driving performance.

Now that we have shown how road geometry influences a driver's behavior, we are left with the question: What are the implications of these findings? The results do not necessarily indicate an increase or decrease in safety on slopes, since safety factors and accident statistics do not form part of the dataset or the study. The net effect of road grade on driving behavior remains an empirical issue.

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Declaration of Conflicting Interests

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ORCID iDs

Jeanne-Marie Gerber https://orcid.org/0000-0003-2128-7293

Johan W. Joubert https://orcid.org/0000-0001-6631-1803

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