A skid resistance prediction model for an entire road network

Abstract

This article predicts the available minimum skid resistance in the road network of Biscay (Spain) with data collected in the summer season when friction values are at a minimum. Firstly, it was observed that pavement structure does not influence skid resistance. Therefore, roadway segments with available data about the surface layer of single or double carriageway roads were analyzed. Two models were developed: 1) short model with only the surface material, average annual daily traffic, and number of lanes (no pavement history required) and 2) a long model which adds the required Polished Stone Value to improve the prediction. These models can help road agencies to identify the roads where lower skid resistance values are more probable to be obtained to focus their attention and efforts.

Keywords

Skid resistance; friction; pavement performance model; pavement deterioration; pavement management system; deterministic model; deterioration model; surface layer; pavement management

1. Introduction

Among the characteristics that are collected and evaluated for roadway pavements, skid resistance is consistently studied as a key parameter of functional evaluations [1-4]. The interest in this metric lies in the frictional resistance that is generated between the vehicle tires and the pavement surface, which is a fundamental component of the driving task, allowing drivers to maneuver and guide their vehicles safely, in both longitudinal and transversal directions. With higher friction in the tire-pavement contact, drivers can better control their vehicles [4-6]. Road collisions are usually reported to be the result of multiple factors, normally grouped by factors related to driver, vehicle, and the roadway condition [7-9]. Despite their multiple factor nature, a relationship between accidents and pavement surface characteristics, such as friction and texture, has been established in the literature [10,11]. Road collision analyses have demonstrated that the rate of wet crashes increases with low friction values and a higher pavement friction was concluded to significantly reduce the accident rate. Although this relationship has been proven consistently, it is difficult to quantify precisely and, hence, most of the studies are empirical [12-14]. Consequently, road agencies must monitor and control the friction level provided on their roads, by designing and maintaining appropriate pavement surfaces and related treatments [9,15,16]. Therefore, a skid resistance predictive model is necessary in pavement management systems, which allows advance knowledge of the available pavement friction, as a function of different factors [9,17,18].

The Regional Government of Biscay (RGB) in Spain collects friction values in the road network under its control by means of the Sideway-force Coefficient Routine Investigation Machine (SCRIM) to measure the skid resistance for road safety considerations. This paper presents a predictive model for the available skid resistance for asphalt pavement in newly constructed and in maintained and rehabilitated roads, as a function of the factors that have a statistically-significant influence on it and are available in the database of the pavement management system. Thus, the highway administration of the RGB could forecast in advance the estimated available skid resistance, compare them with established thresholds and take appropriate measures, if necessary.

2. Factors affecting skid resistance and proposed models for asphalt pavements

2.1. Factors affecting skid resistance in asphalt pavements

Pavement friction is defined as "*the force that resists the relative motion between a vehicle tire and a pavement*" [7]. The resistive force is generated as the vehicles tire rolls or slides over the road surface. Pavement friction is said to be the result of a complex interaction between adhesion and hysteresis [4,19,20]. Adhesion appears at the pavement–tire interface, it is said to be related to the micro-level asperities of the aggregates of the pavement, i.e., the microtexture. Hysteresis is attributed to the macro level asperities of the surface, the macrotexture. Pavement surface texture is the deviations of the pavement surface from a true planar surface. The scales of surface texture were defined in the XVII World Road Congress in Brussels in 1987 by the World Road Association (PIARC) as a function of the wavelength (λ), and amplitude (A) of the deviations [21], shown in Table 1.

Table 1. Classification of the deviations of a pavement.

Level of texture	**Wavelength, λ (mm)**	**Amplitude, A (mm)**
Micro-texture	$0 < \lambda < 0.5$	$0.001 < A < 0.5$
Macro-texture	$0.5 < \lambda < 50$	$0.1 < A < 20$
Mega-texture	$50 < \lambda < 500$	$1 < A < 50$
Roughness or unevenness	$\lambda > 500$	$1 < A < 200$

Microtexture depends on the surface properties of the aggregates and on the bituminous material which provides adhesion. Macrotexture is a function of the mixture properties of the asphalt mix, such as the shape, size, and gradation of the aggregates. While micro-texture and macro-texture are necessary properties for pavement friction, mega-texture and roughness should be avoided. Factors affecting pavement friction are usually classified in four categories [7,12,15,20], shown in Table 2.

Table 2. Factors affecting available pavement friction

Pavement Surface Characteristics	Vehicle Factors	Tire Properties	Environment
1. Microtexture **2. Macrotexture** **3. Material properties** 4. Mega-texture / unevenness 5. Temperature	**Slip speed**, as a function of: 1. Vehicle speed, V 2. Slip ratio, SR 3. Driving maneuver: 3a. Turning 3b. Overtaking	**1. Tread design and condition** **2. Inflation pressure** 3. Rubber composition and hardness 4. Foot print 5. Load 6. Temperature	**1. Temperature** **2. Water** (rainfall, condensation) **3. Snow and ice** **4. Contaminants** (salt, sand, dirt, mud) 5. Wind

Note: Key factors in each area are shown in bold.

There is a wide range of skid resistance measuring devices available for measuring skid resistance. They are usually grouped according to the three main operating principles: the longitudinal friction coefficient, sideway force coefficient (SFC), and sliders or stationary or slow-moving measurement principles [18].

SCRIM is a sideways force measuring device developed by the Transport and Road Research Laboratory (TRRL) in the UK. For the SCRIM testing, equipment is mounted on a truck chassis and it has a standardized test wheel placed in the middle of the truck, between the front and rear axles, fixed at 20 degrees to the line of the truck chassis and connected to a water supply. When the truck moves forward, the test wheel is rotating, but slides in the forward direction because of the angular difference. The standard test speed is 50 km/h. The Side-force Coefficient (*SFC*), obtained from the SCRIM, is the ratio of the sideway force to vertical reaction between the tire and the pavement surface, with a value ranging from 0 to 1. A SCRIM reading, *SR*, is the output of each subsection of the tested highway, usually 5, 10, or 20 m long, and it is the average *SFC* value over the entire subsection length, expressed as an integer value, and multiplied by 100. These SR values come directly from the SCRIM machine and must be corrected for speed. When the truck-mounted style of SCRIMs were introduced, leaving the SCRIM motorbikes, an "*index of SFC*" factor was introduced to correlate existing historical records with present measures, with the aim of maintaining the data consistency. Its value in the UK is 0.78 and is applicable to all UK SCRIMs in use [22]. Consequently, the SCRIM Coefficient, *SC*, is calculated for each sub-section for which a valid *SR* is available with Equation (1).

$$SC = \left(SR\left(50\right)/100\right)\cdot 0.78 \tag{1}$$

The *SC* is an *SFC* value corrected for speed and machine variability. It is expressed as a decimal fraction, with two decimal places. According to previous Spanish standards, SCRIM Coefficients (*SC*) values had to be expressed as a decimal fraction, from 0 to 1 [23]. However, since 2001, SC is expressed from 0 to 100, i.e., multiplied by 100 [24]. The SCRIM Coefficient is adjusted for temperature and speed, but no "index of SFC" is applied. Nevertheless, during testing, each measurement follows established standards, with primary regards to tire properties, water supply, vehicle speed, slip ratio, etc. After a road agency has selected a specific device to collect data, the pavement surface characteristics and environmental factors are the only variables, while other characteristics, from Table 2, are held constant to the extent possible.

Factors affecting the pavement texture are related to the aggregate, binder and asphalt properties, and the post-placement treatment, as shown in Table 3. As shown, the characteristics of the selected asphalt mix for the surface layer influence available friction. However, as the micro-texture has a vital role in the skid resistance, the aggregate properties become a fundamental characteristic. Aggregate properties like hardness and mineralogy, shape, texture, angularity, abrasion or wear resistance, and soundness were demonstrated to have an influence on the available friction [3,16,25-32]. Nevertheless, the most important property is the polish resistance, defined as the capability to retain its microtexture after being grinded and sheared by repeated traffic loadings [18]. This idea of "*retained skid resistance*" has been traditionally highlighted in definitions, representing that the aggregate was polished to a certain degree.

Table 3. Factors affecting asphalt pavement microtexture and macrotexture

Factor	Microtexture	Macrotexture
Maximum aggregate dimension		X
Coarse aggregate type	X	X
Fine aggregate type		X
Mix gradation		X
Mix air content		X
Mix binder		X

The Polished Stone Value (PSV) is said to be the most widely method for evaluating aggregate polish resistance [9,16,33]. A higher value of PSV indicates a better polish resistance. Standards are similar internationally [34-36].

Water on the pavement surface is a key environmental factor [15,37]. With dry and clean surfaces, a high skid resistance can be obtained, but when the pavement surface gets slightly wet at the onset of a rainfall event, an important reduction in the friction is observed because the water film over the surface acts as a lubricant between the tire and the pavement and also reduces the contact area between the two. Therefore, the majority of skid resistance tests are conducted in wet conditions.

There is a wide range of possible surface contaminants (snow, ice, frost, dust, clay, loose gravel, sand, vehicle contaminants, e.g. oil, fuel, rubber, fallen leaves, etc) and they may interfere with the friction mechanisms and reduce its values. However, the influence of individual contaminants has not been developed [15,38].

Except in the case of extreme climate conditions, temperature does not affect the frictional properties of aggregates of bituminous layers. However, since both tire rubber and bituminous materials are viscoelastic materials, they are more sensitive to temperature changes [39]. As a general guide, with increasing air temperature, the friction tends to decrease. Tire temperature is normally proportional to air temperature and higher temperatures imply lower skid resistances. Water temperature has no effect on friction and a higher pavement temperature implies a decreasing friction coefficient. Various formulas were developed to consider its influence, since some friction measuring devices are more sensitive to temperature changes.

With regard to age, a general model is accepted internationally to represent skid resistance performance with time (Figure 1a). For a new pavement, an initial skid resistance increase appears if the aggregates are covered by a bituminous film. After the bituminous film is worn away, the aggregate microtexture is exposed to traffic and, hence, skid resistance increases. Then, once exposed, aggregates suffer from a normal polishing process and their friction level is reduced, until an equilibrium phase is achieved, where the skid resistance tends to follow an asymptotic value [40]. Previous research has shown that during this equilibrium phase, as long as constant traffic volumes are maintained, seasonal and short-term variations are the only fluctuations. However, no consensus exists about the duration of each phase. For the elimination of the bitumen cover of the aggregates, it depends on the binder type and heavy traffic characteristics [41]. In Spain, this increasing skid resistance phase is expected to last for approximately 2 or 3 months [42,43]. However, for Stone Mastic Asphalt (SMA) surfaces with a high binder quantity, it was shown that this phenomenon can dominate the path of the life-cycle of skid resistance performance [44]. Woodwart et al. [45] showed that a polymer modified surface had not still completed the aggregate exposure after 4 years of traffic. Regarding the polishing phase duration, disagreement also appears in the published literature with four or five year-duration examples [38] and examples of shorter time frames ranging from half a year to one year [43,46].

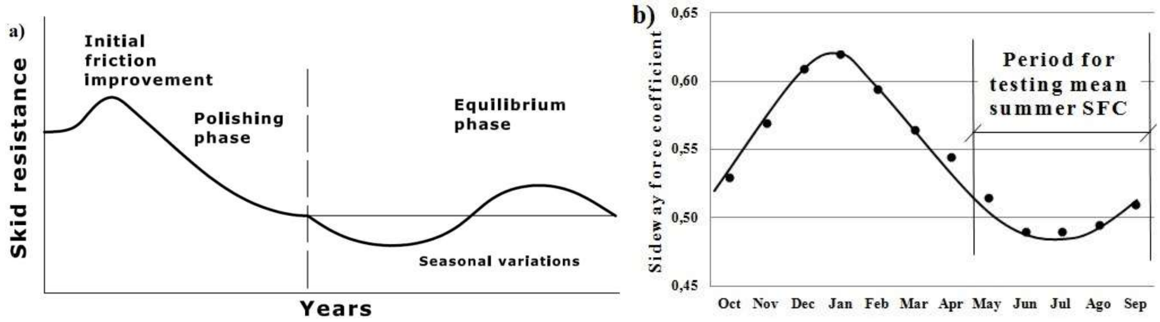


Figure 1. a) Skid resistance performance with time. b) Seasonal variations of skid resistance in equilibrium phase trough the year.

The seasonal variations in friction, which appear in the equilibrium phase, have been documented since 1931 [47], with the lowest friction values on wet road surfaces in the summer and higher values in the winter (Figure 1b). This phenomenon is likely to be caused by the combined effect of traffic and weather on the surface aggregate. On dry roads, generally in the summer, the polishing effect action of traffic is dominant, but, when the road pavements are wet for long periods, normally in winter, surfaces recover some of their former texture and harshness [48]. The magnitude of these seasonal variations is primarily dependent on the geological history and petrography of the aggregates used for the pavement surface. The first study about seasonal variations was conducted in the UK with SCRIM devices on multiple road sections, on pavement in the equilibrium phase, every month over 11 years, from 1958 to 1968 [49]. Apart from the studies in the UK [48, 50-52], in other countries similar evidence of these fluctuations has been observed [25,43,53-55]. For pavements in the stable phase, differences between years are related to changes in the climate but are less important than the seasonal variations [49]. Since road agencies must assure a minimum friction on the roads in their network, knowing the minimum level of skid resistance available is a vital interest in their pavement management system and, hence, it is preferable to evaluate the network in the summer. For example, the British highway agency has employed the Mean Summer SCRIM Coefficient, *MSSC*, to determine the network and project level skid performance (Hosking and Woodford 1976). The *MSSC* is calculated from the mean of 3 SC values for each region in the summer months. The friction value is obtained at its lowest and also when the variation is the least, with measurements in the summer every 3 years, on roads in the equilibrium phase [49], which produces the "worst case" skid resistance values. The Characteristic SCRIM Coefficient, CSC, is proposed in the UK as the standardized value obtained in a month from May to September, every year in a different month and adjusted according to the observed variation in the previous 3 years in that area [56]. Figure 2 explains the differences in data collection between the plans. For modeling the seasonal variations of skid resistance, sinusoidal models have been the dominant model type proposed in the literature [54,55,57-59].

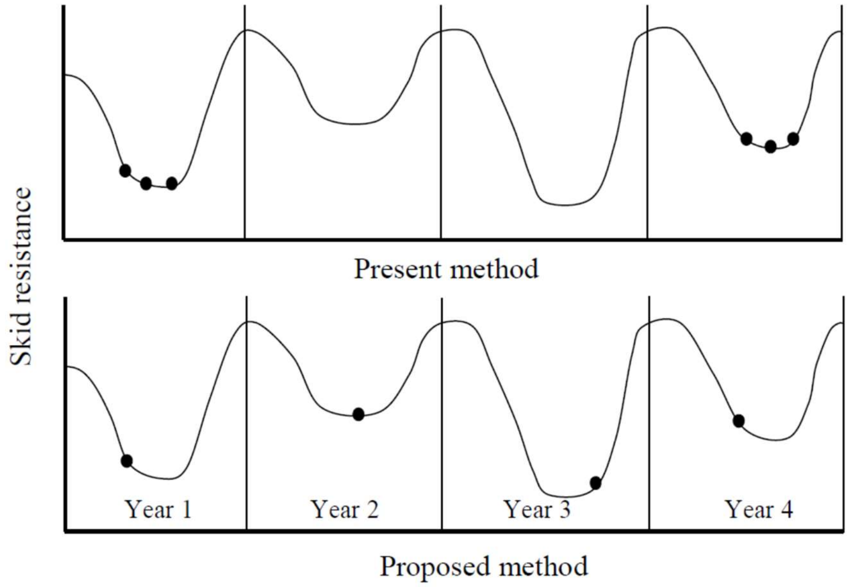


Figure 2. Data collection plan for calculation of MSSC and CSC

The amount of polishing is directly related to the traffic intensity, and especially to heavy traffic intensity [38,60]. Keneddy et al. [61] indicated that, if other conditions were equal, a road with the highest heavy vehicle volume would have the lowest skid resistance. Heavy traffic is responsible for polishing away the fine-scale microtexture, and a higher heavy traffic volume means a lower skid resistance [48]. Figure 3a shows this idea based on research carried out in UK with aggregates with PSV between 58 and 60 [50,51].

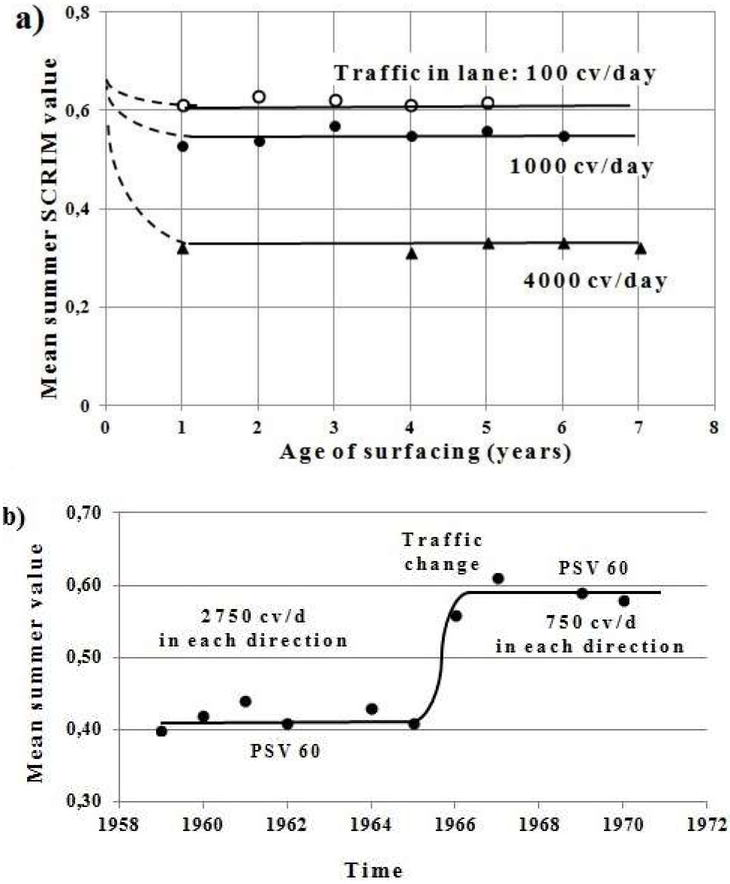


Figure 3. Mean Summer SCRIM Coefficient (MSSC) variation: a) with constant heavy traffic volume, b) with changing heavy traffic volume.

As shown in Figure 3a, the initial drop of the *SC* value is due to the polishing phase, but it does not continue after the equilibrium phase is reached. Therefore, the heavy traffic effect must not be considered cumulative year over year, since it only depends on the heavy traffic intensity (and the aggregate properties), if weather conditions remain unchanged [17,38,42,62]. Nevertheless, if heavy traffic intensity changes, i.e. the Annual Average Daily Heavy Traffic, available skid resistance also changes, even increasing its value, as occurred in the A4 road in Colnbrook (UK), when a freeway was opened [62] (Figure 3b). This phenomenon was also verified in the N-VI in Leon (Spain) [42].

2.2. Proposed skid resistance predicting models for asphalt pavements

One of the first skid resistance models was developed at the UK Transport and Road Research Laboratory (TRRL). Szatkowski and Hosking [62] conducted a data collection survey of *SFC* over the time period 1960-1970 across 139 roadway segments. *SFC* values were an average value of mean summer values with known aggregate PSV which resulted in the development of Equation 2, with a Pearson coefficient (R) of 0.92.

$$MSSC = 0.024 + 0.663 \cdot 10^{-4} \cdot Q_{CV} + 1 \cdot 10^{-2} \cdot PSV \qquad (2)$$

Where *MSSC* is the Mean Summer SCRIM Coefficient measured by a SCRIM device at 50 km/h (from 0 to 1), *PSV* is the Polished Stone Value of the aggregates (with a range from 0 to 100) and Q_{cv} is the number of commercial vehicles (CV) per lane per day. In the UK, a CV was defined as a vehicle over 1500 kg (15 kN) mass. Szatkowski and Hosking [62] also proposed an equation with total traffic flow, expressed as total vehicles per lane and day (Q_{tv}) (Equation 3). The equation had a correlation coefficient (R) of 0.84, and hence, this equation was not recommended.

$$MSSC = 0.024 + 0.15 \cdot 10^{-4} \cdot Q_{TV} + 1 \cdot 10^{-2} \cdot PSV \qquad (3)$$

Equation 2 was regarded as "*major advancement in the field of skid resistance*" [50,63] since it enabled the ability to predict the level of skidding resistance available, based on the PSV of the aggregates and the traffic flow. Moreover, it provided a method for a planning or design-level estimation of the properties of the stone required to provide an ultimate skid resistance given the commercial traffic flow [50], which was foundational for setting the standards for constructing new roads in the UK. This equation also showed that the effect of traffic on *SFC* is not cumulative from year to year. Nevertheless, a more complete research study was conducted and demonstrated that Equation 2 predicted higher values on roads with lower levels of heavy traffic and underestimated the available friction with higher levels of heavy traffic volumes [64]. Thus, new equations were proposed, of the form of Equation 4, where the values of the coefficient *A*, *B,* and *K* were established according to the corresponding investigatory level employed in the UK, from I to VII [64]. These equations have an average determination coefficient (R^2) of 0.10. Therefore, *PSV* and traffic continue to be the main factors but they can only explain 10 % of the total variation.

$$MSSC = A \cdot PSV - B \cdot \ln(Q_{CV}) + K \qquad (4)$$

During the preparation of the predictive specification policy of New Zealand (NZ), a national SCRIM survey was conducted in 1995 [65]. The research used prediction factors including: traffic data, aggregate quarry source, *PSV,* and site location, which resulted in an equation similar to Equation 2 (the reference in that moment), developed for New Zealand (Equation 5).

$$SFC_{50} = 0.018 + 0.311 \cdot 10^{-4} \cdot CVD + 0.637 \cdot 10^{-2} \cdot PSV \qquad (5)$$

Where SFC_{50} is the Mean Summer SCRIM Coefficient measured at 50 km/h (in decimal fraction), *CVD* is the number of commercial vehicles per lane and day (in NZ, a commercial vehicle is a vehicle with a mass over 34 kN (3500 kg) and *PSV,* the Polished Stone Value (from 0 to 100). The equation obtained a determination coefficient (R^2) of 0.28. This value could be improved, up to 0.43, by including the chip size in the prediction. Multiple reasons were provided to explain the poor correlation of the equation, such as the error in the commercial vehicle values, variation in PSV and geological properties, climate variations, and masses of commercial vehicles. Moreover, in the research in the UK, skid resistance was measured in straight roadway segments, whereas the NZ data were obtained in curves and stressed sections. Consequently, the study recommended increasing the PSV by 5 units to compensate for the additional polishing that occurred to NZ aggregates. Therefore, the final prediction equation of the NZ skid resistance policy was Equation 6 [66].

$$PSV = 100 \cdot ESC_{50} + 0.00663 \cdot CVD + 2.6 \tag{6}$$

Where ESC_{50} is the Equilibrium Skid Resistance coefficient, which is the *SFC* measured by the SCRIM device corrected for Mean Summer SCRIM Coefficient (*MSSC*) and for yearly variations, at a measurement speed of 50 km/h.

Pérez-Acebo et al. [17] developed a friction model to estimate the minimum skid resistance on two-lane roads by means of the values collected in the winter along 23 sections of new interurban two-lane roads, with different surface layer materials without rehabilitation or maintenance improvements before the data collection. The difference between winter and summer data (Figure 1b) was introduced based on seasonal variation for each bituminous mix as suggested by other researchers [43,59], and the proposed model is shown in Equation 7.

$$MSSC = 30.19 - 0.82 \cdot \sqrt{H.AADT} + 0.76 \cdot PSV_{req} \tag{7}$$

Where *MSSC* is the Mean Summer SCRIM Coefficient, *H.AADT* is the Annual Average Daily Heavy Traffic in the lane with most heavy traffic (a heavy vehicle weighs more than 3500 kg), expressed in heavy vehicles per day per lane and PSV_{req} is the required Polished Stone Value (PSV) in the construction project, according to the regulations in the country, expressed in a scale from 0 to 100. The age of the pavement and the total thickness of the bituminous layers were not affecting factors. The determination coefficient of the model was 0.696 and all the selected variables were statistically significant.

Texas A&M University researchers developed a model that combines previous skid resistance prediction in a laboratory as a function of aggregate characteristics and gradation with in situ validation. The resulting models were based on both laboratory and field measurements in correspondence with surface characteristics. Rezaei and Masad [67] related the complete process of the model, which included two phases. In the first phase, the main result was Equation 8, employed to describe the changes in the International Friction Index (IFI) values:

$$IFI(N) = a_{mix} + b_{mix} \cdot \exp(-c_{mix} \cdot N) \tag{8}$$

Where IFI is the International Friction Index, a_{mix}, b_{mix} and c_{mix} are coefficients and represent the terminal, initial and rate of change of IFI, respectively, and N is the number of polishing cycles, expressed in thousands. The coefficients of Equation 8 were calculated for different mixes and resulted in determination coefficients over 0.87 for all mixes. The values of the coefficients (a_{mix}, b_{mix}, and c_{mix}) and equations are presented in Rezaei et al. [68] for typical mixes. In the second phase, Rezaei and Masad [67] developed a skid resistance prediction model, which includes the aggregate texture and gradation of the aggregates and traffic volume from field measurements, i.e. the IFI is expressed as a function of traffic volume instead of polishing cycles. They defined the Traffic Multiplication Factor (TMF) as indicated in Equation 9:

$$TMF = \frac{AADT(for\ outer\ lane) \cdot years\ in\ service \cdot 365}{1000} \tag{9}$$

Where *AADT* is the annual average daily traffic for the most critical lane in the highway, the outermost lane. The relationship between TMF and the number of polishing cycles, *N*, was found using a non-linear least-square regression analysis (Equation 10):

$$N = TMF \cdot 10^{\left(1/\left(A + B \cdot c_{mix} + C / c_{mix}\right)\right)} \tag{10}$$

Where *A*, *B* and *C* are regression coefficients and are -0.421, -58.95 and 5.834·10-6, respectively. Consequently, IFI can be predicted as a function of TMF by Equation 11.

$$IFI(TMF) = a_{mix} + b_{mix} \cdot \exp\left(-c_{mix} \cdot TMF \cdot 10^{\left(1/\left(A + B \cdot c_{mix} + C / c_{mix}\right)\right)}\right) \tag{11}$$

Equations 8 and 11 showed that the decrease of skid resistance depends on the aggregate characteristics but in both cases it tends to an asymptotic value after polishing cycles. These polishing cycles can be identified with real traffic which validates the pattern presented in Figure 1a. Conversely, contrary to the Equation 2, TMF does not consider the isolated effect of heavy traffic, but instead includes the total traffic volume, assuming a similar effect from all vehicles.

Similarly, Khasawneh [69] analyzed the polishing behavior of Hot Mix Asphalt specimens made based on eight different mix formulas in the laboratory, by means of the British Pendulum Number (BPN). The greater polishing effect was achieved during the first hour of polishing but, the BPN stabilizes after roughly 5 or 6 hours of continuous polishing. Wang et al. [70] obtained similar conclusions. Li et al. [3] developed a skid resistance model based on the pavement surface and aggregate texture properties, with field and laboratory data, but without including traffic volumes. Goulias and Awoke [32] calculated the maximum number of Equivalent Single Axle Loads that a pavement can sustain before reaching the established minimum level for friction, based on aggregate properties. Therefore, the aim of this research is to develop a skid resistance prediction model for a real road network as a function of the most pertinent factors.

3. Pavement management system of the Regional Government of Biscay

Biscay is one of the three provinces that compose the autonomous region of the Basque Country in Spain. It has a relatively small surface (2,217 km^2) with a population of approximately 1,150,000 inhabitants. The autonomous region of the Basque Country has a special administrative status within Spain and each of the three provinces has its own responsibilities regarding the road network. Consequently, the Regional Government of Biscay (RGB) manages all the interurban roads in Biscay, except the municipal roads. Hence, the RGB can plan, finance, project, construct, rehabilitate, and maintain the entire road network, which has a total length of more than 1200 km. Bituminous materials are the only materials used on roads of Biscay, and, hence, only flexible and semi-rigid pavement structures exist. With the aim of better allocating limited available funds; in 2010 the RGB developed its own pavement management system (PMS), called Stage Agenda. The essential inputs for the database of any PMS are indicated in Table 4 [1]. The RGB introduced an exhaustive list of inputs for the inventory data, which included: road name and segments included on the road, initial and ending points of each segment, segment length, geographical coordinates every 10 m, carriageway geometric data (including identification of lanes in each direction), interchanges, bridges, and drainage systems in the road.

Table 4. Inputs and examples of the data that must be included in any pavement management system

Input	Example of data to be introduced
Inventory data	Segment start and end points, road designation, functional classification, segment length, carriageway and shoulder width, number of lanes in each direction, etc. Pavement characteristics and work history.
Traffic history data	Traffic volumes, Equivalent single-axle load (ESAL), axle load spectra, etc.
Environmental data	Rainfall, temperatures, frozen index, etc.
Pavement condition data	Pavement condition indices, usually divided in 3 categories: distresses, structural capacity, surface characteristics (roughness, surface texture, and friction, noise).

Traffic history is collected and published annually for the entire network. For every road segment, the published document [71] provides information about the Annual Average Daily Traffic (AADT) (including both directions), the percentage of heavy vehicles, and the Annual Average Daily Traffic of Heavy Traffic in the project lane (H.AADT). Based on Spanish laws [72], a heavy vehicle is defined as any vehicle that weighs over 3500 kg and the project lane is considered the lane with the highest quantity of heavy vehicles. Regarding traffic distribution, each of the lanes on two-lane roads is considered to have half of both total and heavy traffic. In the case of freeways or multilane highways (two-carriageway highways) with two lanes per direction, the lane on the right is assumed to support all the heavy traffic in that direction, normally assumed to be the half of the traffic in both directions. If the two-carriageway highway has 3 or 4 lanes, the lane on the right is considered to have 85% of the heavy traffic in that direction (half of both directions).

Due to the small surface area of the province of Biscay, environmental data are not considered an essential factor because of the homogeneous oceanic climate of the entire province. The only environmental data are the accumulated precipitation (mm) at the nearest meteorological station to the tested road 15 days before the SCRIM took skid resistance values in 2016.

The RGB tracks pavement data as projects are completed, which have been documented since the RGB assumed responsibility of the roadway network in 1983. Some roadways have not had new pavement segments in that time period, so every roadway does not have project information. Additionally, maintenance and rehabilitation (M&R) activities have been recorded since 2000. Complete information about each project can be found in the PMS:

- Project data. Detailed information about the project: name, project manager and contractor, type of project, date of redaction, date of the end of the works, etc.
- Pavement information. Exhaustive information about extended pavement section: road denomination, initial and final Kilometer Point (KP) of the project, type of pavement activity (one of the most important features): New Segment, if the entire pavement section is new, from surface layer to base or subbase; or M&R work, if surface layer was only affected), and complete information about pavement layers: employed materials in each layer and their denomination, their thickness and binders.

Once this information is introduced in the PMS, two types of files can be obtained from the PMS software when examining each road:

- Pavement Structure File: This file presents the entire road divided in different segments as a function of the known pavement structure. If the complete pavement section is known, the file presents all the available information: thickness and materials of all the layers (surface layer, base and subbase) and the exact date when it was open to traffic. In the segments with incomplete pavement section, available data are provided.
- Surface Layer File: This file presents the entire road divided in segments according to the material in the surface layer. Although the entire pavement section is unknown, information about the surface layer can be found because the M&R work history since 2000 are available in the PMS. If a superficial treatment was applied, such as slurries, it is denoted, considering them differently from surface materials.

The RGB collects pavement condition data in the form of skid resistance data using SCRIM. SCRIM has a long tradition in Spain but it is not necessary to apply the correlation coefficient (0.78) because all the measures were conducted with truck style SCRIMs. Consequently, all the SCRIM values, both in Spain and in Biscay, can be regarded as SCRIM Coefficients (*SC*). Data collection efforts were performed on the entire road network in 2000, 2002 (partially), 2004, 2007, 2011, and 2016. For data in 2000, 2002, 2004, and 2007, the date of the data collection was not precisely listed. In 2011, most of the data were collected in February and March. As previously noted, friction values in winter are at their maximum. On the contrary, in 2016, the RGB collected skid resistance data in summer, when values are at their minimum and the variation is at their least. SCRIM Coefficient data are provided every 20 m of the road, indicating the exact initial and final KP. On single carriageway roads, friction values are taken from one of the two lanes, without indicating the exact lane. For double carriageway roads, separate data are provided for each direction. In each direction, friction values are registered in the right lane, the lane with the majority of the heavy traffic.

4. Analysis methodology

4.1. Skid resistance prediction model

There are several types of prediction models in the literature, but deterministic and probabilistic models which have attracted the greatest attention [73-75]. Skid resistance models published in the literature, as shown in section 2, are deterministic models. Consequently, a deterministic model, based on a multiple linear regression was established as the type of model to be used for this study. Furthermore, unlike Artificial Neural Network (ANN) models that can be considered a black box [75-76], with deterministic models, it is possible to directly know and understand the variables that really affect the dependent variable.

Multiple linear regression (MLR) analysis is a statistical technique used for analyzing the relationship between a quantitative variable (metric) and various independent variables, which are also quantitative. The aim of the MLR analysis is to employ the independent variable, whose values are known, to predict the dependent variable (response). Additionally, it allows for the inclusion of independent variables that are qualitative (no metric) if fiction variables are used (regression models with fiction variables), after transforming to quantitative variables. In MLR analysis some assumptions are made [77-79].

Alternatively, Analysis of Variance (ANOVA) is a statistical technique used for analyzing the relationship between a quantitative dependent variable and various qualitative independent variables. The Analysis of Covariance (ANCOVA) is a statistical technique employed for analyzing the relationship between a quantitative dependent variable and various independent variables, which can include qualitative and quantitative variables. Lastly, the General Linear Multiple (GLM) regression model is the most general form of linear regression modeling, including a MLR model with quantitative variables and the MLR models with qualitative and quantitative variables at the same time, and, hence, it includes all the models of ANOVA and ANCOVA [79].

4.2. Analysis approach and selected variables

The road network of Biscay is divided in five network levels: preferential interest, basic, complementary, provincial, and local. Data for local roads are not introduced in the PMS and necessarily were excluded from this study. These roads represent 46.2% of the network (603.1 km), but their mobility impact is minimal with only 6.5% of the total movement (303 million veh·km). In the first phase, road segments with fully documented pavement structures (i.e., with information about surface, base and subbase layers) were used evaluate the impact on available friction of the pavement type (flexible or semi-rigid), the quantity of layers, their thickness, and employed materials. These data was obtained from the Pavement Structure File of each road. Previous research has indicated that there is no consistent relationship between pavement structure and skid resistance [80-82]. Through the application of phase 1, if the results showed that structural properties of the pavement did not influence the skid resistance data, a different approach would be adopted for further steps.

In phase 1, only segments of two-lane roads were analyzed because the existence of additional available lanes in that direction may result in different polishing action on the pavement. Furthermore, the friction data of all the individual sections (20 m in length) were available which allowed for the observation that a wide variance of friction results within a roadway segment with the same predictive values. For example, for a 500 m roadway segment with the same data characteristics (traffic volumes, age, and pavement section), 25 values of 20 m long sections were available and displayed substantial variance for friction data. Consequently, the mean SCRIM Coefficient for each segment with similar characteristics (pavement structure, pavement age, and traffic volumes) was calculated based on the data of the 20 m sub-segments that compose it. Unlike probabilistic models, which show a range of variation for the predicted variable [74,75,83,84], this type of calculation is typical in deterministic models, as they attempt to calculate a mean value for the predicted variable as a function of some independent variables.

The Mean Summer SCRIM Coefficient (*MSSC*) was selected as the dependent variable to be predicted, as the mean value of a segment with similar characteristics (traffic, pavement section, and age). Friction values from 2016 were used to develop a model that predicts the friction value when it is at its minimum for consistency with the Transport Research Laboratory, which established the

SCRIM Coefficient data collection period during the summer results in its minimum value [49,56] (Figure 2).

Quantitative and qualitative potential predictor variables, the independent variables, were considered and the following list enumerates the quantitative variables:

- Annual Average Daily Traffic (*AADT*): AADT of the year of the data collection (2016).
- Annual Average Daily Traffic of Heavy Traffic (*H.AADT*): Number of heavy vehicles (weight over 3500 kg) per day and lane in the project lane (the lane with the most heavy traffic).
- Age (*Age*): Difference between the year of the data collection and the year when the new segment was carried out or the rehabilitation or maintenance work was finished.
- Real age (*R.Age*): Difference between the year of the data collection and the year when the new segment was carried out or the rehabilitation or maintenance work was finished, expressed in decimal format (i.e, 6 months equals 0.5 year). For example, if the data collection is carried out in the final days of June 2016, it is computed as 2016.5. Thus, it is possible to derive a more accurate age of the pavement.
- Total vehicles (*TotVeh*): Total number of vehicles that crossed the section since it was first constructed (in case of new segments) or when it was rehabilitated or maintained until the data collection, in thousand of vehicles.
- Total heavy vehicles (*TotH.Veh*): Similar to *TotVeh* but refers to the heavy vehicles that crossed the section in the project lane of the segment, in thousands of heavy vehicles.
- Required Polished Stone Value, PSV_{req}: Minimum PSV required according to the existing standard at the time of the project (the actual Polished Stone Value of the aggregates used for each road was not recorded). Although it was not the real value, it can be assumed that contractors only used aggregates that were slightly above the established limit in each situation. The standards establish the required PSV as a function of the surface layer material and the heavy traffic category of the roadway segment. This approximate value was introduced based on the influence of this factor in other models [49,66].
- Rainfall data, *Rain15*: Rainfall data, in mm, recorded 15 day before the data collection at the nearest meteorological station to the road. It is the only available data related to rainfalls, not indicating the measured rain intensities.
- Total thickness of bituminous layers, *TotBit*: Total sum of the thicknesses of the bituminous layers in the pavement section, in cm.

The qualitative predictor variables included:

- Pavement type, *PaveType*: Distinguishes between two possibilities: flexible pavements (1) and semi-rigid (2). More information about the complete pavement structure is known, but initially the influence of the pavement type was isolated for assessment.
- Surface denomination, *SurfDen*, and surface type, *SurfType*: Distinguishes between the denominations of the surface layer material (*SurfDen*) and, if gathered according to similar properties, in surface layer types (*SurfType*) (Table 5). The surface layer denominations (*SurfDen*) in Table 5 were grouped as indicated in the other columns because, in some analyses, few data exist in some of the surface denominations which led to grouping them according to similar characteristics. For example, although discontinuous mixes (BBTM type) and porous asphalts (PA) are different, they share some characteristics (ability to drain rain water). Similarly, the asphalt concrete mixtures which can have different gradations, semi-dense (S) and dense (D), but they share some attributes. Consequently, they were grouped to avoid groups with only one or two examples.

Table 5. Possible surface layer materials and levels of variables for surface layer materials

Surface denomination (SurfDen)	**Surface Type (SurfType)**	**Surface Denomination 2 (SurfDen 2)**

AC 16 surf S (Asphalt Concrete semi-dense) (1)	Asphalt concrete (AC) (1)	AC 16 (1)
AC 22 surf S (Asphalt Concrete semi-dense) (2)	Asphalt concrete (AC) (1)	AC 22 (2)
AC 16 surf D (Asphalt Concrete dense) (3)	Asphalt concrete (AC) (1)	AC 16 (1)
AC 22 surf D (Asphalt Concrete dense) (4)	Asphalt concrete (AC) (1)	AC 22 (2)
BBTM 11A (Discontinuous mixing) (5)	Discontinuous and porous (2)	BBTM 11A (3)
BBTM 11B (Discontinuous mixing) (6)	Discontinuous and porous (2)	BBTM 11B (4)
PA 11 (Porous asphalt) (7)	Discontinuous and porous (2)	PA (5)
LB2 (Slurry) (8)	Slurry (3)	LB2 (6)

5. Results and discussions

5.1. Model for known entire pavement section

The first phase of this study was conducted only using roadway segments with full pavement information. For pavement classified as New Segment, i.e., pavements that have not yet experienced any M&R activities, there were 49 observations (19 flexible pavement and 30 semi-rigid). Observations that were younger than 2 years were eliminated based on findings from Kokkalis [46], which showed that the equilibrium phase or stationary period of pavement friction was achieved after 2 years. Navarro et al. [43] also exposed that, when analyzing new pavement surfaces in the province of Gipuzkoa, also in the Basque Country and with a similar climate to Biscay, the equilibrium phase began after 2 years. Therefore, to remove sections that did not achieve the stationary phase which could bias the analysis, sections with a real age lower than 2 years were discarded. Consequently, 42 sections were employed for modeling.

The following analysis was conducted (and repeated in successive analyses). The correlation between the dependent variable (MSSC) and the independent quantitative variables was observed by means of the Pearson coefficient (*R*) (Table 6).

Table 6. Correlation between the dependent variable and the independent variables (Pearson coefficient) in segments classified as New Segment with a real age not lower than 2 years.

Independent Variables	Correlation with MSSC (Pearson coefficient, R)	Significance of the correlation (bilateral)
AADT	-0,493	0,001
H.AADT	-0,322	0,038
Age	0,152	0,336
R.Age	0,149	0,345
TotVeh	-0,274	0,079
TotH.Veh	-0,257	0,100
PSV	-0,491	0,001
Rain 15	-0,138	0,385
TotBit	-0,362	0,018

The variables with best correlation with *MSSC* were *AADT*, PSV_{req}, *TotBit,* and *H.AADT*. After observing the plot of the dependent variable (*MSSC*) vs. each of the independent variables, the curves that best fit the data were calculated (Table 7) and variables were transformed as suggested by the equations to obtain better correlation. However, in all the analyses, the best curve was not always selected, as typically, quadratic and cubic curves fit better but they do not reproduce the pattern described in the literature. In other cases, if the difference in the determination coefficient between the linear correlation and others is very low ($\Delta R^2 < 0.05$), the linear model was maintained, implying that the independent variable was not transformed.

Table 7. Equations that best correlate each independent variable individually with the dependent variable for segments classified as New Segment with real age not lower than 2 years.

Independent Variable	Equation type	Resume of the model					Parameter estimates	
		R^2	F	Degrees of freedom 1	Degree of freedom 2	Sig.	Intercept	b1
AADT	Logarithm	0,284	15,828	1	40	< 0,001	88,501	-4,382
H.AADT	Logarithm	0,141	6,591	1	40	0,014	63,84	-2,33
Age	Linear	0,023	0,950	1	40	0,336	49,337	0,167
R.Age	Linear	0,022	0,914	1	40	0,345	49,392	0,165
TotVeh	Logarithm	0,126	5,776	1	40	0,021	77,916	-2,794
TotH.Veh	Inverse	0,105	4,716	1	40	0,036	49,169	609,59
PSV	Linear	0,241	12,706	1	40	0,001	90,295	-0,84
Rain15	Linear	0,019	0,771	1	40	0,385	53,342	-0,074
TotBit	Linear	0,131	6,044	1	40	0,018	59,048	-0,473

With qualitative variables, the analysis included a Levene test to contrast the hypothesis of the groups defined by the factor variable coming from the population with the same variance. This test is complemented with a *t* test to compare mean values of the levels obtained applying the factor (qualitative variable) by means of the difference between their means. The *t* test is applied when there are only 2 possible groups in each of the qualitative variables. If there are more than two groups, an ANOVA (Analysis of the Variance) was conducted.

Then, multiple linear models were evaluated with the transformed quantitative variables, in this case natural logarithms applied to *AADT*, *H.AADT,* and *TotVeh,* according to Table 7. Models were accepted if:

1) They had global significance - the Fisher-Snedecor test with a p-value below 0.05.
2) All the introduced variables had individual significance - 95% significance that the coefficient of the variables are different from 0 (p-value < 0.05) using the Student's t test.

The aim was to isolate which introduced variables in the model to predict MSSC have a true impact on the friction. This analysis was conducted with the functions Step by Step and Forward of the IBM SPSS v24. The analysis showed that the unique independent variable was Ln*AADT* (the natural logarithm of AADT), was the one with the highest correlation, $R^2 = 0.266$, without being able to introduce more variables if significance of the coefficients was required. Then, General Linear Models (GLM) were applied including the two qualitative variables (*PaveType* and *SurfType*) and the quantitative independent variables that best correlate with MSSC (dependent variable). The variables *PaveType*, *SurfTyp*e, and Ln*AADT* showed low significance together. After several trials, Ln*AADT* was almost always a significant variable and, PSV_{req} was near the 90% of confidence to be a true variable (different from zero).

The analysis of the roadway segments with M&R activities, segments that were rehabilitated or maintained and their entire pavement structure was known, included 60 observations after removing the values with a real pavement age less than two years. The variables that best correlated with *MSSC* were *AADT* (R = 0.443) and *H.AADT* (*R* = 0.436). The analysis of the curves that best fit the MSSC indicated that for *AADT*, *H.AADT*, *TotVeh,* and *TotH.Veh* a logarithmic transformation was most appropriate. The multiple linear regression (MLR) analysis showed that the only variable included in the model was Ln*AADT*. The GLM analysis, after combining different possibilities with the qualitative variables, indicated that the best model with all the variables significant had the form of Equation 12, with a R^2 of 0.503:

$$MSSC = Intercept + LnAADT + SurfType \tag{12}$$

After developing the models for fully known pavement segments grouped according to New Segment or M&R sections, the main variables affecting the skid resistance were the *AADT* (especially with its natural logarithm), *H.AADT,* and PSV_{req}. *H.AADT* and PSV_{req} were identified in the literature as the primary variables affecting skid resistance. Other variables that were not significant included: *Age*, *R.Age*, *TotBit*, and *Rain15*. TotVeh and TotH.Veh showed relatively good correlation (0.38 < R < 0.20). With regard to the qualitative variables, *PaveType* (the division between flexible and semi-rigid pavements) was not significant. Conversely, *SurfType* was significant for M&R segments. The important factors were similar in both provisional models, so a similar analysis was conducted with all the observations (42+60) and an additional qualitative variable, *WorkType*, to distinguish between New Segment and M&R sections. With the 102 observations of completely known pavement segments with a real age not less than 2 years, a similar analysis was conducted and in the MLR analysis, Ln*AADT* was the only variable included in the model. Various GLMs were examined and *WorkType* and *PaveType* showed low correlation. The best model obtained a determination coefficient of 0.466, Equation 13., with all the variables with a significance of 90%. An alternative GLM model with the variables proposed by Szatkowski and Hosking (1972) and *SurfType* obtained a lower R^2 (0.387), but all the variables were significant.

$$MSSC = Intercept + LnAADT + PSV_{req} + SurfType \tag{13}$$

The complete analysis with pavements sections of known characteristics led to the crucial finding that the details of the complete pavement structure are not required to understand and predict pavement friction. This analysis demonstrated that *PaveType*, the variable distinguishing between flexible and semi-rigid pavements did not influence the friction prediction. Additionally, *TotBit*, which indicates the total thickness of bituminous layers in cm showed low correlation with the dependent variable (MSSC) and was not included in any model. Moreover, the analysis according to groups of *WorkType* (New Segment and M&R) showed that it was not an influencing factor; it was a qualitative variable with low significance.

The idea that the pavement structure does not influence or does not have a relationship with surface characteristics has been documented in literature [17,80,81]. The remaining variables (*AADT*, *H.AADT*, PSV_{req}, *TotVeh*, *TotH.Veh*, *Age*, *R.Age,* and *SurfType*) can also be obtained if the data about the surface layer is known. The Surface Layer file of the PMS of the Regional Government of Biscay can be used to define the characteristics of the surface layer. Traffic data were also available [71]. Consequently, the entire road network managed by the RGB could be examined to predict the skid resistance (excluding local roads).

5.2. Model for sections with known surface layer

The Surface Layer file was used to divide the roads of the network according to surface layer and when the last project was conducted on that segment. After the roadway segment was divided according to surface characteristics, the traffic data were used to make another division, which did not necessarily coincide with the project information division. The two divisions of the road were used to create segments with the same characteristics, in terms of both the pavement surface and traffic, with variable length (and number of observations) (Figure 4). The average value for the segment with the same characteristics was calculated due to the potential for substantial variability within the observations in the segment.

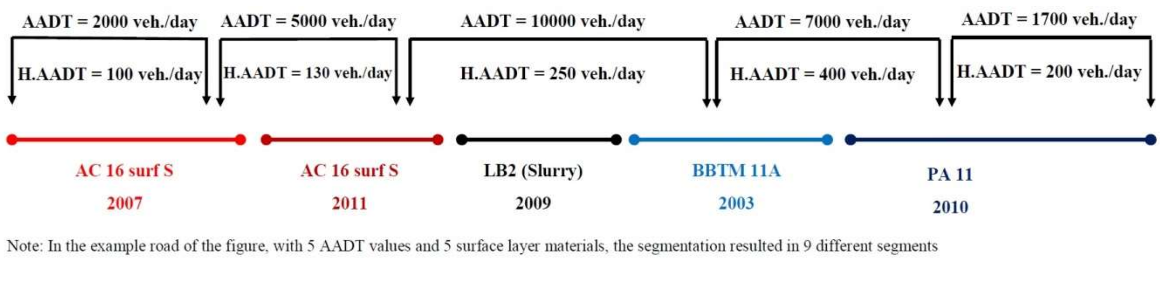


Figure 4. Examples of road length division by surface characteristics and traffic data for analysis for skid resistance modeling.

All roadway types were included in the analyses, i.e. single carriageway roads (two-lane roads) and double carriageway roads (multilane highways and motorways). There were 928 observations, but 114 have a real age less than 2 years and, hence, they were discarded because they did not reach the stationary phase [43,46]. Additionally, some outliers (18) were removed from the analysis because the pavement values were derived from only 1 or 2 observations (sections of 20 and 40 m), and they were considered as not representative. Consequently, 796 observations were included in the following analyses.

The quantitative variables are *AADT*, *H.AADT*, PSV_{req}; *Age*, *R.Age*, *TotVeh*, *TotH.Veh,* and *Rain15*. A qualitative variable to account for each possible material in the surface layer was considered, but due to low sample size for some materials, a new variable (*SurfDen2*) was created that based on a representative quantity of data for each material of Asphalt Concrete (AC), as shown in Table 5. AC mixes were divided according to the maximum diameter of aggregates, 16 and 22, which was thought to have a higher influence than the gradation of the mixing (dense or semi-dense). Moreover, another qualitative variable was created, *RoadType*, which distinguishes between single and double carriageway roads, to determine if this distinction has influence on the skid resistance modeling.

The correlations between the *MSSC* (dependent variable) and the quantitative independent variables showed that the best Pearson coefficients (*R*) were found with *AADT*, *H.AADT,* and PSV_{req} (Table 8).

Table 8. Correlation between the dependent variable and independent variables (coefficient of Pearson) in all the segment with known surface layer and a real age not lower than 2 years

Independent Variables	Correlation with MSSC	Significance of the correlation (bilateral)
AADT	-0,343	< 0,001
H.AADT	-0,307	< 0,001
Age	-0,118	0,001
R.Age	-0,118	0,001
TotVeh	-0,263	< 0,001
TotH.Veh	-0,23	< 0,001
PSV	-0,35	< 0,001
Rain 15	-0,086	0,014

Possible transformations of the variables were studied. The correlation with *AADT* and *H.AADT* was improved with a natural logarithm. Transformations of these transformations were also analyzed. Transformations considered in the analysis are shown in Table 9.

Table 9. Correlation between the dependent variable and some transformed independent variables (coefficient of Pearson) in all the segments with known surface layer and a real age not lower than 2 years

Independent Variables	Correlation with MSSC	Significance of the correlation (bilateral)
LnAADT	-0,574	< 0,001
LnH.AADT	-0,516	< 0,001
1/LnAADT	0,606	< 0,001
1/LnH.AADT	0,548	< 0,001
(AADT)^1/2	-0,454	< 0,001
(H.AADT)^1/2	-0,407	< 0,001
LnAADT	-0,556	< 0,001
LnH.AADT	-0,516	< 0,001

Several GLMs were also developed and tested. The combinations of all the qualitative variables typically had low significance, so models with only a subset of the variables were also considered. This evaluation found that the qualitative variable *RoadType* had substantial influence on the predicted values (obtaining a higher R^2). The variable *H.AADT* reflects the quantity of lanes that can exist on a double carriageway road, as explained in section 3. Nevertheless, because *AADT* showed a greater correlation to *MSSC* than *H.AADT* (Tables 6, 7, 8 and 9), a freeway with an *AADT* of 50.000 vehicles/day is substantially different than a two-lane or a three-lane carriageway. The quantity of vehicles in each lane is different and consequently, an additional qualitative variable was included, *Lanes*, and its levels are shown in Table 10.

Table 10. Types of roads and its classification according to the qualitative variables RoadTypes and Lanes

Type of road	Levels of variable *RoadType*	Levels of variable *Lanes*
Unique carriageway, two-lane road	1	1
Double carriageway, two lanes per carriageway in each direction	2	2
Double carriageway, three or four lanes per carriageway in each direction*	2	3

* In the traffic data of the RGB, sections with 3 or 4 lanes per carriageway are indicated similarly and hence, they cannot be distinguished

General Linear Models were built and tested with the new variables and to consider the surface material, variations of the same model were studied with *SurfType*, *SurfDen,* and *SurfDen2*. The best GLMs, with the highest R^2 and all the significant (or almost significant) variables are shown in Table 11.

Table 11. Proposed General Linear Models in all the segments with known surface layer and a real age not lower than 2 years

Proposed model	R^2	Adj R^2	Comments and observations
MSSC = Int + LnAADT + SurfType(f) + Lanes(f) + Lanes*LnAADT + PSV*SurfDen2*Lanes*LnAADT	0,555	0,532	All variables have a p-value < 0,03
MSSC = Int + LnAADT + SurfDen2(f) + Lanes(f) + Lanes*LnAADT + PSV*SurfDen2	0,537	0,522	PSV*SurfDen2 has low significance (p=0,729)
MSSC = Int + LnAADT + SurfDen2(f) + Lanes*LnAADT + PSV*SurfDen2*LnAADT	0,542	0,528	PSV*SurfDen2*LnAADT has medium significance (p=0,117)
MSSC = Int + LnAADT + SurfDen2(f) + Lanes(f) + Lanes*LnAADT + PSV*SurfDen2*LnAADT	0,546	0,528	PSV*SurfDen2*LnAADT has medium significance (p=0,139)
MSSC = Int + LnAADT + SurfDen2(f) + Lanes(f) + Lanes*LnAADT + PSV*SurfType*LnAADT	0,542	0,430	All variables have a p-value < 0,05
MSSC = Int + LnAADT + SurfDen2(f) + Lanes(f) + Lanes*LnAADT + PSV*SurfType*LnAADT*Lanes	0,554	0,537	All variables have a p-value < 0,01
MSSC = Int + LnAADT + SurfDen2(f) + Lanes(f) + Lanes*LnAADT + SurfType*LnAADT*Lanes	0,536	0,530	All variables have a p-value < 0,01
MSSC = Int + LnAADT + SurfDen2(f) + PSV(f) + Lanes*LnAADT	0,503	0,495	All variables have a p-value < 0,01
MSSC = Int + LnAADT + SurfDen2(f) + Lanes(f) + PSV(f) + Lanes*LnAADT	0,531	0,522	PSV has low significance (p=0,881)
MSSC = Int + LnAADT + SurfDen2(f) + Lanes(f) + Lanes*LnAADT	0,530	0,524	All variables have a p-value < 0,01
MSSC = Int + LnAADT + SurfDen2(f) + Lanes(f) + Lanes*LnAADT + SurfDen2*PSV*LnAADT	0,540	0,528	SurfDen2*PSV*LnAADT has medium significance (p=0,139)
MSSC = Int + LnAADT + SurfDen2(f) + Lanes(f) + Lanes*LnAADT + SurfDen2*PSV*LnAADT*Lanes	0,560	0,534	All variables have a p-value < 0,04

Note: Int = Intercept

Table 11 represents a summary of the extensive set of models that were built, tested, and evaluated. From the analysis, the following ideas were extracted:

- The quantitative variables that produced the best models were Ln*AADT* and 1/Ln*AAD*T and the best performing qualitative variables included: PSV_{req}, *RoadType*, *Lanes*, *SurfType,* and *SurfDen2*. *SurfDen* was expected to be one of the most influential factors because it determines all the possible surface layer materials. However, it was not the one that best correlated because there are some values (levels) with 1 or 3 observations. Material characteristics described by *SurfType* and *SurfDen2* resulted in better results.
- *H.AADT* produced worse models than *AADT* (or their transformations). When both variables were introduced, *H.AADT* usually became statistically insignificant and was removed.
- The inclusion of qualitative variables let to better models than models without them.
- The qualitative variable *Lanes* produced better models than *RoadType*.
- The introduction of 1/Ln*AADT***Lanes* or Ln*AADT***Lanes* always improved the results and obtained higher R^2 values than using *RoadType*. Hence, the importance of the variable *Lanes*

was apparent. which better described the presence of 3 (or 4) lanes in a double carriageway road.

- Although Ln*AADT* (or 1/Ln*AADT*) and Ln*AADT**Lanes* (or 1/Ln*AADT**Lanes*) were included in the model, the inclusion of *Lanes* as an additional variable improved the model and was always significant.
- If 1/Ln*AADT* was combined with Ln*AADT**Lanes* (or vice versa), the first one became insignificant. Ln*AADT* or 1/Ln*AADT* must be employed in both variables to avoid becoming statistically insignificant.

Based on the findings from the analysis and the determination coefficient (R^2) of the models, to the two following proposed models best represent the friction available in the road network of Biscay:

- A short model, with three variables and a combination of two variables, is recommended as an option to avoid a long list of applied coefficient, in the form of Equation 14 with a R^2 = 0.530 and all the variables were significant (p-value < 0.001)

$$MSSC = Intercept + LnAADT + SurfDen2 + Lanes + Lanes * LnAADT \tag{14}$$

- A long model, with the variables included in Equation 14 and an additional combination of some variables result in a higher R^2 = 0.560 and all the variables significant with a 95% of confidence (p-value < 0.04) (Equation 15)

$$MSSC = Intercept + LnAADT + SurfDen2 + Lanes + Lanes * LnAADT$$

$$+ SurfDen2 * PSV * Lanes * LnAADT \tag{15}$$

Although a better short model and a better long model could be obtained independently, these models use the same variables as a balance between the statistical results and consistency during the application of the models. The only difference between both proposed equations is the last component of Eq. 15. PSV_{req} functions as a qualitative variable (according to the different values established by Spanish regulations).

Table 12 shows the test of Between-Subject effects for the model of Equation 14, showing that all the variables are significant (p < 0.001). Table 13 presents the estimations of the parameters (coefficients) of the model.

Table 12. Test of Between-Subjects effects for model of Equation 14, proposed short model.

Origin	Type III Sum of Squares	Degree of freedom	Mean Square	F	Sig.	Partial eta-squared	Non centrality parameter	Observed Power
Corrected model	26815,861	10	2681,586	88,638	< 0,001	0,53	886,382	1,000
Intercept	3333,343	1	3333,343	110,182	< 0,001	0,123	110,182	1,000
LnAADT	631,574	1	631,574	20,876	< 0,001	0,026	20,876	0,995
Lanes	1950,421	2	975,211	32,235	< 0,001	0,076	64,47	1,000
Lanes*LnAADT	2315,593	2	1157,797	38,27	< 0,001	0,089	76,541	1,000
SurfDen2	5284,665	5	1056,933	34,936	< 0,001	0,182	174,681	1,000
Error	23748,739	785	30,253					
Total	2015919,12	796						
Corrected total	50564,6	795						

Table 13. Parameter estimates for model of Equation 14, short model

Parameters	B	Std. Error	t	Sig.	95% CI		Partial eta-squared	Non centrality parameter	Observed Power
					Lower	U`pper			
Intercept	78,497	21,451	3,659	< 0,001	36,389	120,606	0,017	3,659	0,955
LnAADT	-2,321	1,894	-1,226	0,221	-6,038	1,396	0,002	1,226	0,232

[Lanes=1]	26,693	21,607	1,235	0,217	-15,722	69,107	0,002	1,235	0,235
[Lanes=2]	-16,663	22,030	-,756	0,450	-59,907	26,581	0,001	0,756	0,118
[Lanes=3]	0[a]	.	.	.	.	.	.	.	.
[Lanes=1] * LnAADT	-3,352	1,915	-1,750	0,081	-7,112	,408	0,004	1,750	0,416
[Lanes=2] * LnAADT	1,328	1,955	,679	0,497	-2,510	5,166	0,001	0,679	0,104
[Lanes=3] * LnAADT	0[a]	.	.	.	.	.	.	.	.
[SurfDen2=1]	-6,989	0,562	-12,433	< 0,001	-8,093	-5,886	0,165	12,433	1,000
[SurfDen2=2]	-5,047	1,391	-3,628	< 0,001	-7,778	-2,316	0,016	3,628	0,952
[SurfDen2=3]	-5,468	0,680	-8,046	< 0,001	-6,802	-4,134	0,076	8,046	1,000
[SurfDen2=4]	-4,213	1,857	-2,269	0,024	-7,859	-,568	0,007	2,269	0,620
[SurfDen2=5]	-7,467	0,959	-7,789	< 0,001	-9,349	-5,586	0,072	7,789	1,000
[SurfDen2=6]	0[a]	.	.	.	.	.	.	.	.

[a] Set to zero because this parameter is redundant.

Figure 5a and 5b present the diagrams of dispersion by level and provide graphic information about the variance homogeneity which allows for detecting the possible existence of a relationship between the size of the means and the size of the variance. As the variances are not equal, as tested previously by the Levene test, points in both figures are not horizontally aligned.

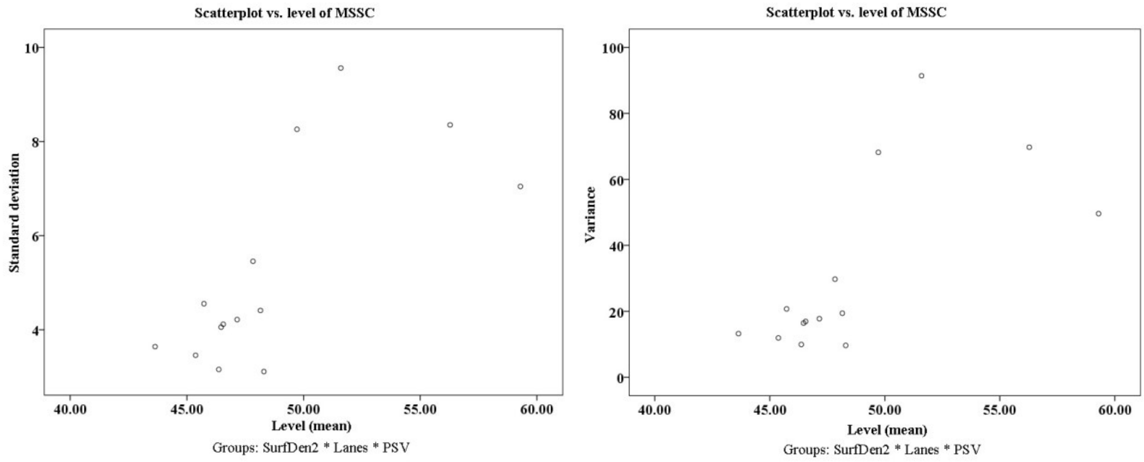


Figure 5. Scatterplots by level for Equation 14 a) Standard deviation, b) Variance.

The plot of residuals of Figure 6 allows for observations about their randomness and independence. The plot of predicted values vs. standardized residuals is random (there is not pattern) and the errors are independent. The residual variances are homogeneous because the dispersion of the standardized residuals is similar along all the values of predicted values. Predicted vs. Observed values can be better observed in Figure 7.

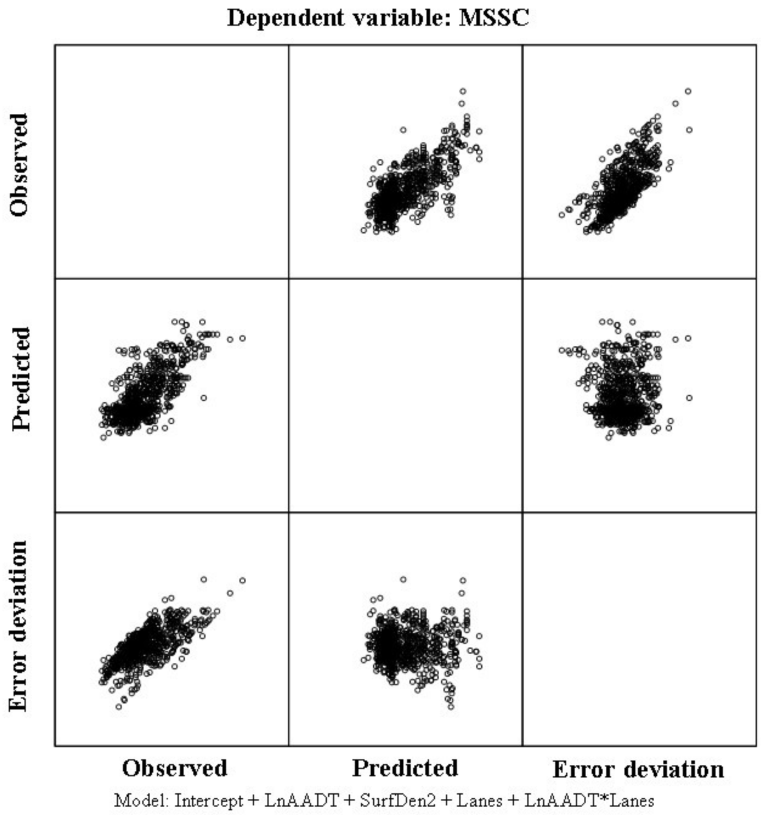


Figure 6. Plot of residuals (standardized), observed and predicted values of model of Equation 14

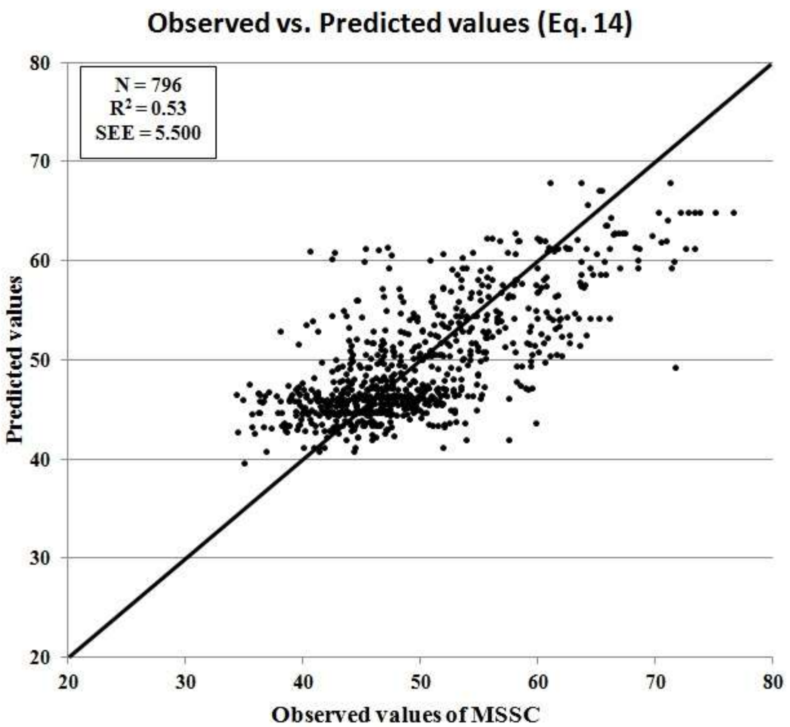


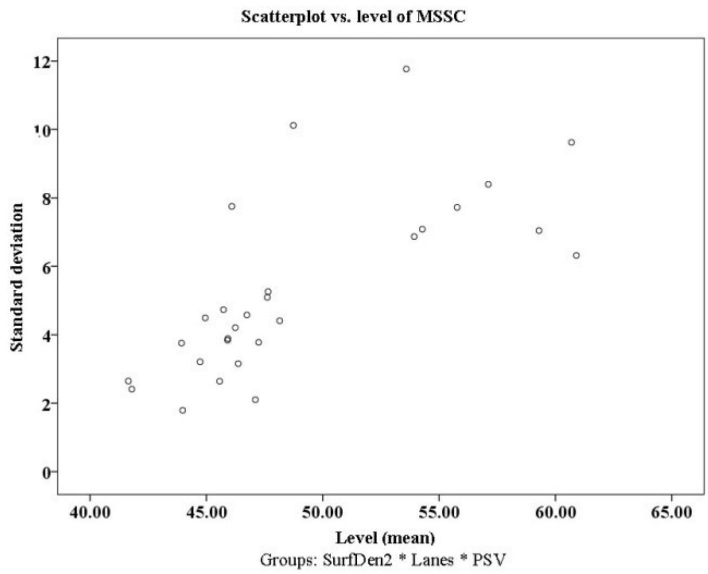
Figure 7. Observed vs. Predicted values for Equation 14.

With regard to the model proposed in Equation 15, the test of Between-Subjects effect of the model is presented in Table 14. All the variables had significance over 95% (p-value < 0.05). The estimation of the parameters (coefficients) of the model (Equation 15) is displayed in Table 15.

Table 14. Test of Between-Subjects effects for the model of Equation 15, proposed long model

Origin	Type III Sum of Squares	Degree of freedom	Mean Square	F	Sig.	Partial eta-squared	Non centrality parameter	Observed Power
Corrected model	28298,071[a]	43	658,095	22,226	< 0,001	0,560	955,701	1,000
Intercept	1711,608	1	1711,608	57,806	< 0,001	0,071	57,806	1,000
LnAADT	652,245	1	652,245	22,028	< 0,001	0,028	22,028	0,997
Lanes	263,004	2	131,502	4,441	0,012	0,012	8,882	0,763
Lanes*LnAADT	870,993	2	435,496	14,708	< 0,001	0,038	29,416	0,999
SurfDen2	899,968	5	179,994	6,079	< 0,001	0,039	30,394	0,996
PSV * SurDen2 * Lanes * LnAADT	1482,21	33	44,915	1,517	0,033	0,062	50,058	0,992
Error	22266,529	752	29,610					
Total	2015919,12	796						
Corrected total	50564,6	795						

Figure 8a and 8b show the diagrams of dispersion by level. As shown, the points in both plots are not horizontally aligned, indicating that there are not homogeneous variances between the levels of the qualitative variables.



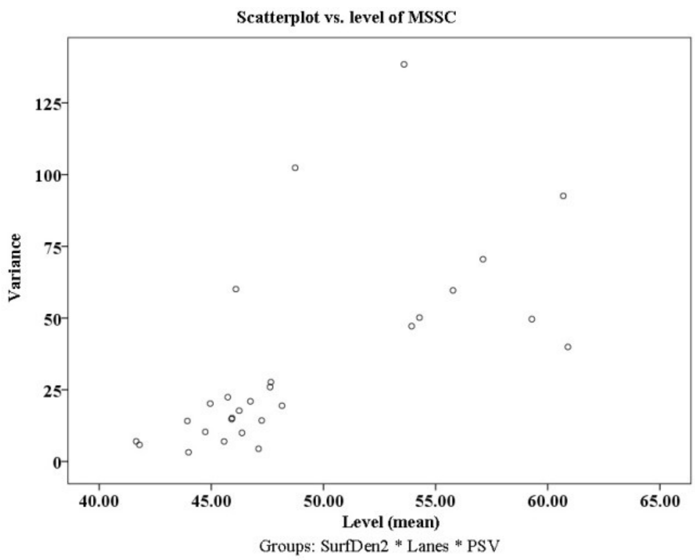


Figure 8. Dispersion diagrams by level for Equation 15, a) Standard deviation, b) Variance.

Table 15. Parameter estimates for the model of Equation 15, long model

Parameters	B	Std. Error	t	Sig.	95% CI Lower	95% CI U`pper	Observed Power
Intercept	114,946	26,275	4,375	0,000	63,364	166,527	0,992
LnAADT	-2,065	2,420	-0,853	0,394	-6,817	2,686	0,136
[Lanes=1]	9,473	25,685	0,369	0,712	-40,949	59,896	0,066
[Lanes=2]	-19,756	24,738	-0,799	0,425	-68,319	28,807	0,125
[Lanes=3]	0[a]	.	.	.	.	.	.
[Lanes=1] * LnAADT	-5,719	2,497	-2,291	0,022	-10,620	-0,818	0,629
[Lanes=3] * LnAADT	1,817	2,227	0,816	0,415	-2,554	6,189	0,129
[Lanes=3] * LnAADT	0[a]	.	.	.	.	.	.
[SurfDen2=1]	-34,317	7,609	-4,510	0,000	-49,255	-19,379	0,995
[SurfDen2=2]	63,566	37,759	1,683	0,093	-10,560	137,692	0,390
[SurfDen2=3]	-40,151	10,373	-3,871	0,000	-60,515	-19,787	0,972
[SurfDen2=4]	-0,722	50,872	-0,014	0,989	-100,590	99,147	0,050
[SurfDen2=5]	-47,639	18,074	-2,636	0,009	-83,121	-12,157	0,749
[SurfDen2=6]	0[a]	.	.	.	.	.	.
[PSV=40]*[SurfDen2=1]*[Lanes=1]* LnAADT	3,243	0,923	3,515	0,000	1,432	5,054	0,939
[PSV=40]*[SurfDen2=2]*[Lanes=1]*LnAADT	-7,108	3,993	-1,780	0,075	-14,946	0,731	0,428
[PSV=40]*[SurfDen2=2]*[Lanes=2]*LnAADT	-10,560	4,398	-2,401	0,017	-19,194	-1,926	0,669
[PSV=40]*[SurfDen2=6]*[Lanes=1]*LnAADT	-1,060	0,842	-1,258	0,209	-2,713	0,594	0,242
[PSV=44]*[SurfDen2=1]*[Lanes=1]*LnAADT	3,063	0,939	3,262	0,001	1,220	4,906	0,903
[PSV=44]*[SurfDen2=2]*[Lanes=1]*LnAADT	-10,389	5,242	-1,982	0,048	-20,679	-0,099	0,508
[PSV=44]*[SurfDen2=6]*[Lanes=1]*LnAADT	-0,374	0,238	-1,570	0,117	-,842	0,094	0,348
[PSV=45]*[SurfDen2=1]*[Lanes=1]*LnAADT	3,115	0,844	3,691	0,000	1,459	4,772	0,958
[PSV=45]*[SurfDen2=1]*[Lanes=2]*LnAADT	-1,595	1,684	-0,947	0,344	-4,900	1,710	0,157
[PSV=45]*[SurfDen2=1]*[Lanes=3]*LnAADT	-1,090	1,627	-0,670	0,503	-4,284	2,105	0,103
[PSV=45]*[SurfDen2=2]*[Lanes=1]*LnAADT	-7,302	4,254	-1,716	0,087	-15,654	1,050	0,403
[PSV=45]*[SurfDen2=2]*[Lanes=3]*LnAADT	-9,791	3,716	-2,635	0,009	-17,086	-2,496	0,749
[PSV=45]*[SurfDen2=3]*[Lanes=1]*LnAADT	4,993	1,401	3,565	0,000	2,243	7,742	0,945
[PSV=45]*[SurfDen2=5]*[Lanes=1]*LnAADT	5,007	2,237	2,239	0,025	,617	9,398	0,609
[PSV=45]*[SurfDen2=5]*[Lanes=2]*LnAADT	-0,328	0,423	-0,776	0,438	-1,159	0,503	0,121
[PSV=45]*[SurfDen2=6]*[Lanes=1]*LnAADT	-0,435	0,143	-3,038	0,002	-0,716	-0,154	0,859
[PSV=50]*[SurfDen2=1]*[Lanes=1]*LnAADT	2,903	0,842	3,446	0,001	1,249	4,557	0,931
[PSV=50]*[SurfDen2=1]*[Lanes=2]*LnAADT	-1,130	1,666	-0,678	0,498	-4,401	2,141	0,104
[PSV=50]*[SurfDen2=2]*[Lanes=1]*LnAADT	-8,084	4,293	-1,883	0,060	-16,511	0,343	0,468
[PSV=50]*[SurfDen2=2]*[Lanes=3]*LnAADT	-9,397	3,716	-2,529	0,012	-16,692	-2,102	0,714
[PSV=50]*[SurfDen2=3]*[Lanes=1]*LnAADT	3,834	1,125	3,406	0,001	1,624	6,043	0,925
[PSV=50]*[SurfDen2=3]*[Lanes=2]*LnAADT	-0,663	1,424	-0,465	0,642	-3,459	2,133	0,075
[PSV=50]*[SurfDen2=3]*[Lanes=3]*LnAADT	-0,392	1,384	-0,283	0,777	-3,109	2,326	0,059
[PSV=50]*[SurfDen2=4]*[Lanes=1]*LnAADT	-0,468	5,442	-0,086	0,931	-11,151	10,215	0,051
[PSV=50]*[SurfDen2=4]*[Lanes=2]*LnAADT	-4,427	5,199	-0,851	0,395	-14,633	5,780	0,136
[PSV=50]*[SurfDen2=5]*[Lanes=1]*LnAADT	4,482	1,939	2,311	0,021	0,675	8,289	0,636
[PSV=50]*[SurfDen2=5]*[Lanes=2]*LnAADT	-0,091	0,357	-0,254	0,799	-0,792	0,610	0,057
[PSV=50]*[SurfDen2=5]*[Lanes=3]*LnAADT	0,112	0,264	0,423	0,672	-0,407	0,630	,071
[PSV=50]*[SurfDen2=6]*[Lanes=1]*LnAADT	0[a]	.	.	.	.	.	.
[PSV=50]*[SurfDen2=6]*[Lanes=2]* LnAADT	-3,604	1,801	-2,001	0,046	-7,140	-0,068	0,515
[PSV=55]*[SurfDen2=3]*[Lanes=2]*LnAADT	-0,626	1,408	-0,445	0,657	-3,390	2,138	0,073
[PSV=55]*[SurfDen2=3]*[Lanes=3]*LnAADT	-0,320	1,390	-0,230	0,818	-3,049	2,410	0,056
[PSV=56]*[SurfDen2=3]*[Lanes=2]*LnAADT	-0,570	1,408	-0,405	0,686	-3,334	2,194	0,069
[PSV=56]*[SurfDen2=3]*[Lanes=3]*LnAADT	-0,456	1,385	-0,329	0,742	-3,175	2,264	0,062
[PSV=56]*[SurfDen2=5]*[Lanes=2]*LnAADT	0[a]	.	.	.	.	.	.
[PSV=56]*[SurfDen2=5]*[Lanes=3]*LnAADT	0[a]	.	.	.	.	.	.

Figure 9 shows that there is no pattern, and, hence, the errors are independent in the plot Predicted values vs. Standardized residuals. This plot also shows that the dispersion is similar along all the predicted values, indicating that the residual variances are homogeneous. In Figure 10 a more detailed plot of Observed vs. Predicted values for Equation 15 is displayed.

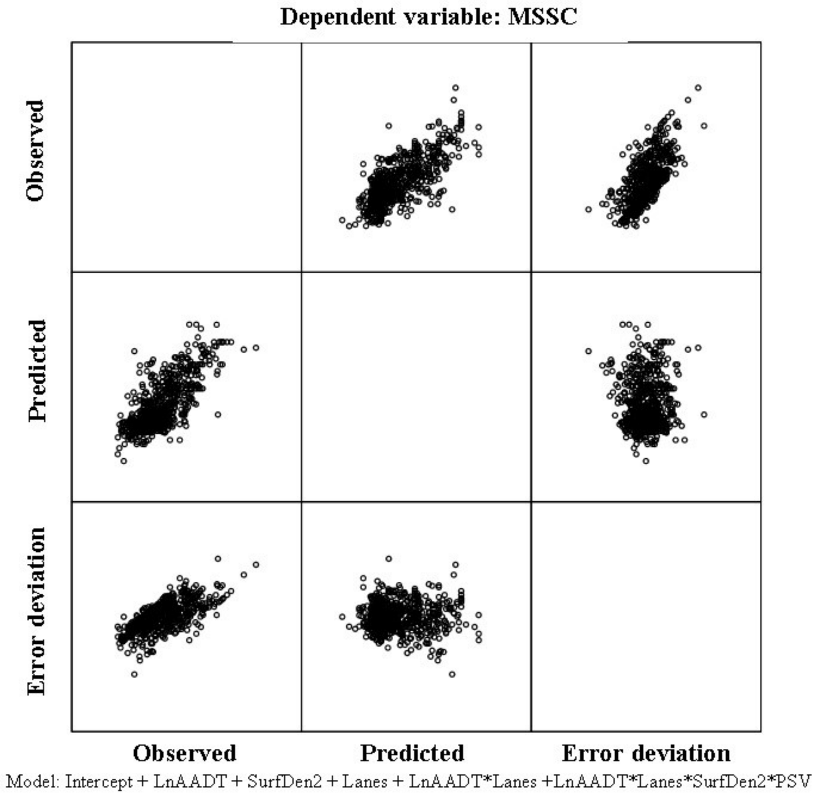


Figure 9. Plot of residuals (standardized), observed and predicted values of the model of Equation 15.

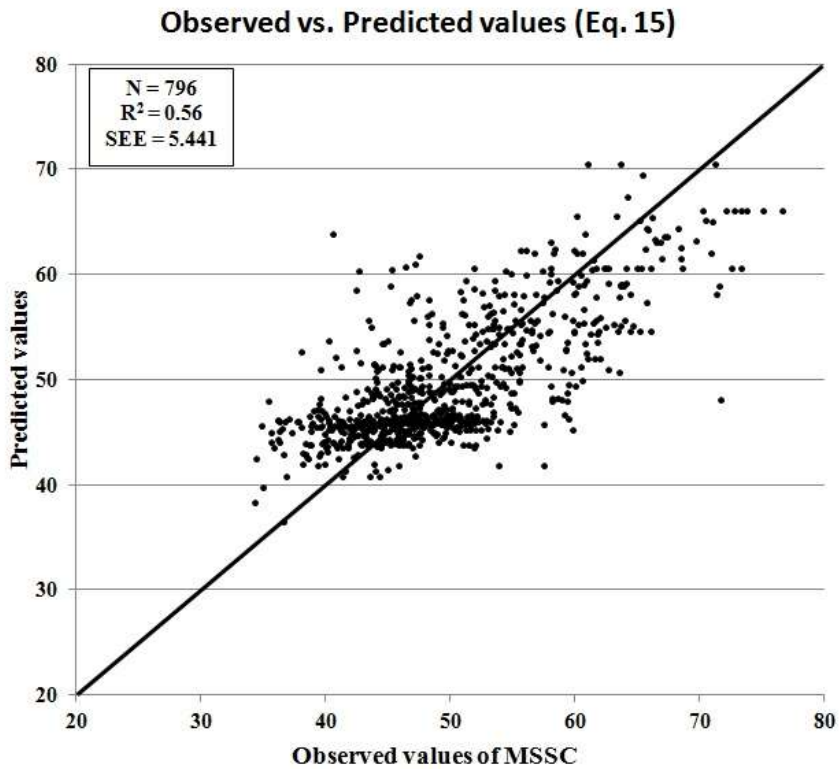


Figure 10. Observed vs. Predicted values for Equation 1.

Although the goodness of the models is not very high (0.53 and 0.56) and the scattering observed in Figures 7 and 10 can be relatively high, developed models improve the determination coefficient of similar models for predicting the available skid resistance for an entire network. Due to the probabilistic nature of the pavements [85,86], the typical range for predicting pavement indices at network level with deterministic models is between 0.50 and 0.60, and, hence, in accordance with models of other authors and institutions [87-90]. Moreover, the probabilistic nature of the pavements was also observed when the mean SCRIM Coefficient value was obtained in a homogeneous segment. Hence, despite the prediction, highway administrations will continue collecting friction data on the network, because sections with higher and lower values will be present within the homogeneous section and, hence, it will be still necessary to identify those sections with lower values. These models help to identify the segments that are more probable to have low skid resistance and the factors that influence it.

5.3. Summary of the proposed models

The short model, which has a determination coefficient of 0.530, is expressed by Equation 16:

$$MSSC = 78.497 - 2.321 \cdot LnAADT + A_{LANES} + B_{SURF} + C_{LANES} \cdot LnAADT \quad (16)$$

Where

- MSSC is the Mean Summer SCRIM Coefficient, expressed in a range from 0 to 100.
- Ln*AADT* is the natural logarithm of the Average Annual Daily Traffic of the road, in both directions, expressed in vehicles/day
- A_{LANES} is the coefficient that considers the type of road and takes the values presented in Table 16

Table 16. Values of the coefficient A_{LANES} in Equation 16.

Type of road	A_{LANES}
Two-lane roads, with one lane in each direction	26,693
Double carriageway motorways, with two lanes in each direction	16,663
Double carriageway motorways, with three or four lanes in each direction	0

- B_{SURF} is the coefficient that takes into account the surface layer material and takes the values shown in Table 17.

Table 17. Values of the coefficient B_{SURF} in Equation 16.

Surface layer material	B_{SURF}
AC 16	-6,989
AC 22	-5,047
BBTM 11A	-5,468
BBTM 11B	-4,213
PA 11	-7,467
LB2	0

- C_{LANES} is the coefficient that affects the value of the Ln*AADT*, to reflect the more accurate distribution of traffic in the right lane and takes the values shown in Table 18.

Table 18. Values of the coefficient C_{LANES} in Equation 16.

Type of road	C_{LANES}
Two-lane roads, with one lane in each direction	-3,352
Double carriageway motorways, with two lanes in each direction	1,328
Double carriageway motorways, with three or four lanes in each direction	0

For a more precise value, a long model is also proposed, Equation 17, with a slightly better determination coefficient (R^2 = 0,560).

$$MSSC = 114{,}946 - 2{,}065 \cdot LnAADT + A_{LANES} + B_{SURF} + C_{LANES} \cdot LnAADT + D_{S-P-L} \cdot LnAADT \qquad [17]$$

Where

- *MSSC* is the Mean Summer SCRIM Coefficient, expressed in a range from 0 to 100.
- Ln*AADT* is the natural logarithm of the Average Annual Daily Traffic of the road, in both directions, expressed in vehicles/day.
- A_{LANES} is the coefficient that considers the type of road and takes the values presented in Table 19

Table 19. Values of the coefficient A_{LANES} in Equation 17 (long model).

Type of road	A_{LANES}
Two-lane roads, with one lane in each direction	9,473
Double carriageway motorways, with two lanes in each direction	-19,756
Double carriageway motorways, with three or four lanes in each direction	0

- B_{SURF} is the coefficient that takes into account the surface layer material and takes the values shown in Table 20.

Table 20. Values of the coefficient B_{SURF} in Equation 17 (long model)

Surface layer material	B_{SURF}
AC 16	-34,317
AC 22	63,566
BBTM 11A	-40,151
BBTM 11B	-0,722
PA 11	-47,639
LB2	0

- C_{LANES} is the coefficient that affects the value of the Ln*AADT*, to reflect the more accurate distribution of the traffic in the left lane and takes the values presented in Table 21.

Table 21. Values of the coefficient C_{LANES} in Equation 17, (long model).

Type of road	C_{LANES}
Two-lane roads, with one lane in each direction	-5,719
Double carriageway motorways, with two lanes in each direction	1,817
Double carriageway motorways, with three or four lanes in each direction	0

- D_{S-P-L} is the coefficient that considers the combination of the surface layer material, the required Polished Stone Value of the aggregates in the regulation and the type of road. Multiple combinations exist for the levels of these factors, which results in a long list of values which are presented for each combination. They are listed according to the road type, which only has 3 levels (Tables 22 to 24).

Table 22. Values of the coefficient $D_{S\text{-}P\text{-}L}$ for two-lane roads, with one lane in each direction in Equation 17, (long model).

Surface layer material	PSV					
	40	44	45	50	55	56
AC 16	3,243	3,063	3,115	2,903	-	-
AC 22	-7,108	-10,389	-7,302	-8,084	-	-
BBTM 11A	-	-	4,993	3,834	-	-
BBTM 11B	-	-	-	-0,468	-	-
PA 11	-	-	5,007	4,482	-	-
Slurry	-1,060	-0,374	-0,435	0	-	-

Table 23. Values of the coefficient $D_{S\text{-}P\text{-}L}$ for double carriageway motorways, with two lanes in each direction in Equation 17, (long model).

Surface layer material	PSV					
	40	44	45	50	55	56
AC 16	-	-	-1,595	-1,130	-	-
AC 22	-10,560	-	-	-	-	-
BBTM 11A	-	-	-	-0,663	-0,626	-0,570
BBTM 11B	-	-	-	-4,427	-	-
PA 11	-	-	-0,328	-0,091	-	0
Slurry	-	-	-	-3,604	-	-

Table 24. Values of the coefficient $D_{S\text{-}P\text{-}L}$ for double carriageway motorways, with three or four lanes in each direction in Equation 17, (long model).

Surface layer material	PSV					
	40	44	45	50	55	56
AC 16	-	-	-1,090	-	-	-
AC 22	-	-	-9,791	-9,397	-	-
BBTM 11A	-	-	-	-0,392	-0,320	-0,456
BBTM 11B	-	-	-	-	-	-
PA 11	-	-	-	0,112	-	0
Slurry	-	-	-	-	-	-

All possible combinations of the levels of the three factors (*Lanes*, PSV_{req} and *SurfDen2*) are not proved because some combinations are impossible. For example, a three lane motorway will have a high traffic category requiring a high PSV. Moreover, for motorways with high volumes, in Biscay it is preferably recommended to employ discontinuous mixes and porous asphalts, since the rainfall data throughout the year is high due to the oceanic climate. For applying these results, if a combination is not displayed in Table 22 to 24, only the short model should be used (Equation 16).

As shown, unlike models developed for other surface characteristics, such as roughness or distress [90-92], in the proposed models of this paper, the cumulative total number of vehicles (*TotVeh*) or heavy vehicles (*TotH.Veh*) were not the key influential factors after a specific quantity of vehicles have crossed the segment and it reaches the stationary phase. Similarly, the age does not influence the value, as long as the material was exposed to traffic for at least two years. This corresponds to what curves of laboratory tests show, where the friction tends to an asymptotical value. As the only variations in the stationary phase are seasonal changes, while the average traffic volume per day continues to be the unique affecting factor. However, the Annual Average Daily Traffic was employed instead of the Annual Average Daily Traffic of heavy vehicles, contrary to previous research [17,66]. Szatkwoski and Hosking [62] indicated that including the AADT of total traffic resulted in a good correlation (R = 0.84) (Equation 3), but lower than with the commercial vehicles per day and lane (R = 0.91). This study included a substantial quantity of observations (796) and therefore, sample size did not appear to lead to a biased analysis. At this point, it is difficult to know if the polishing action observed in laboratory tests is similar to the polishing action produced by heavy vehicles or all vehicles (combining heavy vehicles and passenger cars), because roadways with exclusively heavy vehicles or passenger vehicles are not present. As shown in different research findings, the equilibrium phase is reached after some polishing cycles, and from then, the values are asymptotical. However, laboratory conditions are not able to reproduce the field conditions, when vehicles polish the surface aggregates and the weather conditions apply seasonal variation to the surface. Finally, as the total traffic became a key factor for predicting the available friction, the number of lanes on the roadway must be considered to appropriately divide the traffic per lane.

On the other hand, although the influence of a rainfall on the available friction on a road has been known for decades, at network level, its influence was not proved, especially when data collection is conducted in similar conditions; in summer season with approximate rainfall data recorded 15 days before the data collection.

Finally, the advantage provided by the short model is that the only necessary information is the traffic volume (*AADT*), the number of lanes on the road, and the material in the surface layer. Therefore, it is possible to predict the available friction in a section if only the surface material is identified along with the traffic volume. For the long model, the date of the most recent pavement improvement must be known to determine the required PSV when the work was conducted.

6. Conclusions

Models are proposed for predicting the skid resistance in the entire road network of Biscay, in Spain. Due to the great quantity of information included in the Pavement Management System of the Regional Government of Biscay, deterministic models were used to forecast the minimum available friction based on values collected during the summer in 2016. Taking advantage of the fully known pavement structure of some segments, initially only segments with completely known pavement sections on two-lane roads (unique carriageway) were studied. Results showed that the pavement type (flexible of semi-rigid), the total thickness of bituminous layers, and the type of the last work conducted on the road (a new road or a rehabilitated or one that was maintained) do not influence the skid resistance. Variables that truly influenced friction were the traffic volume (total or only heavy traffic), the surface layer material, and the required Polished Stone Value. Taking this finding into account for further statistical evaluations, it was possible to analyze all the roadway segments if the surface layer material, its age, and traffic volumes were known. All the types of roads, single and double carriageway highways, were introduced in the analysis.

As the Average Annual Daily Traffic, including all the vehicles on the roadway, became the main variable, it was necessary to add a new variable, *Lanes*, to consider the quantity of lanes for each road type. After the analysis of several multiple linear regression models and General Linear Models, which can include qualitative and quantitative variables, two models were proposed. The short model, which can be referred as the basic one, only considers the Average Annual Daily Traffic of the whole road in both directions, the surface layer material, and the quantity of lanes of the road. Therefore, it is not necessary to know the work history of the road as long as the surface material can be identified and the traffic volumes are counted. The long model, which can be regarded as a complementary one, provides a better correlation by including the required Polished Stone Value according to the Spanish regulations in force when the work was conducted. Hence, the activities on the road must be recorded to apply this model. These models can be employed by the Regional Government of Biscay to identify the segments predict the future available skid resistance in any road of the network. The models indicate the affecting factors on skid resistance and help road agencies to identify the segments that are more probable to have low friction values.

FUNDING

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