THE FUTURE OF TRANSPORT

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## Investigation of the impacts of climatic conditions on skid resistance variation

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## Report details

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## Executive summary

Variations in skid resistance measurements over time, both within and between years, have been observed since measurements began over 80 years ago and have been the subject of many studies aimed at developing a better understanding of these variations. However, there is no clear consensus on the approach to quantify seasonal variation of skid resistance measurements. Nonetheless procedures such as seasonal correction of annual network survey data and long term monitoring of benchmark sites in England, coupled with QA procedures and standards that define the operational conditions for skid resistance measurement devices enables measurements to be adjusted to account for allows these variations and so minimise their impact on the management of skid resistance.

Most of the models developed to assess seasonal and short-term climatic trends on skid resistance measurements are often very site/region dependent or developed for specific skid resistance measurement devices. Therefore, transferability of these models to other regions is challenging and in most cases unfeasible.

One of the most promising and recent skid resistance prediction models addressing seasonal and short term climatic trends was developed in Ireland by PMS and the National University of Ireland. The model used data from the long-term monitoring of PMS' quality assurance site in Ireland and is based on relationships with weather trends (accumulated rainfall and temperature). Similarities in weather conditions, skid resistance policy and measurement devices between Ireland and England allowed a hypothesis that this model might be applied successfully in England to be proposed.

Work undertaken in this project investigated different ways of applying the Irish model to the Strategic Road Network (SRN) in England. This was done initially by applying the model on several of the National Highways benchmark sites, but that approach was not successful. The model was then adjusted using data collected from a dynamic calibration site on A329M and a nearby weather station. Although this did not result in a positive outcome, the analysis did suggest that the model might be improved by using a larger set of skid resistance data gathered at more frequent intervals over time.

Based on these findings, a machine learning approach was explored as a relevant way to assess large numbers of variables and their dependencies. For that purpose, skid resistance data from 7 survey vehicles covering the period 2013-2019 were obtained from WDM's dynamic calibration site in Bristol. These data were combined with relevant texture data and weather data from nearby weather stations. Data from A329M dynamic calibration site was also included in the model. A machine learning approach resulted in a model, that combines skid resistance, texture and various weather factors (air temperature, relative humidity, cumulative rainfall for different numbers of days) to give a strong accuracy of $R^2 = 0.81$.

Promising results obtained with the created machine learning model (Random Forest) were then tested on 16 selected benchmark sites. The model was expanded by including historical skid resistance, texture and weather data from these sites to adapt the model for a wider range of surfaces and locations across the English SRN. Results of that work were inconclusive, with the model giving a prediction score of $R^2 = 0.67$, but when used to predict skid resistance data and compared against real measurements in 2019 and 2020 it showed that the

prediction error was varying by up to 20%. Some of the sites, mainly having similar texture values to the base reference data (A329M and Bristol dynamic calibration sites) had skid resistance values predicted with very low error (0-5%).

Overall, the developed machine learning model showed potential to predict skid resistance values but further model improvement would be needed in order to provide more consistently accurate results. The inclusion of traffic information is suggested as a way to improve the model's accuracy as the skid resistance variation would then be taking account of both changes in weather and traffic conditions.

It is likely that the current model is too broad to cover the whole country given the wide variation in weather conditions across the country, and it could potentially be better to develop models for different regions to represent their particular climatic conditions. However, the development of models for different regions on the SRN would require the selection of reference data site(s) in that region having long-term historical skid resistance data at frequent intervals. This could potentially be facilitated by increased monitoring of some of the benchmark sites.

If the machine learning based skid resistance prediction model is improved further, there are several application areas where its use could be beneficial:

- The model could define a range of skid resistance values for a particular site under specific weather conditions. This would provide an indication of the skid resistance levels expected on a dynamic calibration site when measurements are made, which could then be compared to the actual measurements to support QA procedures.
- When tested and validated at network level, the model could be used to support/improve the current LECF correction approach to predict skid resistance at various locations on the SRN and support maintenance decisions.
- The model could also be used to investigate if any bias is introduced into the skid resistance measurements due to drift in the performance of the fleet and/or changes to test tyres from year to year, which can currently be masked by the seasonal corrections.
- Prediction of the skid resistance at high risk sites - for example, sites reported as being below the IL but not requiring detailed investigation following assessment using the National Highways crash model, could be monitored by predicting their skid resistance values if the forecast is showing a long, dry period, or other weather anomalies that could result in a significant decrease in skid resistance. Early identification of such sites could provide the opportunity for improved management through, for example, temporary warning signs or speed limits to mitigate any increase in collision risk.

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# 1 Background for this work

## 1.1 Seasonal and short-term skid resistance variation

Skid resistance measurement variations over time have been a question of interest since skid resistance measurements began on road networks and much research has been carried out to investigate influencing factors for variations in skid resistance. These can be associated with different material properties, performance of skid resistance measurement devices, trafficking, and climatic conditions. A combination of all these influencing factors may lead to variations in skid resistance measurements within and between years. To respond to these influencing factors, various procedures and standards have been developed to assure the quality of the performance of skid resistance measurement devices or to ensure the consistency of the properties of the materials laid on roads.

A study carried out by TRL (Hosking and Woodford, 1976) established a consensus that skid resistance measurements are subject to seasonal variations (Figure 1). Seasonal variations were investigated by undertaking friction measurements using the portable skid resistance tester (the pendulum) on a number of sites at two-weekly intervals during the period 1958 to 1968. Differences in the obtained values were unable to be explained solely by the temperature difference between measurements, as the effect of a 10°C temperature difference on the same day is much more limited than a 10°C temperature difference between early spring and mid-summer. Therefore, other phenomena such as polishing, wear and weathering were suggested as additional influencing factors acting together with the climatic conditions.

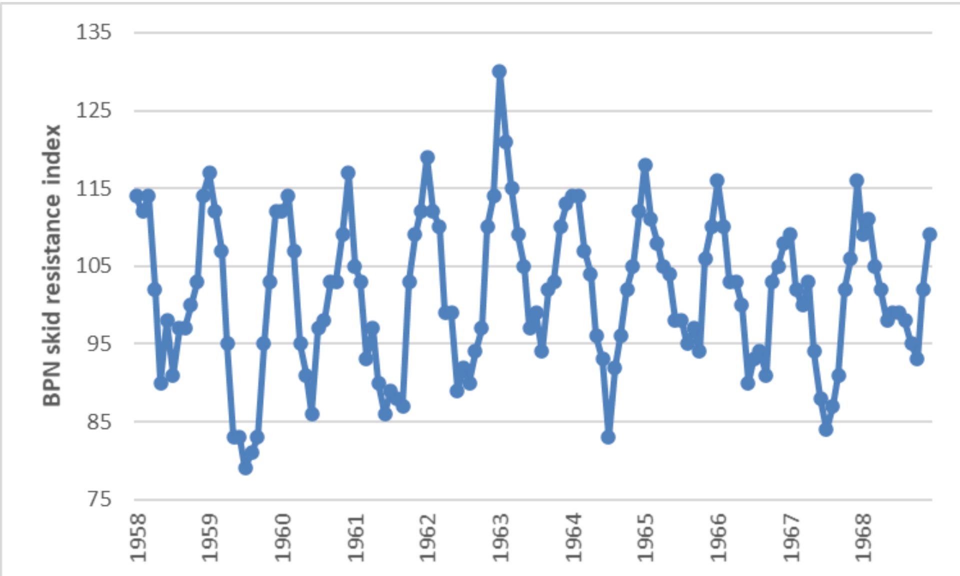


**Figure 1: Monthly index of seasonal change in skid resistance (Hosking and Woodford, 1976)**

As summarised by van Bijsterveld and del Val (2016) follow up research studies, carried out in various countries, tried to quantify the seasonal variation but no consensus was found on either the quantification of seasonal variations or the background or real causes. However, the following phenomena contributing to temporal variations in skid resistance were identified and assessed by various authors:

- Polishing of the aggregate affecting the microtexture and thereby reducing friction. The polishing effect is directly related to traffic intensity, especially heavy vehicle numbers (Oliver *et al.*, 1988) and the nature of the aggregates (Bessa *et al.*, 2014).
- Weathering of aggregate observed that on the roads where traffic intensity decreased significantly due to changes in the network (e.g. the opening of a by-pass) the friction values increased over time (Sanjuan and Gutierrez-Bolivar, 2003). This may also be associated with the asphalt mixture ageing as reported by Kane *et al.* (2013)
- Accumulation of dust, detritus, rubber or other substances that may act as a lubricant, especially in the presence of water (Oliver *et al.*, 1988;Croney and Croney, 1998;Hill and Henry, 1978).

Another source of uncertainty in quantifying seasonal variations in measurements arises from the different methods for determining skid resistance. Measurements made by different devices will be influenced by (van Bijsterveld and del Val, 2016):

- The type of tyre used, including the type of rubber, inflation pressure, surface profile (smooth or ribbed), contact surface area, etc;
- The way the friction is created; this could be by mounting the wheel at an angle to the direction of travel, applying a fixed slip ratio or locking the wheel;
- The amount of water on the road surface during the test;
- The test speed; and
- The vertical load on the wheel.

As part of the skid resistance management policy on the Strategic Road network (SRN), National Highways commission single annual skid resistance surveys (SASS). These surveys are carried out over the course of the summer, when skid resistance is typically at its lowest levels, and are split over three survey periods (early, middle and late). It is known that skid resistance varies over the survey season (Figure 2) and between years and the SASS approach enables data to be adjusted for these variations by the application of correction factors called the "Local Equilibrium Correction Factors" (LECF) (National Highways, 2019). To monitor the ongoing trends in skid resistance levels, National Highways established a series of benchmark sites. These sites are surveyed in all three of the survey periods during the survey season and enable both within year and between year trends in the skid resistance to be assessed (Brittain, 2020).

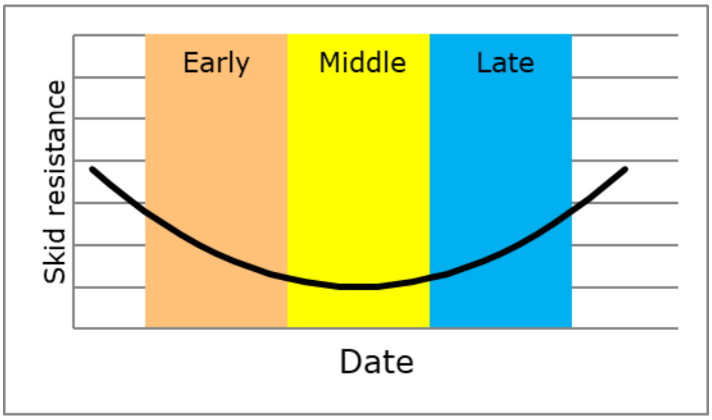


**Figure 2: Expected seasonal variation of skid resistance over the summer (Brittain, 2020)**

Application of the seasonal correction factors for skid resistance measurements and monitoring of the benchmark sites works well in practice. This aim of this study was to investigate if models utilising weather data could be developed to predict skid resistance and whether such models could provide benefit to the management of skid resistance at the network level.

## 1.2 Seasonal and short-term skid resistance variation models

Although, a lot of work has been carried out in the past to investigate the impact of weather conditions and create models to predict skid resistance values based on the specific weather conditions, no consensus can be found on the quantification of climatic impacts on skid resistance variation. However, previous research studies on weather and skid resistance models tested different approaches to address skid resistance seasonal variation and resulted in interesting findings that were found to be useful in this project work.

In a study carried out in the USA (Anderson *et al.*, 1986) a skid number prediction model for asphalt and Portland cement concrete (PCC) sites was developed to predict end-of-season skid number from a single measurement made at any time during the season. The model is empirical, and it is based on a prediction equation developed through regression analysis of data obtained from field test sites.

$$SN_{64}\tilde{F} = (lnSN_{64} - b_0 - b_2ADT - b_3JDAY - b_4DSF - b_5AIRT)/b_1$$

Where:

$SN_{64}F$ – end-of-season skid resistance estimated from a predictor model;
$SN_{64}$ – skid-resistance measurement made in accordance with ASTM E274 at 64km/h (40mph) using the ASTM Standard Test Tyre E501;
$b_0 \ldots b_i$ – regression coefficients developed for different states from a set of 12-16 pavement test sites with varying levels;
ADT – average daily traffic, vehicles/day/test lane;
JDAY – Julien calendar day;
DSF – dry spell factor, $\ln(t_r+1)$, where $t_r$ is number of days since last daily rainfall of 0.1in. (2.5mm) or more, $t_r \leq 7$ and DSF<2.08;
AIRT – air temperature at time of test, $^oF$

Outcomes of this model showed that 90 percent of the predicted values are within -3.51 and +3.88 skid numbers of the measured values for the bituminous sites and within -3.75 and +3.54 skid numbers for the concrete sites. Modelling also showed that JDAY and $SN_{64}F$ were the most significant factors causing changes in skid resistance; air temperature had little effect, and the dry spell factor and average daily traffic had only minimal effect. However, it should be also noted that this prediction equation was site-specific and varied from season-to-season.

Jaywickrama *et al.* (1998) investigated variations in skid numbers measured on the same pavement at different times and found a general long-term trend in skid number variations. They found that, as the temperature rises the skid numbers decrease in magnitude and as the temperature falls the skid numbers increase in magnitude. It follows a cyclical pattern with the lowest skid numbers in the summer months and the highest skid numbers in winter or early spring. Another significant observation was that the asphalt pavements assessed follow a very similar skid variation pattern suggesting that the variations observed are not random but occurred in response to some common factor that influenced both pavements. Furthermore, sudden increases (or peaks) in skid number that were observed appear to be closely associated with significant rainfall events especially when they occur after extended periods of dry weather. Rainfall in the summer months, however, is not associated with high skid numbers. This is possibly due to the counteracting effects of higher temperatures and other factors, such as heavier traffic in summer.

A study undertaken in Canada (Ahammed and Tighe, 2008) investigated the seasonal and long term variations of both asphalt (AC) and concrete (PCC) pavements' surface friction showing that the seasonal variations for both asphalt and concrete pavements' wet surface friction are similar. The study also developed models to represent seasonal variation of pavement surface friction and indicated the main predictor variables.

The models developed for PCC pavements were:

$$SNs = 21.767 - 0.717\,Y + 40.345\,R - 0.198\,S$$

$$SNs = 35.840 - 0.240\,V + 35.486\,R - 0.308\,S - 0.131\,T$$

Where:
SNs – Skid Number at speed S,
S – vehicle speed in km/h,
Y – pavement age in years after an early age increase in friction (age since construction minus 2.5 years),
V – cumulative traffic passes in million after an early age increase in friction (total traffic since construction minus traffic passes in 2.5 years),
T – friction test temperature in °C, and
R – Rank for different textures of PCC pavements relative to average friction number exhibited by all surface textures (astroturf drag 0.87, burlap drag 0.92, broom drag 0.93, diamond ground 0.96, astroturf drag & tining 0.98, grooved float 0.99, tining 1.04 and burlap drag & transverse groove 1.08).

Both models were found to be statistically significant at 5% significance level with all the predictor variables (p-values less than 0.05). The coefficient of determination ($R^2$ value) was 0.592 for the first model and 0.701 for the second model.

The models developed for AC pavements were:

$$SNs = 63.079 – 1.208\ Y + 5.321\ DW + 2.697\ FNF - 0.179\ S - 0.242\ T$$

$$SNs = 59.644 - 0.265\ V + 5.901\ DW + 3.691\ FNF - 0.133\ S - 0.293\ T$$

Where:
SNs – Skid Number at speed S,
S – vehicle speed in km/h,
Y – pavement age in years after an early age increase in friction,
V – cumulative traffic passes in million after an early age increase in friction,
T – friction test temperature in °C,
DW – dry versus wet weather code (dry weather = 1 and wet weather = 0), and
FNF – freeze versus no freeze weather code (no freeze = 1 and freeze = 0).

Both models were found to be statistically significant at 5% significance level with all the predictor variables (p-values less than 0.05). The coefficient of determination ($R^2$ value) was 0.484 for the first model and 0.412 for the second model.

Another study to determine the friction values of different asphalt mixtures and to develop statistical models for microtexture (expressed as British pendulum number (BPN) and measured using the British pendulum tester) and macrotexture (expressed as mean texture depth (MPD)) as functions of traffic, climate, and surface mix characteristics was carried out by (Ongel *et al.*, 2009). The main aim of this study was to help in selecting pavement surface mixes for skid resistance and to aid the development of improved mix designs for different traffic and climate regions. A large number of parameters that might have an influence on skid resistance were analysed; their coefficients and the regression coefficients against BPN (Table 1) and MPD (Table 2) were calculated.

**Table 1: Regression analysis for microtexture**

| Model number | Explanatory variable | | | Constant term | $R^2$, % |
|---|---|---|---|---|---|
| | Name | Coefficient | P-value | | |
| 1 | Age (years) × Annual degree days >30°C | -0.0003 | 0.01 | 60.68 | 9.5 |
| 2 | Age (years) × Annual number of days >25°C | -0.006 | 0.01 | 61.07 | 9.0 |
| 3 | Average annual daily truck traffic on the coring lane (AADTTCL) | -5.61 | 0.01 | 58.74 | 8.3 |
| 4 | ESAL | -5.05 | 0.04 | 58.48 | 6.0 |
| 5 | Annual degree days >30°C | -0.001 | 0.04 | 60.77 | 5.9 |
| 6 | Age (years) | -0.70 | 0.04 | 60.50 | 5.4 |
| 7 | NMAS (mm) | 0.53 | 0.10 | 65.34 | 4.0 |
| 8 | Age (years) × Average annual rainfall (mm) | 0.0007 | 0.09 | 59.46 | 3.8 |
| 9 | Age (years) × Annual number of wet days | -0.006 | 0.11 | 59.62 | 3.5 |
| 10 | Mixture type | -2.82 | 0.14 | 59.39 | 3.0 |
| 11 | Average annual rainfall (mm) | 0.003 | 0.15 | 55.92 | 2.9 |
| 12 | Average annual maximum daily air temp (°C) | -0.50 | 0.18 | 69.27 | 2.5 |
| 13 | Fineness modulus | -2.57 | 0.21 | 70.94 | 2.3 |
| 14 | Annual number of days >25°C | -0.021 | 0.22 | 60.75 | 2.1 |
| 15 | Air void content, % | -0.18 | 0.33 | 60.23 | 1.3 |
| 16 | Coefficient of uniformity ($C_u$) | 0.04 | 0.45 | 57.02 | 0.9 |
| 17 | Rubber inclusion | -1.04 | 0.58 | 58.32 | 0.4 |
| 18 | Annual number of wet days | 0.006 | 0.72 | 57.29 | 0.2 |
| 19 | Annual freeze-thaw cycles | 0.54 | 0.77 | 57.30 | 0.1 |
| 20 | Average annual daily traffic on the coring lane | -0.00009 | 0.45 | 58.20 | 0.8 |

**Table 2: Regression analysis for macrotexture**

| Model number | Explanatory variable | | | Constant term | R2, % |
|---|---|---|---|---|---|
| | Name | Coefficient | P-value | | |
| 1 | Fineness modulus | 0.213 | 0.00 | 1.89 | 48.7 |
| 2 | NMAX × Mixture type | 0.014 | 0.00 | 2.85 | 45.8 |
| 3 | Air void content, % | 0.017 | 0.00 | 2.74 | 37.6 |
| 4 | Mixture type | 0.170 | 0.00 | 2.86 | 37.6 |
| 5 | Coefficient of uniformity ($C_u$) | -0.005 | 0.00 | 3.08 | 35.6 |
| 6 | Age (years) × Average annual rainfall (mm) | 0.00003 | 0.00 | 2.89 | 24.2 |
| 7 | Age (years) | 0.016 | 0.01 | 2.90 | 9.4 |
| 8 | Average annual rainfall (mm) | 0.000089 | 0.01 | 2.90 | 8.8 |
| 9 | Annual freeze-thaw cycles | 0.093 | 0.03 | 2.94 | 6.6 |
| 10 | Average annual maximum daily air temp (°C) | -0.013 | 0.06 | 2.94 | 6.6 |
| 11 | NMAS (mm) | -0.005 | 0.39 | 3.03 | 1.1 |
| 12 | Average annual daily truck traffic on the coring lane (AADTTCL) | -0.020 | 0.63 | 2.97 | 0.4 |
| 13 | Rubber inclusion | 0.010 | 0.65 | 2.95 | 0.3 |
| 14 | ESAL | -0.015 | 0.73 | 2.96 | 0.2 |
| 15 | Average annual daily traffic on the coring lane (AADTTCL) | 0.0000005 | 0.85 | 2.96 | 0.1 |

Calculated regressions were then transformed into multiple linear regression models for BPN and MPD. Due to non-constant residuals, log transformation was applied to the dependent variable (BPN) and a square-root transformation was applied to the independent variable, number of days above 30°C over the lifetime. Only 12.8% ($R^2$ value) of the variation in microtexture was explained by the model:

$$\begin{aligned}\log BPN = 1.79 - 0.0398\, AADTTCL \\ - 0.00171(Age\ \times Number\ of\ days\ temperature\ > 25)^{0.5}\end{aligned}$$

Log-transformed MPD values were used as the dependent variable. Fineness modulus, air void content, cumulative rainfall (age average annual rainfall), and the interaction of nominal maximum aggregate size (NMAS) with mixture type were used as independent variables. These variables were able to explain 69% (R2 value) of the variation in macrotexture:

$$\begin{aligned}\log MPD = 2.39 + 0.0768\, Fineness\ modulus + 0.00846\, Air\ void\ content \\ + 0.000025\, Age \times Average\ annual\ precipitation \\ + 0.00509\, NMAS \times Mixture\ type\end{aligned}$$

Van Bijsterveld and del Val (2016) investigated the impacts of rainfall and its absence on sideway-force skid resistance measurements. In particular, the relation between rainfall values over 7-day and 15-day periods prior to the measurements were investigated. A positive tendency of increasing sideway-force coefficient (SFC) values with rising rainfall was found, although the correlation was weak ($R^2$ of 0.247 for 7-day accumulated rainfall and 0.203 for 15-day accumulated rainfall). The authors explained that the lower rain intensities coincide with the summer period and its particular seasonal effects. From the dry spell perspective, the study found a decreasing trend in SFC with the length of the dry spell. In a linear regression from data obtained after a dry spell of more than 2 days, a reduction was seen of 0.0018 SFC (calculated from the best fit linear regression line through the measurement results divided by the number of days) units per day of the dry spell, with a correlation coefficient $R^2$ of 0.55.

This means that after a month without rain, a 0.60 SFC (under optimal conditions) would be reduced to less than 0.55.

Plati and Georgouli (2014)investigated air temperature during skid resistance measurements and the cumulative precipitation of the seven days prior to the measurements as relevant predictors of skid resistance variation. As cumulative precipitation did not seem to be statistically significant, for defining the different climatic conditions as far as rainfall is concerned, an indicator variable was used that expresses the dry versus wet weather code, with a value equal to 1 if the cumulative rainfall in the seven days preceding the measurements was greater than 2.5 mm and a value equal to 0 where the cumulative rainfall in the 7 days preceding the measurements was less than 2.5 mm.

A sample size of 203 GripTester measurements were analysed and used as reference skid resistance data to develop a linear regression between skid resistance and weather factors:

$$GN = 0.259 + 0.629\ GN_{in} - 0.004\ TV + 0.061\ DW - 0.006\ T$$

Where:

GN − the measured Grip Number;

$GN_{in}$ − the initial GN defined as skid resistance at the time of the first set of measurements;

TV − the traffic volume expressed as cumulative ADT multiplied with $10^{-6}$;

DW − the dry versus wet weather code (dry weather = 0 and wet weather = 1); and

T −the air temperature, $^{o}$C, during the measurements.

The authors concluded that the measured skid resistance index (Grip Number) is correlated fairly to good ($R^2$=0.79) with the traffic volume, the dry or wet conditions, the air temperature during the measurements, as well as the initial level of skid resistance that was defined using the first set of measurements. This supported the statement that a pavement's skid resistance at a given time is closely related to the initial or a past level of the pavement's friction. Despite the fact that the model showed promising results, the authors recommended that the model should be calibrated to the local conditions and surface type to achieve efficient and consistent results.

Experimental work done in New Zealand by (Wilson, 2006) investigated seasonal and short-term variations of skid resistance. The study, including skid resistance data analysis from a sideway-force skid resistance device and a GripTester, proved the hypothesis that the time period since the last rainfall has a significant effect on the short-term deterioration of measured skid resistance, i.e. that the slope of the short term deterioration line is significantly different from zero and of the magnitude of approximately 0.01 SFC units (or equivalent GN) per day.

The rainfall function analysis indicated that the hypothesis is true, because the weighted rain function (WRF) explained up to 60% of the variation in measured skid resistance with the GripTester device at the Hikurangi site for the 2004/2005 data. However, whilst the slope of the trend could be confirmed when the five Northland sites were normalised, only 5.5% of the variation was explained due to the WRF alone. When analysing the sideway-force skid resistance results, the dry spell factor (DSF) rainfall function explained up to 53% of the variation. The analysis indicated that a prior rainfall history of 7 days gave the best results and an indication of the slope of the equation was:

- An increase of 0.003 x WRF (mm) over a 7-day rainfall period in terms of the GripTester device.
- A decrease of 0.02 x DSF >2mm over a 7-day rainfall period in terms of the sideway-force device.

However, the authors conclude that there are other factors that need to be considered in the analysis, as the prior rainfall history cannot fully explain the variation in measured skid resistance.

Another significant research study on the development of a model for adjusting sideways-force skid resistance data to reflect seasonal variation has been done in Ireland by Pavement Management Services (PMS) and the National University of Ireland (Mulry *et al.*, 2012;Mulry *et al.*, 2016). 864 measurement runs with sideways-force measurement devices were carried out between 2004 and 2015 on the same 7.2 km long survey route that included surface dressing and hot rolled asphalt (HRA) materials.

The study developed a linear regression model for relating SFC skid resistance to the input variables of surface type, average temperature on the day of testing and accumulated rainfall for up to 60 days. The analysis consistently obtained the same values for the regression coefficients for the surface type and average temperature, but the coefficient for accumulated rainfall depended on the number of days rainfall that were counted. Moreover, the P-values for the coefficients for surface type and temperature were consistently equal to 0.00+ (effectively zero) indicating that these variables were highly significant. The P-values for the regression coefficients for the days of accumulated rainfall fluctuated for the first 30 days but remained consistently significant with a P-value of 0.00+ for accumulated rainfalls greater than 30 days, and a value of 0.00+ also for accumulated rainfalls of 8 to 10 days. Consequently, because there was no difference in the significance of the P-values for 10 days and 30 or more days, the accumulated rainfall for the 10 days prior to making the SFC measurement was used as the rainfall parameter included in the regression model.

The model based on surface type, average temperature and accumulated 10 days rainfall and having an $R^2$ of 81.4% is:

Speed Corrected SFC = 0.790xSegment-Type_SD + 0.653xSegment-Type_HRA - 0.010286xAvg. Temp + 0.000152xAccum. Rainfall_10

Where:
Segment-Type_SD = 1 if an observation is taken with surface dressing and is 0 otherwise; Segment-Type_HRA = 1 if an observation is taken with HRA and is 0 otherwise.

The model without accumulative rainfall as an input variable and having $R^2$ of 81.3% is:

Speed Corrected SFC = 0.797xSegment-Type_SD + 0.661xSegment-Type_HRA - 0.010448xAvg. Temp

The models were tested and validated with data from two sideways-force machines and were considered excellent models for predicting the speed-corrected SFC.

# 2 Phase 1. Application of Irish model to England's SRN

Inspired by the positive results from the Irish study (Mulry *et al.*, 2016) it was decided to apply the developed model, or to use a similar approach, to model skid resistance on National Highways Strategic Road Network (SRN). The similarities in climatic conditions, use of the same sideways-force skid resistance measurement devices for network level assessment, use of the same QA procedure for skid resistance measurement devices were also the factors that supported the hypothesis that model developed and tested in Ireland may be also applicable on England's SRN.

## 2.1 Direct application of Irish model

Initially, the Irish model was applied directly and tested using data from several of the National Highways benchmark sites (these are sites used by National Highways to monitor long and short-term variations in skid resistance across the SRN). Input parameters for the model used the following:

- Benchmark sites No 1, 2, 9, 13, 17, 38. These sites were selected as they have HRA surfacings, which was one of the surfacing types used to develop the Irish model; see Appendix A for more details on the location of the selected benchmark sites.
- Weather data (average temperature and cumulative rainfall) acquired from nearby weather stations to individual benchmark sites.
- Site averages of skid resistance data (sideways-force coefficient SFC) from the early, middle and late survey period measurements on the benchmark sites.
- Data covered the period from 2013 to 2016.

The model developed by Mulry *et al.* (2016) was used to calculate predicted SFC values for each benchmark site:

$$\text{Speed Corrected SFC} = 0.790\text{xSegment-Type\_SD} + 0.653\text{xSegment-Type\_HRA} - 0.010286\text{xAvg. Temp} + 0.000152\text{xAccum. Rainfall\_10}$$

Where: Segment-Type_SD = 1 if an observation is taken with surface dressing and is 0 otherwise; Segment-Type_HRA = 1 if an observation is taken with HRA (Hot Rolled Asphalt) and is 0 otherwise.

Calculated values were then compared against measured values and plotted. The results are shown in Figure 3 and the conclusion was drawn that the Irish model cannot be directly applied to the National Highways benchmark sites.

One of the potential reasons for the poor model applicability may have been that the amount of data available was too low; only 3 measurements per year for each benchmark site compared to the 864 individual sideways-force skid resistance measurement runs on the same site used to develop the Irish model. Therefore, it was recommended to select a site on England's SRN with more frequent skid resistance measurement data and repeat the Irish model application (including model adjustment) to England's conditions.

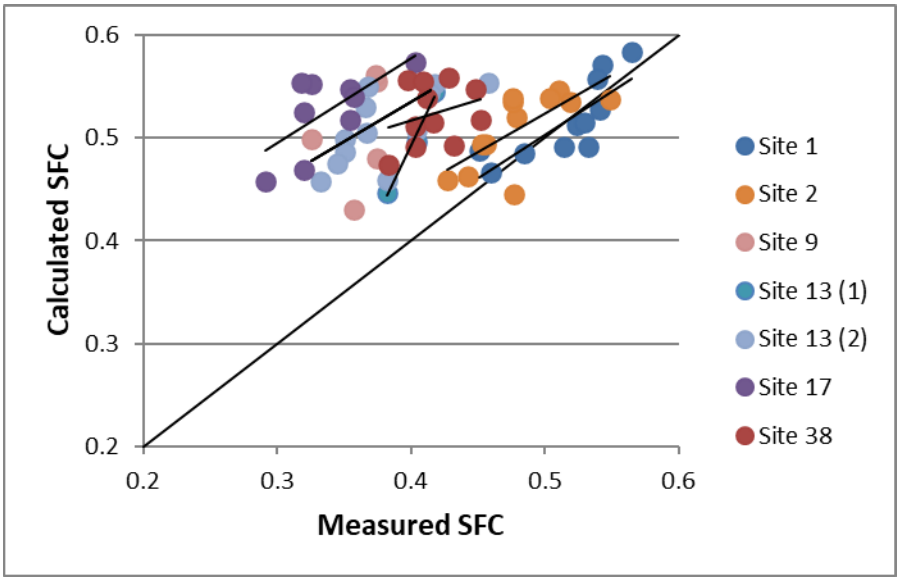


**Figure 3: Irish model application on several benchmark sites on the SRN**

## 2.2 Irish model adjustment to English data

TRL, as part of the QA procedure for sideways-force skid resistance measurement devices in England, maintain and operate National Highways skid resistance development platform (SkReDeP) which incorporated sideway-force measurement equipment. As part of its QA procedure, the device completes periodic dynamic calibration checks that are carried out on a length of the A329M in Berkshire (Figure 4). The dynamic calibration survey route includes sections of different materials (asphalt and concrete) with different skid resistance and texture levels to ensure that there is a sufficient range of skid resistance variation to monitor the consistency of SkReDeP performance. This site provided multiple sets of skid resistance measurements over the year and was therefore selected to support further investigation and development of a weather and skid resistance model.


**Figure 4: Calibration site overview** ***(Map data from ©OpenStreetMap)***

A database of historical sideways-force skid resistance measurements made on three sections of A329M from January 2013 to November 2018 was used as an input data. Detailed historical weather data (10 min averaged data from 2013 to 2018) were sourced from National Highways weather information system (Vaisala weather station at M4 Shurlock Row). This weather station was selected as it is the closest one to A329M.

Relationships between the skid resistance data from A329M and individual (air temperature, road temperature, humidity, dew temperature, dry spell factor, accumulated rainfall, rain intensity) and combined weather factors (dry spell factor and temperature, accumulated rainfall and temperature) were calculated to analyse the trends and possible correlations. Unfortunately, similar to the Irish model (Mulry *et al.*, 2016), no direct correlations between individual or combined weather factors and skid resistance were found. However, weather Figure 5) and skid resistance (Figure 6) variation patterns and trends over the various periods of time were found to be relevant for regression analysis and, therefore were taken into consideration for weather and skid resistance model development.

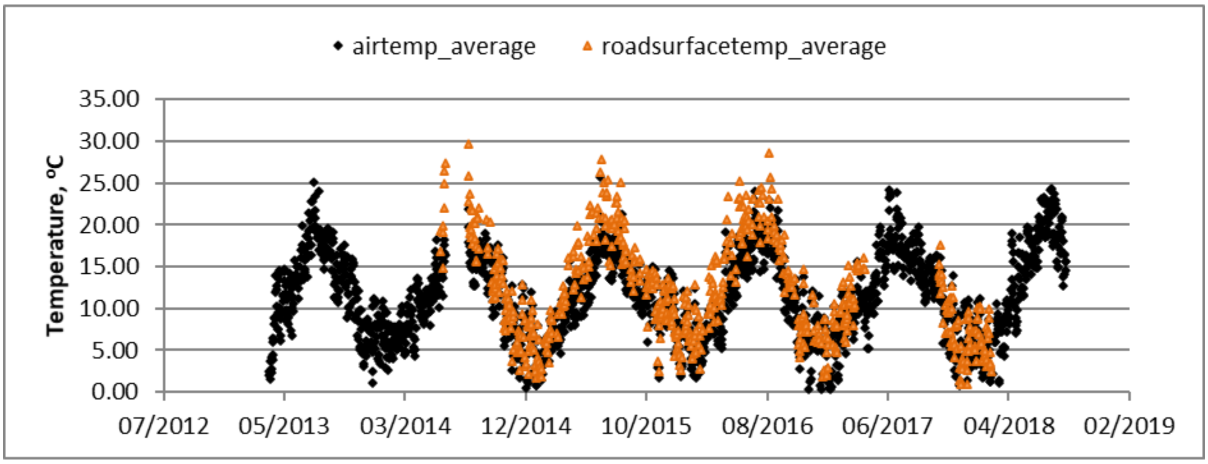


**Figure 5: Air and road surface temperature trends on A329M site**

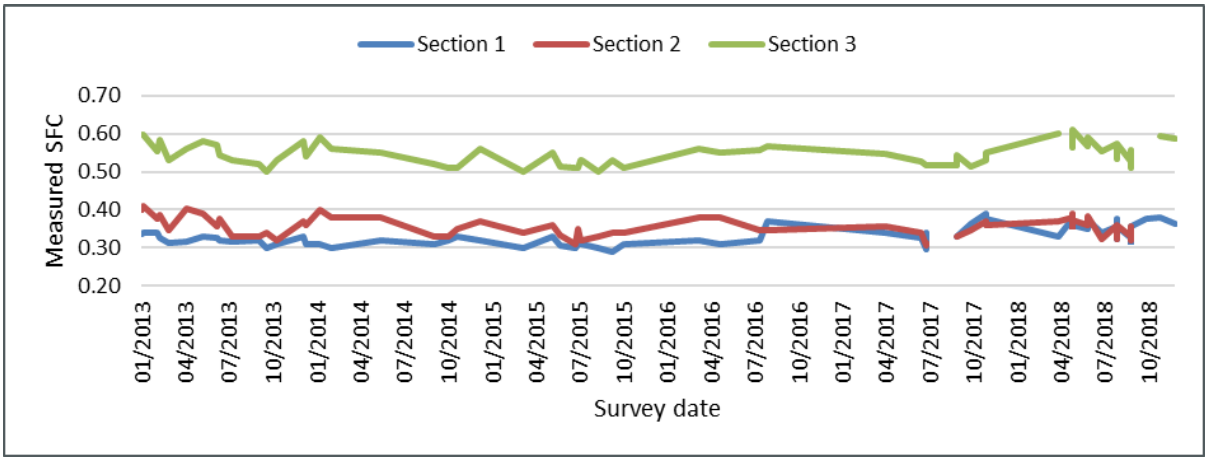


**Figure 6: Average measured sideways-force coefficient on the A329M site sections**

While attempting to replicate the modelling carried out by PMS and the National University of Ireland (Mulry *et al.*, 2016), the main goal was to investigate if there is any correlation between the cumulative rainfall that occurs in a period before a sideways-force skid resistance measurement is made, and the sideways-force coefficient that is measured on the day. Three different types of linear model were investigated:

$$\boldsymbol{SC = \alpha + \beta T + \epsilon}$$

$$SC = \alpha + \beta R_n + \epsilon$$

$$SC = \alpha + \beta T + \gamma R_n + \epsilon$$

Where $\alpha, \beta, \gamma$ are coefficients to be fitted, $\epsilon$ is the error term in the model, $T$ is the air temperature on the day of the measurement and $R_n$ is the cumulative rainfall for the $n$ days previous and inclusive of the day of the measurement.

Each model was applied independently to each section of the A329M, producing the following tables (Table 3, Table 4, Table 5) of coefficients and fits. Adjusted R-squared accounts for the increase in predictive power that happens by simply adding more variables to a regression model. It only increases the value of R-squared if the variables add extra explanatory power to the model, and a negative value indicates that the variables are contributing less than random chance would predict.

**Table 3: Air temperature linear regression model**

| Section | Intercept α | Coefficient 1 β | Adjusted R-Squared | *p*-value |
|---|---|---|---|---|
| 1 | 0.32166 | 0.00075 | -0.00284 | 0.3602 |
| 2 | 0.38368 | -0.00199 | 0.05935 | 0.04362 |
| 3 | 0.56383 | -0.0016 | 0.0437 | 0.07198 |

**Table 4: Cumulative rainfall linear regression model**

| Section | Cumulative Days of Rain | Intercept α | Coefficient 1 β | Adjusted R-Squared | *p*-value |
|---|---|---|---|---|---|
| 1 | 1 | 0.336 | -2.2232 | 0.0771 | 0.0441 |
| 1 | 2 | 0.337 | -1.4162 | 0.0954 | 0.0244 |
| 1 | 3 | 0.3372 | -1.0766 | 0.0718 | 0.0524 |
| 1 | 4 | 0.3364 | -0.6775 | 0.0419 | 0.1413 |
| 1 | 5 | 0.3372 | -0.7136 | 0.0523 | 0.0995 |
| 1 | 6 | 0.3382 | -0.7911 | 0.0664 | 0.0624 |
| 1 | 7 | 0.3387 | -0.7873 | 0.0675 | 0.0602 |
| 1 | 8 | 0.3402 | -0.8101 | 0.094 | 0.0255 |
| 1 | 9 | 0.3407 | -0.8092 | 0.1037 | 0.0187 |
| 1 | 10 | 0.3398 | -0.677 | 0.0803 | 0.0397 |
| 1 | 20 | 0.3441 | -0.4788 | 0.1335 | 0.0071 |
| 1 | 30 | 0.3445 | -0.3142 | 0.1405 | 0.0057 |
| 1 | 40 | 0.3432 | -0.2096 | 0.1045 | 0.0183 |
| 1 | 50 | 0.3429 | -0.1705 | 0.0956 | 0.0243 |
| 1 | 60 | 0.3419 | -0.1289 | 0.0782 | 0.0426 |
| 1 | 70 | 0.3415 | -0.1037 | 0.0715 | 0.0529 |
| 1 | 80 | 0.3404 | -0.0834 | 0.0577 | 0.0831 |
| 1 | 90 | 0.3396 | -0.0704 | 0.0507 | 0.105 |
| 1 | 100 | 0.3396 | -0.063 | 0.0495 | 0.1092 |

| Section | Cumulative Days of Rain | Intercept α | Coefficient 1 β | Adjusted R-Squared | *p*-value |
|---|---|---|---|---|---|
| 2 | 1 | 0.3553 | 0.2791 | 0.0008 | 0.8397 |
| 2 | 2 | 0.3551 | 0.1966 | 0.0012 | 0.8034 |
| 2 | 3 | 0.3557 | 0.0113 | 0 | 0.9869 |
| 2 | 4 | 0.3567 | -0.1488 | 0.0013 | 0.7941 |
| 2 | 5 | 0.3567 | -0.1273 | 0.0011 | 0.8128 |
| 2 | 6 | 0.3562 | -0.0519 | 0.0002 | 0.9218 |
| 2 | 7 | 0.3563 | -0.0599 | 0.0003 | 0.9088 |
| 2 | 8 | 0.3572 | -0.1505 | 0.0022 | 0.7409 |
| 2 | 9 | 0.3571 | -0.1266 | 0.0017 | 0.77 |
| 2 | 10 | 0.3561 | -0.0307 | 0.0001 | 0.9405 |
| 2 | 20 | 0.356 | -0.0102 | 0 | 0.964 |
| 2 | 30 | 0.355 | 0.0182 | 0.0003 | 0.8999 |
| 2 | 40 | 0.3519 | 0.0743 | 0.0088 | 0.5052 |
| 2 | 50 | 0.3525 | 0.0524 | 0.006 | 0.5811 |
| 2 | 60 | 0.353 | 0.0364 | 0.0042 | 0.6462 |
| 2 | 70 | 0.3539 | 0.0212 | 0.002 | 0.7509 |
| 2 | 80 | 0.3537 | 0.0205 | 0.0023 | 0.7313 |
| 2 | 90 | 0.3536 | 0.02 | 0.0027 | 0.7107 |
| 2 | 100 | 0.3538 | 0.0165 | 0.0023 | 0.7349 |
| 3 | 1 | 0.5408 | 0.3408 | 0.0015 | 0.7834 |
| 3 | 2 | 0.5413 | 0.0063 | 0 | 0.9929 |
| 3 | 3 | 0.5417 | -0.0739 | 0.0003 | 0.9055 |
| 3 | 4 | 0.5431 | -0.2805 | 0.0059 | 0.5836 |
| 3 | 5 | 0.5432 | -0.2627 | 0.0058 | 0.5862 |
| 3 | 6 | 0.5427 | -0.1779 | 0.0028 | 0.7081 |
| 3 | 7 | 0.5431 | -0.2143 | 0.0041 | 0.6477 |
| 3 | 8 | 0.5435 | -0.2183 | 0.0056 | 0.5932 |
| 3 | 9 | 0.5433 | -0.1815 | 0.0043 | 0.6408 |
| 3 | 10 | 0.5428 | -0.1269 | 0.0023 | 0.7315 |
| 3 | 20 | 0.5466 | -0.2128 | 0.0218 | 0.292 |
| 3 | 30 | 0.5458 | -0.114 | 0.0153 | 0.3782 |
| 3 | 40 | 0.5432 | -0.0355 | 0.0025 | 0.7239 |
| 3 | 50 | 0.5444 | -0.0483 | 0.0063 | 0.5709 |
| 3 | 60 | 0.5454 | -0.0534 | 0.0111 | 0.4536 |
| 3 | 70 | 0.5446 | -0.0365 | 0.0073 | 0.5434 |
| 3 | 80 | 0.5451 | -0.0382 | 0.01 | 0.4765 |
| 3 | 90 | 0.5431 | -0.0161 | 0.0022 | 0.7403 |
| 3 | 100 | 0.5436 | -0.0191 | 0.0038 | 0.6629 |

**Table 5: Air temperature and cumulative rainfall linear regression model**

| Section | Cumulative Days of Rain | Intercept α | Coefficient 1 β | Coefficient 2 γ | Adjusted R-Squared | *p*-value |
|---|---|---|---|---|---|---|
| 1 | 1 | 0.3337 | 0.0002 | -2.1439 | 0.0777 | 0.1326 |
| 1 | 2 | 0.3374 | 0 | -1.4242 | 0.0955 | 0.0814 |
| 1 | 3 | 0.3361 | 0.0001 | -1.0537 | 0.0719 | 0.1548 |
| 1 | 4 | 0.331 | 0.0004 | -0.6032 | 0.0451 | 0.3158 |
| 1 | 5 | 0.3333 | 0.0003 | -0.6594 | 0.0539 | 0.2504 |
| 1 | 6 | 0.3365 | 0.0001 | -0.7656 | 0.0667 | 0.1780 |
| 1 | 7 | 0.3367 | 0.0001 | -0.7591 | 0.0679 | 0.1723 |
| 1 | 8 | 0.3389 | 0.0001 | -0.7955 | 0.0942 | 0.0843 |

| Section | Cumulative Days of Rain | Intercept α | Coefficient 1 β | Coefficient 2 γ | Adjusted R-Squared | *p*-value |
|---|---|---|---|---|---|---|
| 1 | 9 | 0.3398 | 0.0001 | -0.8001 | 0.1038 | 0.0647 |
| 1 | 10 | 0.3384 | 0.0001 | -0.6624 | 0.0805 | 0.1226 |
| 1 | 20 | 0.3467 | -0.0002 | -0.4941 | 0.1342 | 0.0273 |
| 1 | 30 | 0.3468 | -0.0001 | -0.3225 | 0.141 | 0.0224 |
| 1 | 40 | 0.344 | 0 | -0.2119 | 0.1045 | 0.0633 |
| 1 | 50 | 0.3409 | 0.0001 | -0.1663 | 0.096 | 0.0802 |
| 1 | 60 | 0.3391 | 0.0002 | -0.1238 | 0.079 | 0.1278 |
| 1 | 70 | 0.3373 | 0.0003 | -0.098 | 0.0732 | 0.1495 |
| 1 | 80 | 0.3357 | 0.0003 | -0.0773 | 0.06 | 0.2131 |
| 1 | 90 | 0.3346 | 0.0003 | -0.0643 | 0.0532 | 0.2552 |
| 1 | 100 | 0.3341 | 0.0003 | -0.0573 | 0.0525 | 0.2594 |
| 2 | 1 | 0.3887 | -0.0022 | -0.8949 | 0.0845 | 0.1101 |
| 2 | 2 | 0.39 | -0.0023 | -0.5726 | 0.0859 | 0.1059 |
| 2 | 3 | 0.3937 | -0.0025 | -0.7323 | 0.0952 | 0.0819 |
| 2 | 4 | 0.3939 | -0.0024 | -0.6613 | 0.1003 | 0.0712 |
| 2 | 5 | 0.3953 | -0.0025 | -0.6628 | 0.1026 | 0.0668 |
| 2 | 6 | 0.3959 | -0.0025 | -0.6312 | 0.1001 | 0.0715 |
| 2 | 7 | 0.3957 | -0.0025 | -0.6075 | 0.0993 | 0.0731 |
| 2 | 8 | 0.396 | -0.0025 | -0.5717 | 0.1041 | 0.0640 |
| 2 | 9 | 0.3954 | -0.0024 | -0.5171 | 0.1017 | 0.0685 |
| 2 | 10 | 0.3947 | -0.0024 | -0.4358 | 0.0959 | 0.0805 |
| 2 | 20 | 0.3956 | -0.0024 | -0.236 | 0.0953 | 0.0818 |
| 2 | 30 | 0.3925 | -0.0023 | -0.1135 | 0.0877 | 0.1009 |
| 2 | 40 | 0.386 | -0.0021 | -0.0221 | 0.078 | 0.1313 |
| 2 | 50 | 0.3856 | -0.0021 | -0.0164 | 0.0779 | 0.1317 |
| 2 | 60 | 0.3871 | -0.0021 | -0.0241 | 0.079 | 0.1280 |
| 2 | 70 | 0.3878 | -0.0021 | -0.0257 | 0.08 | 0.1245 |
| 2 | 80 | 0.388 | -0.0021 | -0.0237 | 0.0801 | 0.1240 |
| 2 | 90 | 0.388 | -0.0021 | -0.0217 | 0.0802 | 0.1238 |
| 2 | 100 | 0.3878 | -0.0021 | -0.019 | 0.08 | 0.1243 |
| 3 | 1 | 0.5671 | -0.0018 | -0.5847 | 0.0659 | 0.1820 |
| 3 | 2 | 0.571 | -0.002 | -0.6469 | 0.0756 | 0.1402 |
| 3 | 3 | 0.5733 | -0.002 | -0.6926 | 0.0819 | 0.1181 |
| 3 | 4 | 0.5749 | -0.0021 | -0.7192 | 0.0957 | 0.0809 |
| 3 | 5 | 0.5766 | -0.0021 | -0.7249 | 0.0994 | 0.0729 |
| 3 | 6 | 0.5769 | -0.0022 | -0.6767 | 0.0945 | 0.0835 |
| 3 | 7 | 0.5775 | -0.0022 | -0.6918 | 0.0974 | 0.0772 |
| 3 | 8 | 0.5762 | -0.0021 | -0.5737 | 0.0955 | 0.0814 |
| 3 | 9 | 0.5754 | -0.002 | -0.5087 | 0.0912 | 0.0915 |
| 3 | 10 | 0.5758 | -0.0021 | -0.4735 | 0.0891 | 0.0969 |
| 3 | 20 | 0.586 | -0.0024 | -0.4371 | 0.1381 | 0.0243 |
| 3 | 30 | 0.5829 | -0.0023 | -0.2443 | 0.1211 | 0.0397 |
| 3 | 40 | 0.5779 | -0.0021 | -0.1333 | 0.0909 | 0.0924 |
| 3 | 50 | 0.5773 | -0.002 | -0.1167 | 0.0944 | 0.0838 |
| 3 | 60 | 0.58 | -0.0021 | -0.1148 | 0.1065 | 0.0599 |
| 3 | 70 | 0.5768 | -0.002 | -0.0809 | 0.094 | 0.0847 |
| 3 | 80 | 0.5786 | -0.0021 | -0.0814 | 0.102 | 0.0680 |
| 3 | 90 | 0.5748 | -0.002 | -0.0546 | 0.0839 | 0.1118 |
| 3 | 100 | 0.5751 | -0.002 | -0.052 | 0.0867 | 0.1036 |

The first two models, where temperature and rainfall are used as variables separately, each fail to adequately function in at least one of the sections. A model which uses both temperature and rainfall functions substantially better, although only for a subset of days of cumulative rainfall. Based on this existing data, there was some evidence for prediction of sideways-force coefficient across all the sections tested using 20-40 days of cumulative rainfall. However, the lack of skid resistance measurement data (compared to that used to develop the Irish model) covering a larger variety of weather conditions and number of days through the year reduces the possibility to establish reliable correlations.

Use of shorter cumulative rainfall periods (as was found to be correlating in the Irish model) resulted in poor results. One explanation for the failure is the presence of a lot of dry days in the data. Below are some sample plots (Figure 7, Figure 8) to represent the variation present in the underlying data.

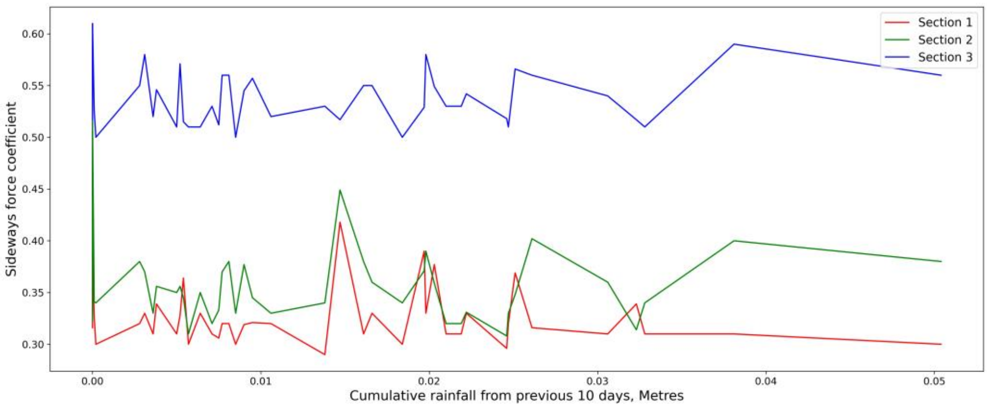


**Figure 7: Influence of cumulative rainfall from previous 10 days before the skid resistance measurements on sideways-force coefficient**

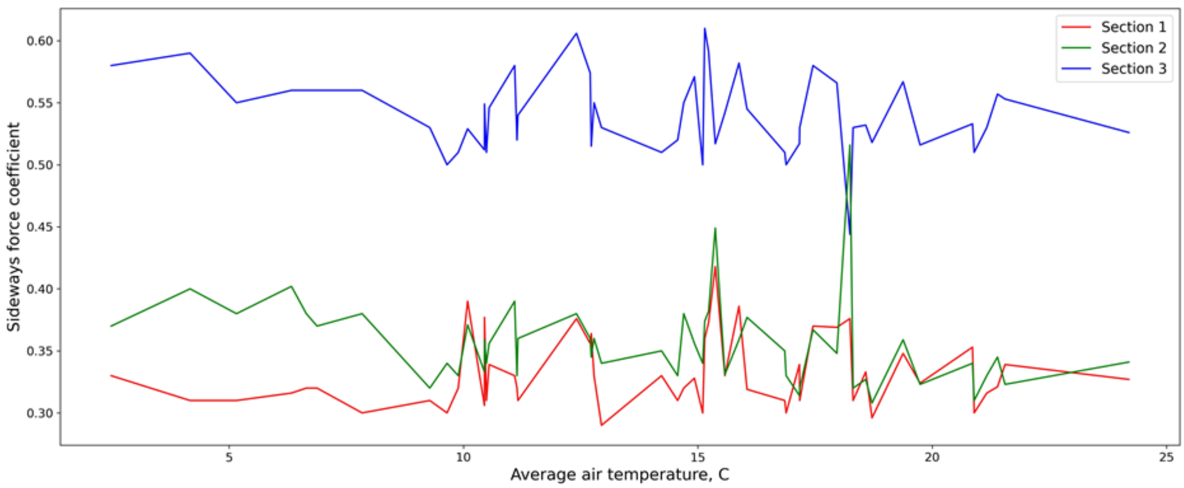


**Figure 8: Influence of average air temperature on sideways-force coefficient**

Summarizing the results from the work in Phase 1, it was concluded that the direct transferability of the Irish model to England’s SRN is not possible because of the Irish model’s suitability for specific sites and specific pavement types.

Detailed analysis of historical weather and skid resistance data showed potential for establishing correlation between weather factors and skid resistance by modifying the Irish model with developed regressions from A329M analysis. However, the practical work showed that more frequent skid resistance measurement data over a longer period of time is needed to establish reliable correlations. Even though, a “window” between 20 and 40 days of accumulated rainfall and air temperature could be potentially used for skid resistance prediction, this cannot guarantee that in extending the model development to a larger variety of pavement types, the multilinear correlation will be found. These limitations could be associated with the large number and complexity of different factors that influence skid resistance.

# 3 Phase 2. Machine learning approach to develop weather and skid resistance model

As the findings from phase 1 had suggested that a site with more frequent (and varying in terms of weather conditions) skid resistance measurements could be used to potentially improve the correlations between weather parameters and skid resistance, the next phase of work investigated the incorporation of additional sites to improve the reference dataset. Besides increasing the dataset for the model, a supervised learning approach was used instead of the previous single and multiple linear regression analysis.

## 3.1 WDM dynamic calibration site in Bristol

The data analysis from the A329M site provided an indication that it might be possible to establish a reliable weather and skid resistance correlation if more frequent skid resistance data (with measurements carried out in over the wider range of weather conditions) was obtained. Therefore, historical skid resistance data was acquired from WDM's dynamic calibration site on A4174 Bristol ring road between Station Road link and the B4465. The data contained historical (2013-2019) weekly skid resistance measurements from 7 sideways-force devices. In addition to the skid resistance data, road surface texture measurement data from SCANNER QA checks from the same site were also obtained. Both skid resistance and texture data were reported at 10m lengths which were used to calculate mean values for the site.

Skid resistance coefficient variations for all the machines on the Bristol dynamic calibration site over the analysed period are shown in Figure 9. It can be seen that the largest SC fluctuations can be linked mainly with the survey date (winter or summer). It was also noticed that during the winter period, the spread of skid resistance data between the different machines was greater than in the summer, suggesting that the accuracy and consistency of the data for skid resistance prediction may be negatively affected. Therefore, in further data analysis, all skid resistance measurements outside the skid resistance survey season were excluded.


**Figure 9: SC variation for sideways-force devices on the Bristol site over the period 2013-2019**

Since the WDM calibration site is located approximately equidistant from 3 National Highways weather stations (see Figure 10), weather data from all 3 weather stations was downloaded and then compared to understand whether the weather trends were comparable and how the model can vary if one or another site is selected (Figure 11 and Figure 12). Out of these three weather stations, the one on A46 was found to have trends of total precipitation and temperature around the middle of the three sites, and was therefore selected for further data analysis to calculate regressions between skid resistance and weather conditions.


Figure 10. WDM dynamic calibration site *(Map data from ©[OpenStreetMap](https://www.openstreetmap.org))*

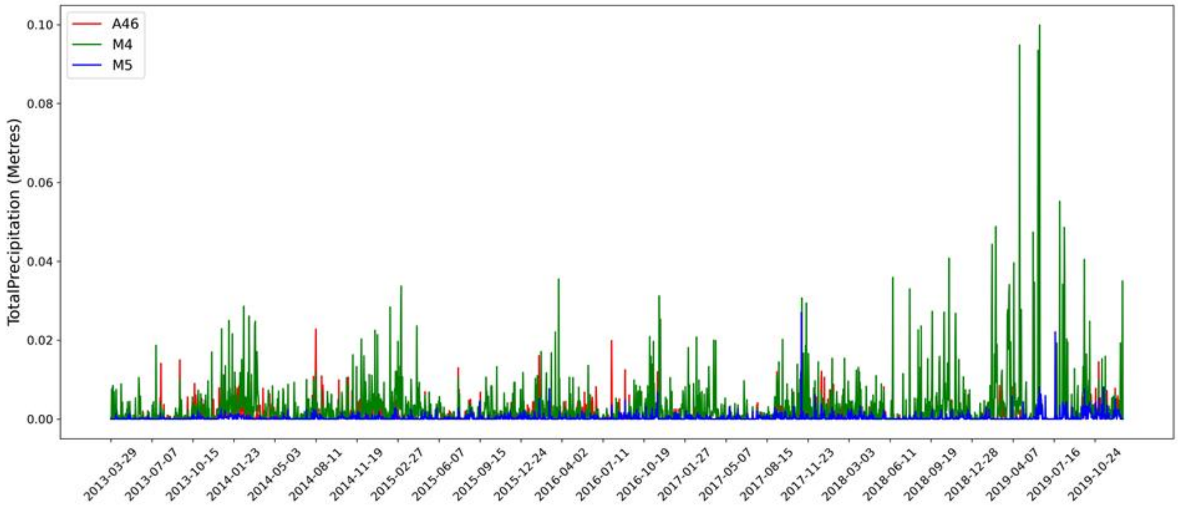


**Figure 11. Total daily precipitation recorded at all three weather stations for the years from 2013 to 2020**

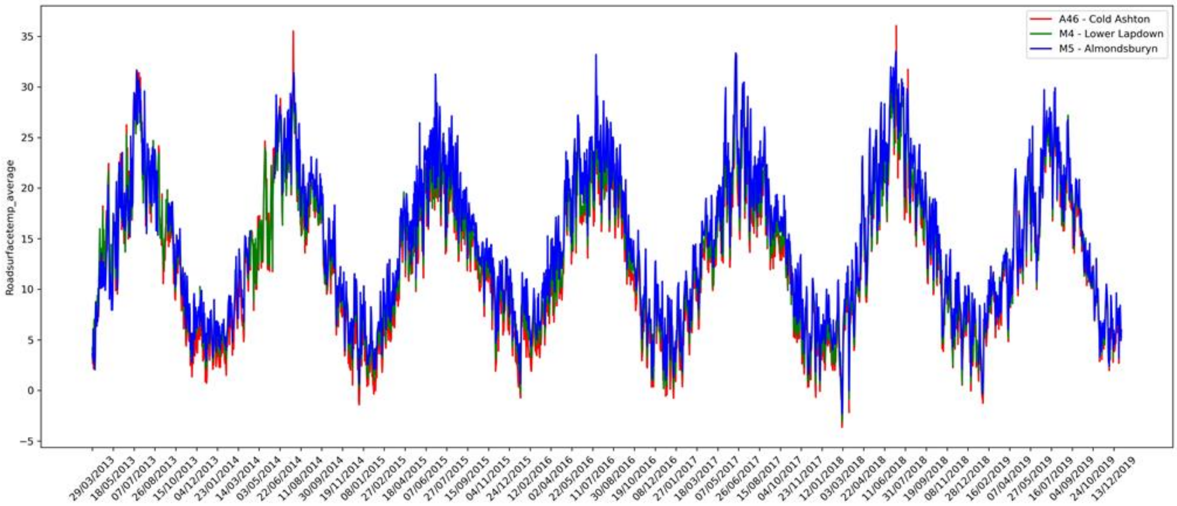


**Figure 12: Average daily road surface temperature recorded at all three weather stations for the years 2013 to 2020**

Detailed data from the A46 weather station were downloaded and a large number of individual weather factors were analysed and compared against skid resistance data on the Bristol site. The following weather factors were analysed:

- Air temperature
- Road surface temperature
- Dew temperature
- Humidity
- Rain intensity
- Cumulative rainfall for periods from 1 to 100 days
- Dry spell factor

Similar to the A329M analysis, no reliable correlation was found between skid resistance and individual weather factors. Figure 13 shows calculated Pearson's Correlation for each individual variable (either weather factor or surface texture) and sideways-force coefficient. This analysis enabled the variables that are the most relevant to SC to be identified, but the initial analysis showed that strong linear regression relationships could not be found.

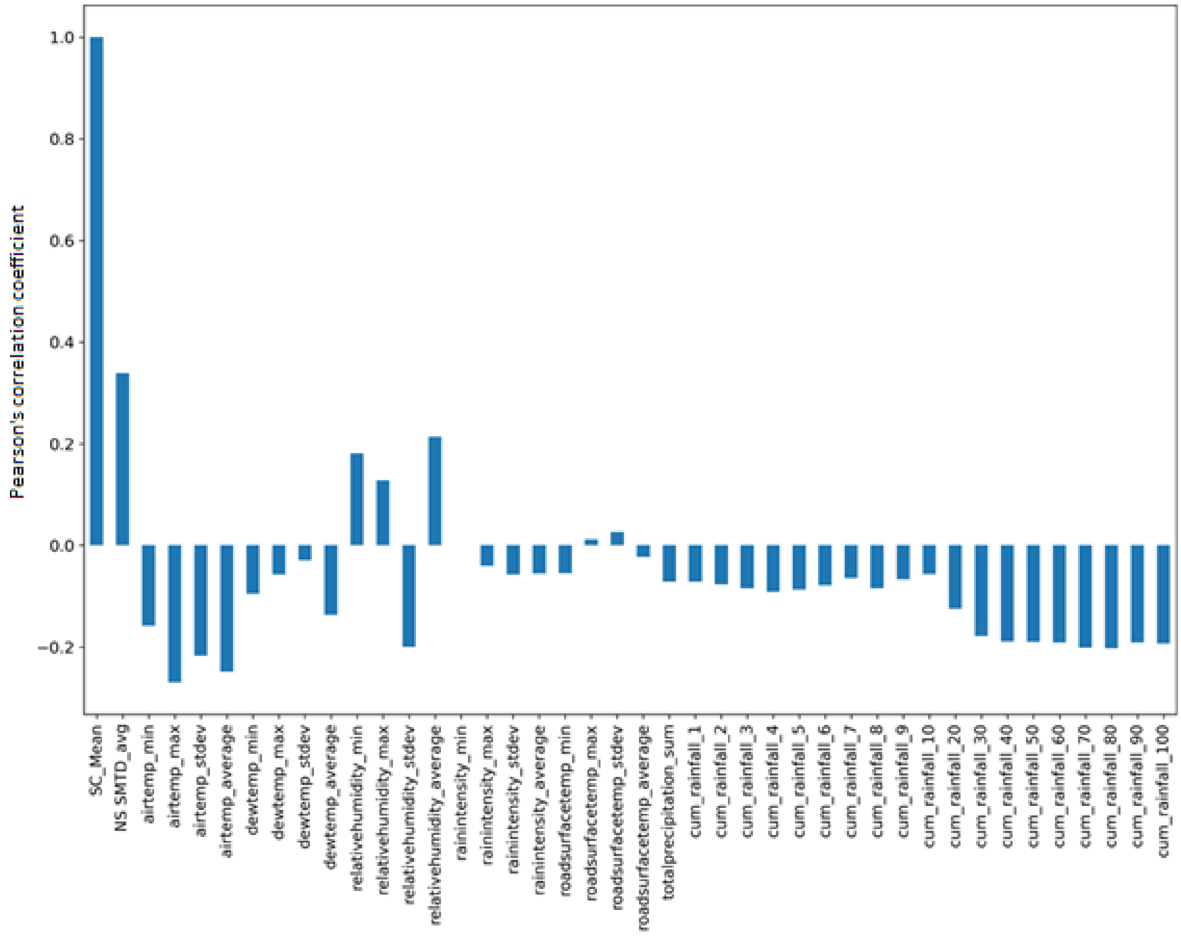


**Figure 13. Pearson's correlation for individual parameters (weather data from A46 weather station) against SC**

## 3.2 Machine Learning approach

Further data analysis aimed to utilise Machine Learning (ML) methods to develop data-driven predictive modelling of skid resistance. Four algorithms were examined:

- Lasso regression (LR).
- Gradient boosting regression (GBR).
- Random Forest (RF).
- Stacking Regressor (SR).

SR is an ensemble learning technique to combine multiple regression models (i.e. LR, GBR and RF) via a meta-regressor. The accuracy of SR mainly depends on the most accurate regression algorithm. RF algorithm is an ensemble learning method for both classification and regression problems; it is the most widely used supervised learning algorithm. RF consists of a large number of individual decision trees that work together (Figure 14). Each individual tree in the RF produces a class prediction and the class with the most votes becomes the prediction of the model. According to the results presented in this work, RF offered the best prediction power.

The predictive model was built using the scikit-learn library and written in Python. The function of the predictive model is to take a set of features X as input and then output an approximation prediction y. Thus, it is important to measure the importance of the features. The correlations among features are checked by visualising the correlation matrix as a heatmap, the most relevant features (i.e. average air temperature, average humidity, average road surface temperature, average texture depth) were selected to reduce the impurity across all trees in the forest. The whole dataset is split randomly into a Train Set (80%) and Test Set (20%). The model is fed with the Train Set and validated by Test Set.

To achieve the best performance of the model, a series of parametric studies have been carried out. Three hyperparameters were investigated, which are *n_estimators*, *max_features* and *max_depth*. *n_estimators* is the number of trees the algorithm builds before taking the maximum voting or taking the averages of predictions. In general, a higher number of trees improves performance and makes the predictions more stable, but it also slows down the computation. Having *n_estimators* = 100 can achieve the best balance between accuracy and time consumption. *max_features* is the maximum number of features random forest considers to split a node. *max_depth* is the maximum number of levels in each decision tree, and 10 is sufficient for good accuracy.

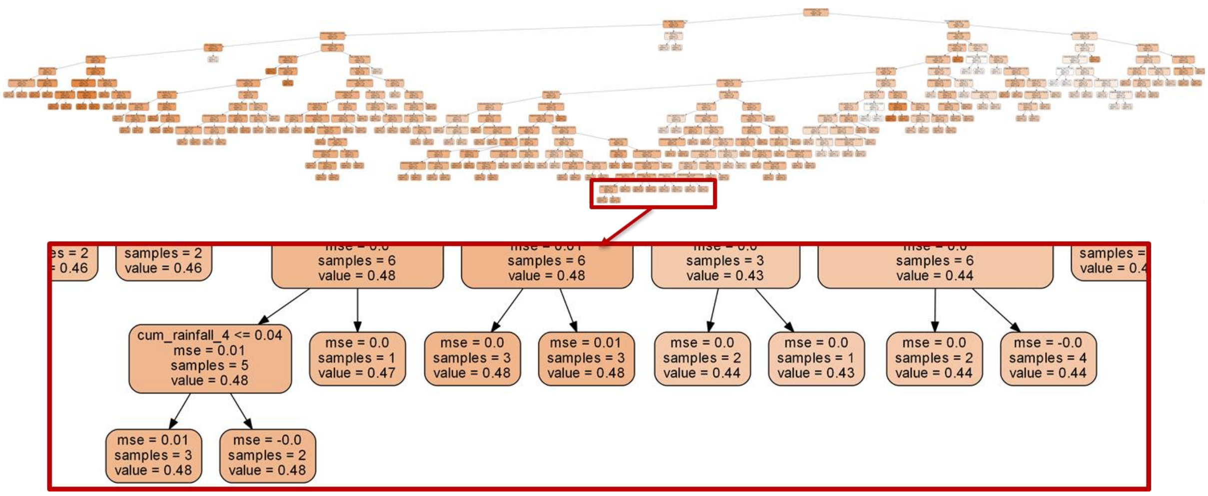


**Figure 14: Example of the RF decision trees used to create ML based skid resistance prediction model**

## 3.3 A329M and Bristol site data analysis

All the data (skid resistance and texture) from Bristol and A329M dynamic calibration sites and weather data from A46 and M4 Shurlock Row weather stations were uploaded to the Machine Learning models. 80% of the randomly selected data was used for training the model and 20% of the randomly selected data points were used to test the model.

The results showed that the Random Forest regression algorithm is the most suitable for skid resistance prediction from weather and texture data (see Figure 15). The highest calculated

$R^2$ values for the Random Forest model, Gradient Boosting and Stacking Regressor were 0.79, 0.81 and 0.81, respectively, which shows a strong relationship between the selected variables (*airtemp_average, relativehumidity_average, NS SMTD_avg , 'cum_rainfall_1', 'cum_rainfall_2', 'cum_rainfall_3', 'cum_rainfall_4', 'cum_rainfall_5', 'cum_rainfall_6', 'cum_rainfall_7', 'cum_rainfall_8', 'cum_rainfall_9', 'cum_rainfall_10', 'cum_rainfall_20', 'cum_rainfall_30', 'cum_rainfall_40','cum_rainfall_50', 'cum_rainfall_60', 'cum_rainfall_70', 'cum_rainfall_80', 'cum_rainfall_90', 'cum_rainfall_100'*) in the analysis. Tests were also completed to investigate whether other combinations of the variables could result in better prediction, but the result was not as good as 0.81.

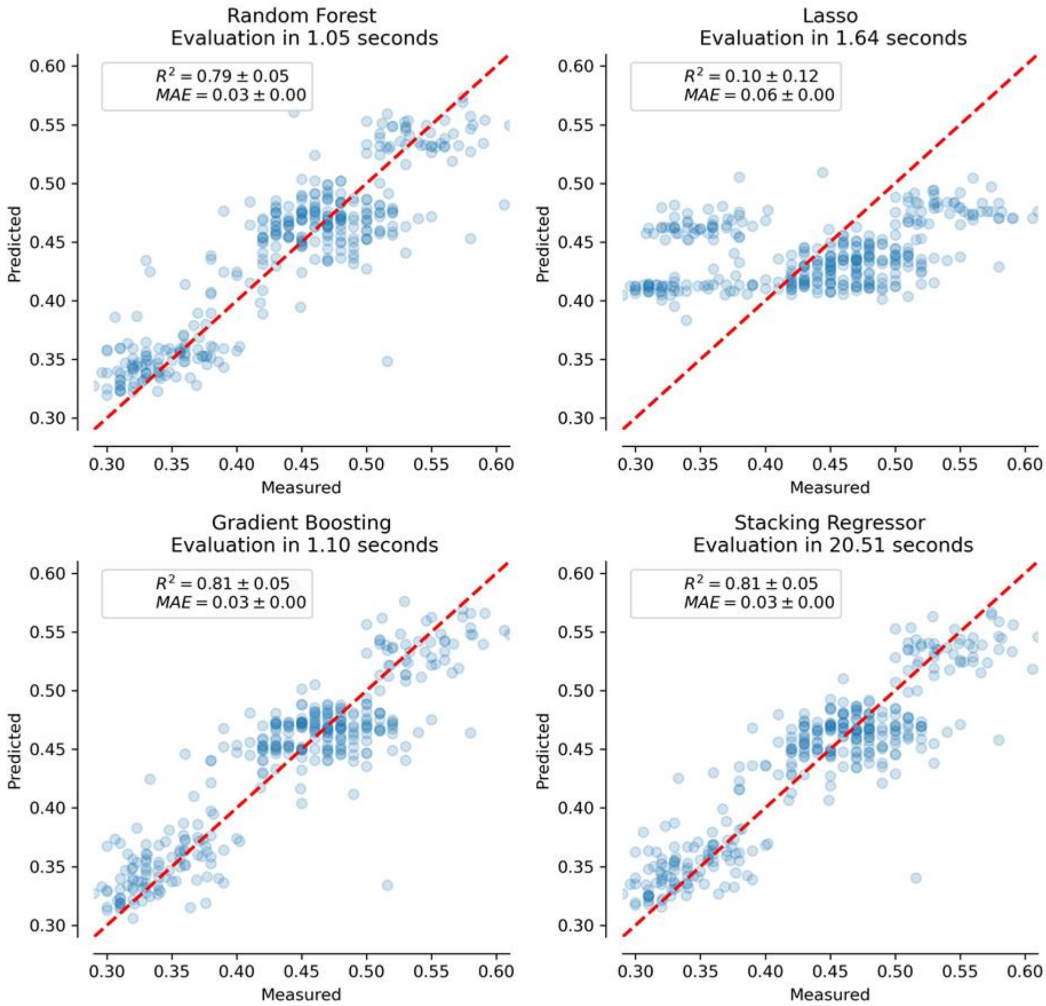


**Figure 15: Different regression models calculated using four machine learning techniques**

The developed ML algorithm provided positive results on predicting SC values based on the created Random Forest decision tree with the tested variables. This model was developed based on the data from two sites – Bristol and A329M calibration sites. Both sites provided a variety in weather conditions and a range of skid resistance and texture levels, although it is not clear how the model would perform on other sites on the SRN.

### 3.4 Model extension to benchmark sites

The outcome from the machine learning showed promising results, however the model was developed using only 2 sites as reference data. Therefore, it was decided to expand the database of the model with the addition of data from benchmark sites and then test the model's performance. For that purpose, 16 benchmark sites were selected on the SRN (locations showed in Figure 16). Sites were selected to meet the following criteria:

- Inclusion of different surface types (asphalt and concrete);
- Have a wider range of skid resistance and texture levels than the Bristol and A329M sites; and
- Have a wider geographical coverage of the English SRN, including coastal and inland sites.

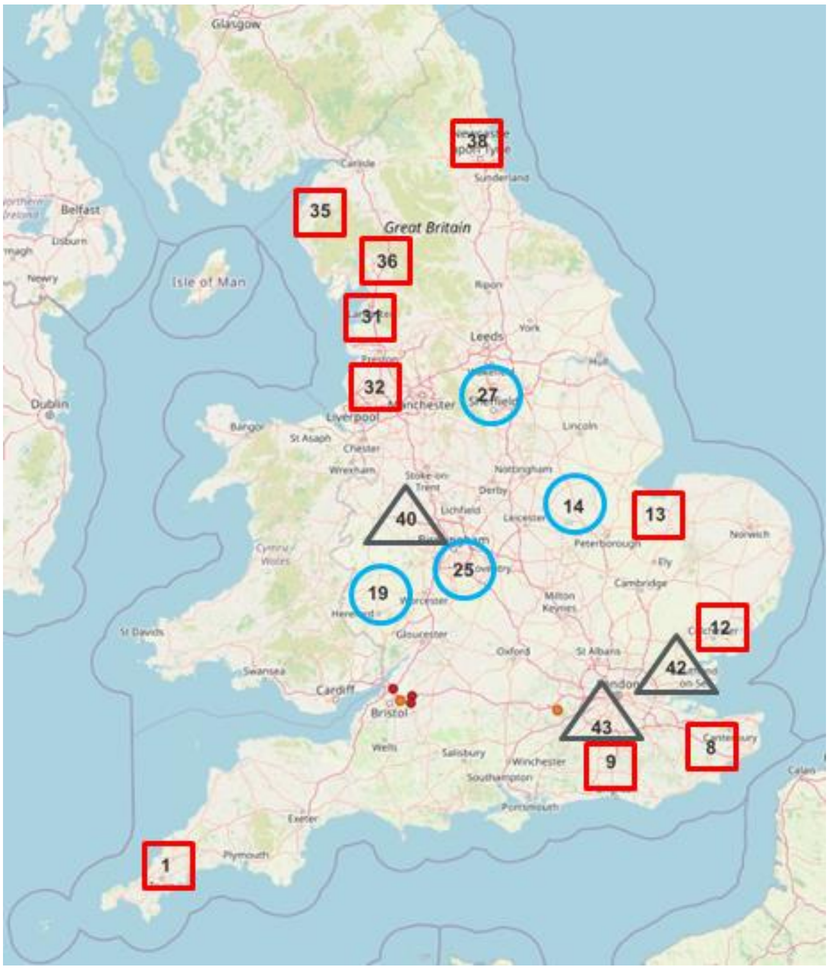


**Figure 16: Benchmark sites selected for model adjustment and testing (rectangular – coastal site, circle – inland side, triangle – sites with concrete pavement)** ***(Map data from ©OpenStreetMap)***

Similar to the previous sites, weather data was sourced from nearby National Highways Vaisala weather stations, skid resistance data has been collected from the annual surveys of these benchmark sites and texture data was downloaded from the National Highways pavement management system (HAPMS). All data covered the period from 2013 to 2020.

First relationships between individual variables and skid resistance were calculated. As shown in Figure 17, the relationships are not strong; only air temperature, road surface temperature, relative humidity and SMTD were higher than ±0.2 for the Pearson's correlation coefficient.

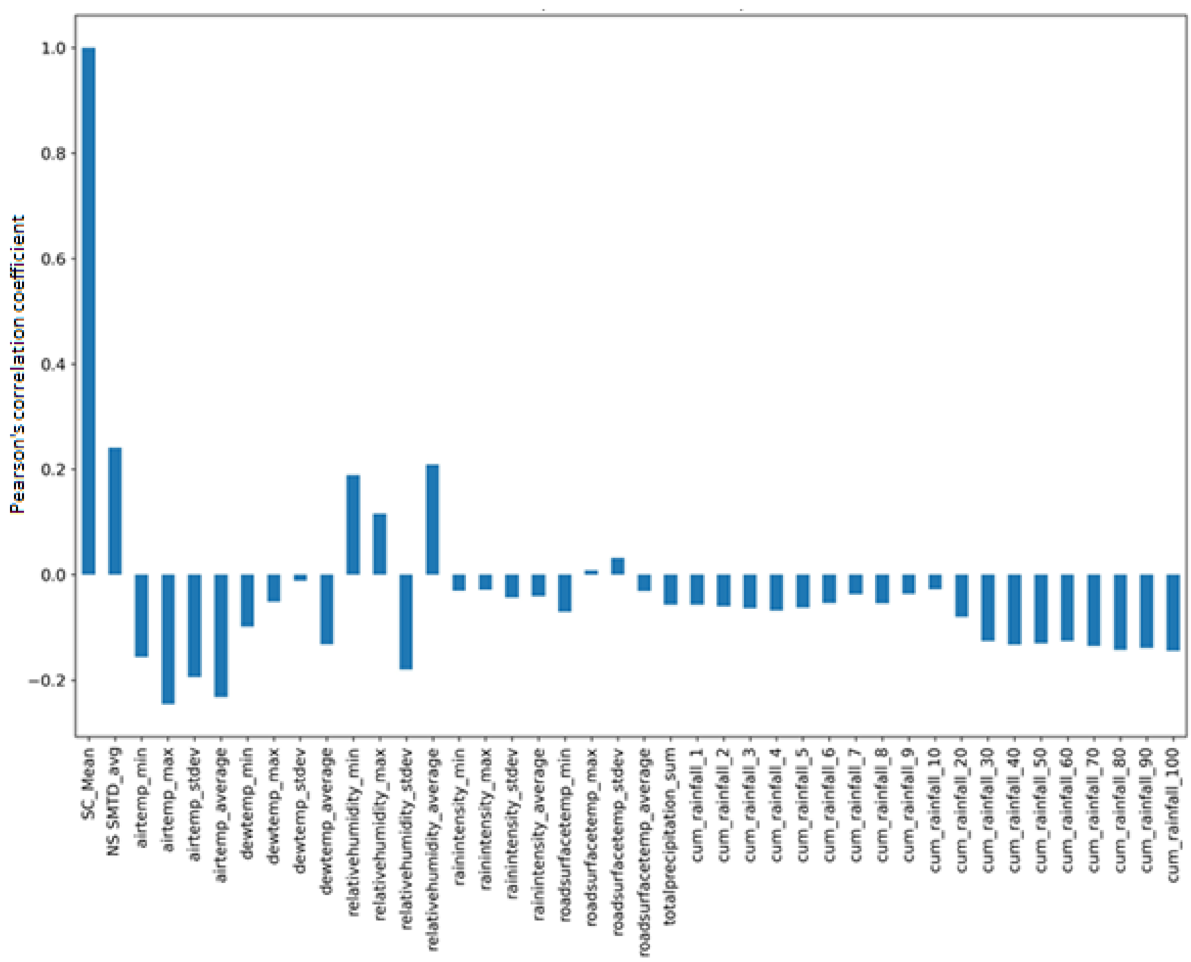


**Figure 17: Relationships between individual variables and skid resistance for the data including Bristol and A329M dynamic calibration sites and selected benchmark sites**

All input data was also used to improve (train) the Machine Learning models to extend the data range and therefore improve the models' applicability on a wider range of sites. Different combinations of the input parameters were tested to see which ones would provide the best prediction performance. As shown in Figure 18, the best model for prediction is Stacking Regressor which is mainly based on the Random Forest model. The highest $R^2$ value (0.67) was achieved with the following input parameters: *airtemp_average, relativehumidity_average, NS SMTD_avg , 'cum_rainfall_1', 'cum_rainfall_2', 'cum_rainfall_3', 'cum_rainfall_4', 'cum_rainfall_5', 'cum_rainfall_6', 'cum_rainfall_7', 'cum_rainfall_8', 'cum_rainfall_9', 'cum_rainfall_10', 'cum_rainfall_20', 'cum_rainfall_30', 'cum_rainfall_40',* *'cum_rainfall_50', 'cum_rainfall_60', 'cum_rainfall_70', 'cum_rainfall_80', 'cum_rainfall_90', 'cum_rainfall_100'.*

The model accuracy decreased when compared against the model for only the Bristol and A329M dynamic calibration sites. The explanation for this is that the A329M and Bristol dynamic calibration sites had lower variability in surface texture (Figure 19) and skid resistance levels compared to the benchmark sites. The main difference between the model for Bristol and A329M dynamic calibration sites and the model including benchmark sites was that the latter did not include data about the cumulative rainfall, as it didn't show a strong enough relationship with skid resistance. The similar observation was also made in the Irish study (Mulry *et al.*, 2016) which showed that the model's prediction ability was not changed much after excluding rainfall data.

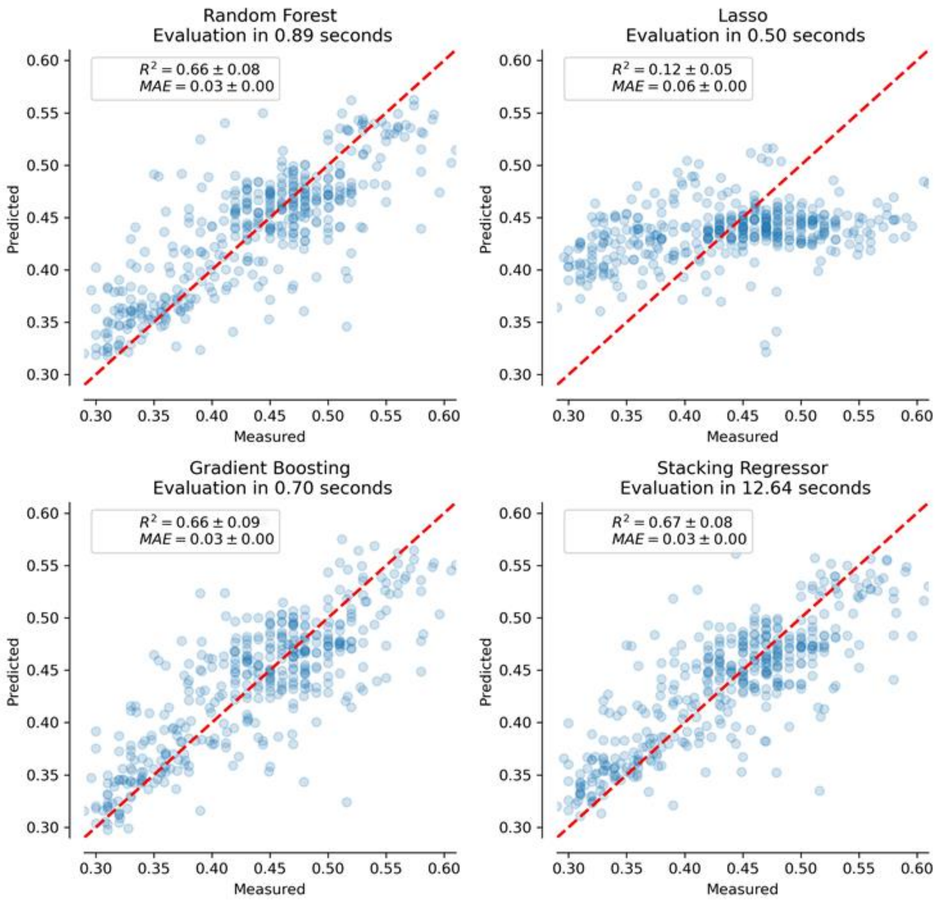


**Figure 18: Different regression models calculated using four machine learning techniques for the Bristol and A329M dynamic calibration sites and benchmark sites**

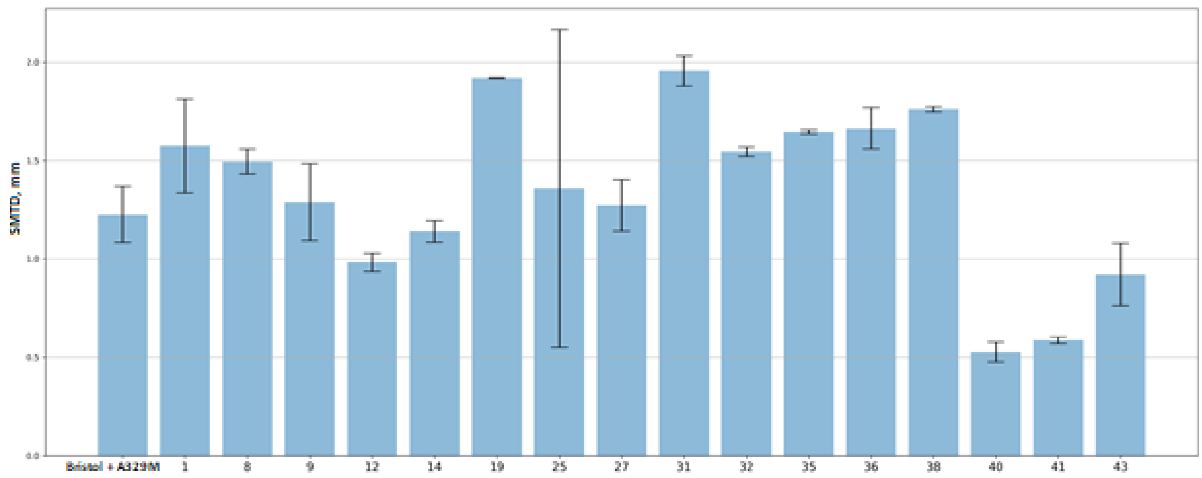


**Figure 19: Texture levels (SMTD) at Bristol and A329M dynamic calibration sites and benchmark sites**

## 3.5 Testing the model

Testing of the new model was done in two stages. The model was first trained with 100% of the 2013-2018 data and then used to predict skid resistance values for 2019 from texture and weather data collected in 2019. This resulted in differences between measured and predicted SC values ranging from 1.9 to 19.4%, as shown in Figure 20. The second round of testing the model was done similarly but using 2013-2019 data to train the model and 2020 weather and texture data to predict 2020 SC values for some of the benchmark sites. It was found that the prediction error for some sites decreased (Sites 14 and 32) but increase for other sites increased (Sites 1 and 43) (Figure 21). These errors can be partly explained by the differences in surface texture levels for these benchmark sites and those making up the majority of the model reference data (Bristol and A329M dynamic calibration sites). The distribution of average SMTD levels on different sites are shown in Figure 19.

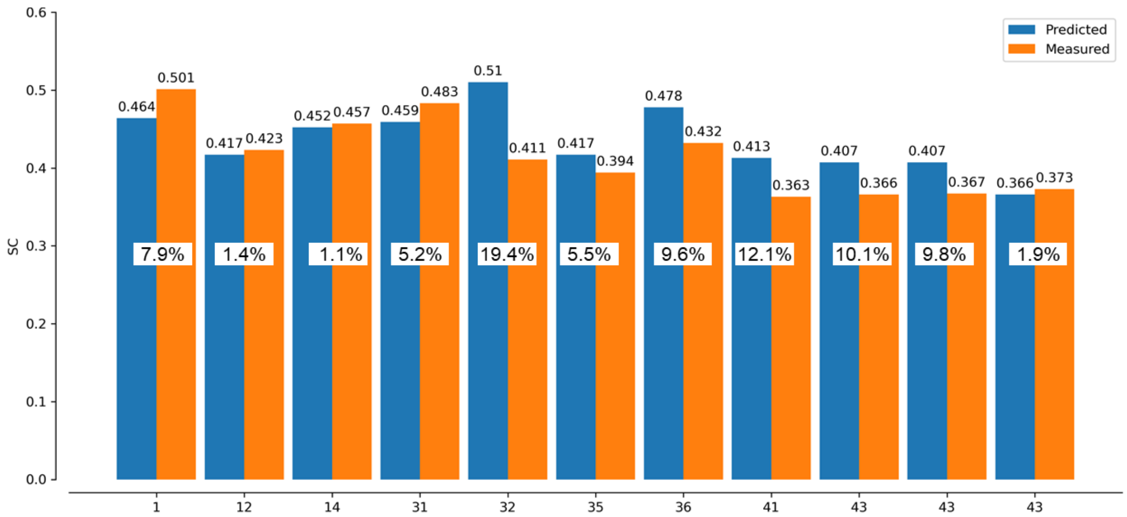


**Figure 20: Measured and predicted SC for benchmark sites when 2013-2018 data used to train the model and predict 2019**

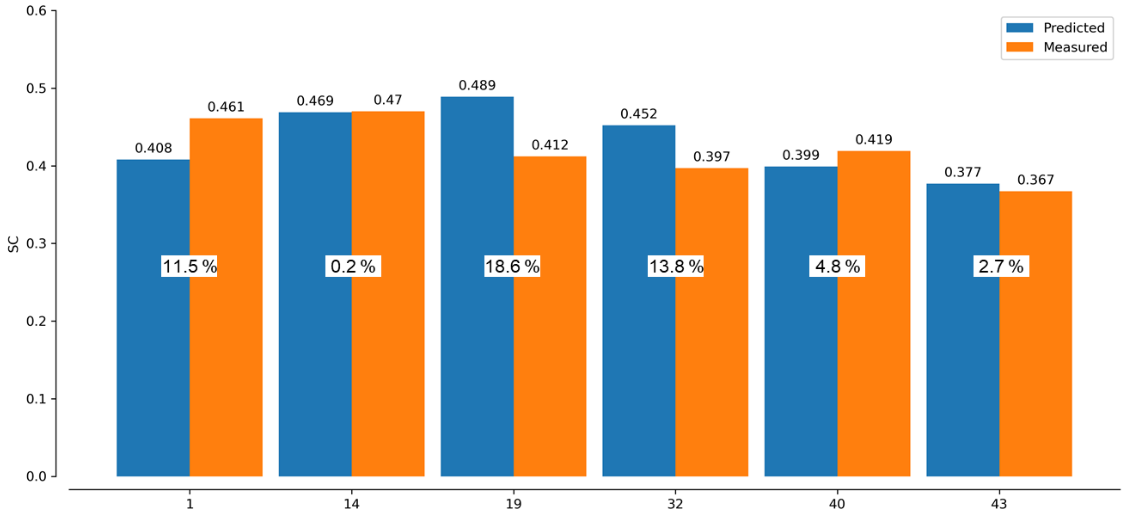


**Figure 21: Measured and predicted SC for benchmark sites when 2013-2019 data used to train the model and predict 2020**

# 4 Conclusions and recommendations

A number of international publications and reports were reviewed from the studies that tried to correlate skid resistance and weather characteristics. Those studies had resulted in several models being developed to predict skid resistance from weather characteristics, however most of the models are either too generic or too complex and site dependant, thus limiting wider application and transferability across regions or countries.

A majority of the models that have been developed focused on adjusting skid resistance measurements by providing a seasonal correction for the measurement devices. Only a few models were developed with a focus on supporting pavement management decisions or predicting the evolution of skid resistance.

The majority of seasonal variation models were based on historical skid resistance variation and weather trends which were more predictable in the past, especially in the regions and countries with more "seasonal" climate. However, the impact of climate change results in less predictable weather with more extreme events or even overlapping of seasons over the year. Therefore, the application of skid-resistance and weather correlation models which are based only on temperature, temperature variation and day of the year become inaccurate and therefore of very limited use.

One of the key points that limit the possibilities to apply the models in other regions is that the models are often developed for particular measurement devices which may have their own confounding factors (such as measurement method, tyre type, etc.) on skid resistance variation.

Short-term skid resistance prediction models which assess temperature, accumulated rainfall, rain intensity and dry spell factor are very dependent on road surface type, surface condition, contaminants, site location and traffic volumes. The literature review showed that short-term skid resistance variation cannot be explained by individual or only a few variables and requires a more holistic approach.

The "Irish weather and skid resistance correlation model", developed by PMS and the National University of Ireland, looked to have initial promise and transferability to the English SRN because of similarities in networks, pavement surfacings and climates between Ireland and England. However, after performing a deeper analysis of this model and trying to apply it directly to several benchmark sites or adjusting it using data from the A329M dynamic calibration site, showed that it is very site dependent and not applicable for a variety of pavement types. It should also be mentioned that the Irish model did not include the texture as an input parameter for skid resistance which was found to be significant factor when predicting skid resistance values.

The project explored a machine learning approach for predicting skid resistance values. Four Machine learning methods (Random Forest, Lasso, Gradient Boosting and Stacking Regressor) we tested of which the most accurate appeared to be Random Forest.

- The machine learning approach was first developed for the Bristol and A329M dynamic calibration sites and showed a strong relationship ($R^2$ of around 0.8 for some of the models) between skid resistance and weather (average air temperature, average relative humidity, accumulated rainfall for 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100 days prior the measurements) and texture (nearside wheel path SMTD) parameters.

- Applicability of the model on several of the National Highways benchmark sites was investigated by expanding (training) the model with the additional input data from 16 benchmark sites. This exercise resulted in the extension of both the texture and skid resistance value ranges and included a larger variety of weather conditions representing the whole country. However, the outcome of applying machine learning on the benchmark sites resulted in a reduced model accuracy – $R^2$ of 0.67.
- For testing purposes, the model was uploaded with the skid resistance data from the selected benchmark sites covering the period 2013-2018, weather data covering 2013-2019 and texture data covering 2013-2019. This allowed the model to predict skid resistance values on the selected benchmark sites for the year 2019. The same steps were then also repeated to predict 2020 skid resistance data. Predicted skid resistance values were compared against the measured skid resistance values showing that the error varied by up to 20%. The smallest errors were mainly observed for the benchmark sites having similar texture levels to the A329M and Bristol dynamic calibration sites.

In summary, the machine learning model developed showed potential to predict skid resistance values, but further model testing and improvement would be needed to provide more accurate results:

- A reduction in $R^2$ value when the model was applied on the benchmark sites indicated that some significant parameters may not have been included in the model that could have potentially resulted in biased data. It is recommended to include traffic data in further model improvement activities as it could provide a relevant input data to represent the contribution of traffic on skid resistance seasonal variation.
- It was observed that when the model is trained with more data from one site, the model's accuracy improves. This suggests that if the model is improved, tested and validated to provide sufficient accuracy, then continuous model updates with additional data would improve its robustness even more.
- It is likely that the current model is too broad to cover the whole country with its widely varying weather conditions, and that it would potentially be better to have models developed for different regions to represent their particular climate conditions. This research study could not carry out such a task as the model creation relied on a large reference data set with multiple measurements on individual sites; as was the case for the Bristol and A329M dynamic calibration sites. Thus, the development of the model for different regions would require selection of the reference data site(s) in that region with frequent and long-term historical skid resistance data.

If the machine learning based skid resistance prediction model is further improved, there are multiple application areas where it could be used:

- For QA purposes - the model could define a range of skid resistance values for particular sites under specific weather conditions. This would provide an indication of the skid resistance levels expected on a dynamic calibration site when measurements are made, which could then be compared to the actual measurements to support QA procedures. Currently the historic range of values for a site will be known and if measurements fall outside that range, then the measurement device would be investigated for potential issues. A more accurate prediction of the expected level on the day of measurement would help to spot issues that may be missed currently.

- When tested and validated at network level, the model could be used to support/improve the current LECF correction approach to predict skid resistance at various locations on the SRN and support maintenance decisions.
- The model can be improved (trained) periodically (e.g. every year) by adding more data to the model and improving its accuracy or to reflect the changing climate conditions and its impact on frictional properties of the road surfaces on the SRN.
- The model could also be used to investigate if any bias is introduced into the skid resistance measurements due to drift in the performance of the fleet and/or changes to test tyres from year to year, which can currently be masked by the seasonal corrections.
- Prediction of the skid resistance at high risk sites - for example, sites reported as being below the IL but not requiring detailed investigation following assessment using the National Highways crash model, could be monitored by predicting their skid resistance values if the forecast is showing a long, dry period, or other weather anomalies that could result in a significant decrease in skid resistance. Early identification of such sites could provide the opportunity for improved management through, for example, temporary warning signs or speed limits to mitigate any increase in collision risk.

# 5 References

**Ahammed AM and Tighe SL (2008).** Long Term and Seasonal Variations of Pavement Surface Friction. *2008 Annual Conference of the Transportation Association of Canada, Toronto, Canada.*

**Anderson DA, Meyer WE and Rosenberger JL (1986).** Development of a procedure for correcting skid resistance measurements to a standard end-of-season value. *Transportation Research Record 1084*, 40-48.

**Bessa IS, Castelo Branco VTF and Soares JB (2014).** Evaluation of polishing and degradation resistance of natural aggregates and steel slag using the aggregate image measurement system. *Road Materials and Pavement Design, 15*(2), 385-405.

**Brittain S (2020).** *Skid resistance benchmark survbeys 2019. PPR950*. TRL Limited, Wokingham.

**Croney D and Croney P 1998.** Design and Performance of Road Pavements, 3rd edition. McGraw-Hill, New York.

**Donbavand J and Brittain S (2007).** *Task 3: Review of Correction Factors (UPR/IE/213/06)*. TRL: Wokingham.

**Hill BJ and Henry JJ (1978).** Short term, weather-related skid ressitance variation. *Transportation researh Record, 836*, 76-81.

**Hosking JR and Woodford GC (1976).** *Measurement of skidding resistance. Part II. Factors affecting the slipperiness of a road surface. TRRL Laboratory Report 738*. Transport and Road Research Laboratory, Crowthorne, United Kingdom.

**Jayawickrama PW, Rachakatla P and Thomas B (1998).** *A comprehensive methodology for predicting field skid resistance of bituminous aggregates based on laboratory test data as well as their past skid performance. Research Study No: 0-1459*.

**Kane M, Zhao D, Chailleux E, Delarrard F and Do MT (2013).** Development of an accelerated pavement test reproducing the effect of natural ageing on skid resistance. *Road Materials and Pavement design, 14*(1), 126-140.

**Mulry B, Brennan MJ and Sheahan JN (2012).** A model for adjusting SCRIMJ skid ressitance data to reflect seasonal variation. *5th Eurasphalt & Eurobitume Congress, 13-15th June 2012, Istanbul.*

**Mulry B, Brennan MJ and Sheahan JN (2016).** The analysis and further development of a model for adjusting SCRIM skid resistance data for temperature and rainfall. *6th Eurasphalt & Eurobitume Congress, 1-3 june 2016, Prague, Czech Republic.*

**National Highways (2019).** *Skidding Resistance. DMRB 7.3.1 CS 228.*

**Oliver JHW, Tredrea PF and Pratt DN (1988).** *Seasonal variation of skid resistance in Australia*. Australian Research Board, Vermonth South.

**Ongel A, Lu Q and Harvey J (2009).** Frictional properties of asphalt concrete mixes. *Transport, 162*(TR1), 19-26.

**Plati C and Georgouli K (2014).** Field investigations of factors affecting skid resistance variations in asphalt pavements. *The Baltic Journal of Road and Bridge Engineering, 9*(2), 108-114.

**Sanjuan E and Gutierrez-Bolivar O (2003).** Study of pavement friction variation with environmental conditions. *Ingeniería Civil, 129*, 83-90.

**van Bijsterveld W and del Val MA (2016).** Towards quantification os seasonal variations in skid ressitance measurements. *Road Materials and Pavement Design, 17*(2), 477-486.

**Wilson DJ (2006).** *An analysis of the seasonal and short-term variation of road pavement skid resistance*. The University of Auckland.

# Appendix A Benchmark site locations

**Table A.1 Location details of the benchmark sites**

| Site No. | Area | Route | Direction | Section(s) | Length (m) | Description | Nodes |
|---|---|---|---|---|---|---|---|
| 1 | 1 | A30 | E/B | 0800A30/400 | 2260 | Studs under A3076 bridge at Mitchell to studs at 2260m | 21435-21460 |
| 2 | 1 | A30 | W/B | 1100A30/115 | 1180 | End of slip On from A377 to studs at 1180m | 492-431 |
| 8 | 4 | M20 | E/B | 2200M20/290 | 1634 | End of slip On at Jct 9 (A20/A28) for 1634m | 5230-1859 |
| 9 | 4 | A23 | N/B | 3800A23/340 | 1402 | Studs just after bridge over approx. 1050m after B2110 (bridge over at Handcross) to studs under footbridge at 1402m | 13078-13216 |
| 12 | 6 | A12 | N/B | 1500A12/294 | 1053 | Studs at Suffolk boundary to start of slip road off to B1029 | 40560-42270 |
| 13 | 6 | A47 | E/B | 2600A47/145, 2600A47/147 | 1348 | Studs under bridge at centre of Terrington St John interchange to bridge at 1348m | 5027-5733-50343 |
| 14 | 7 | A1 | N/B | 2500A1/110 | 2150 | End of slip On from South Witham to Jct Left (to North Witham) | 7005-7015 |
| 17 | 7 | A14 | E/B | 2800A14/120 | 1728 | Studs under bridge 3742m W of A508 (bridge over) to studs under bridge at 1728m | 1820-2022 |
| 19 | 9 | A49 | N/B | 1800A49/320 | 1760 | Jct R (to Stoke Prior) to River Bridge | 43133-43134 |
| 25 | 9 | M40 | S/B | 3700M40/183 | 1403 | End of slip On at Jct 17 (M42 Jct 3a) to start of slip Off at Jct 16 | 29504-29503 |
| 27 | 12 | A616 | W/B | 4405A616/30 | 1717 | Studs L Jct A629 to studs on river bridge at 1717m | 61630-61644 |
| 31 | 13 | M6 | S/B | 2300M6/291 | 1973 | End of slip On at Jct 33 to start of slip Off to Lancaster services | 18323-18239 |
| 32 | 10 | M58 | W/B | 2300 M58/431 | 1570 | End of slip On at Jct 5 to start of slip Off at Jct 4 | 8618-20005 |
| 35 | 13 | A66 | E/B | 0900A66/142 | 1860 | Studs on bridge over B5292 (1950m E of A5086 Rbt) to studs at 1860m | 31347-31507 |
| 36 | 13 | M6 | S/B | 0900M6/373, 0900M6/379 | 1121 | Start of slip Off at Jct 37 (A684) to end of slip On at Jct 37 | 14192-14187-14181 |
| 38 | 14 | A1 | S/B | 2900A1/106 | 1727 | Studs (road under) 2.22km before A19 bridge over to studs at 1727m (25m after Newcastle sign and 45m before start of slip off to A19) | 14063-14002 |
| 40 | 9 | M54 | E/B | 3200M54/784 | 1434 | Asphalt/PQC surface change @ marker post 27/7 to start slip off to J4 | 54006-40100 |
| 41 | 6 | A14 | E/B | 3500A14/632 to 3500A14/716 | 5601 | End slip on J54, Sproughton to start slip off J56, Wherstead | 90366-90301 |
| 42 | 6 | A12 | S/B | 1500A12/158 | 1960 | Baddow Park Overbridge to Slip off | 40950-40960 |
| 43 | M25 DBFO | M25 | C/W | 3600M25/464 | 2004 | MP55/0 to MP57/0 | 21543-21541 |

# Investigation of the impacts of climatic conditions on skid resistance variation

Variations in skid resistance measurements over time have been observed since measurements began and have been the subject of many studies aimed at developing a better understanding of these variations. However, there is no clear consensus on the approach to quantify seasonal variation of skid resistance measurements. Nonetheless procedures such as seasonal correction of annual network survey data and long-term monitoring of benchmark sites in England, coupled with QA procedures and standards that define the operational conditions for skid resistance measurement devices enables measurements to be adjusted to account for allows these variations and so minimise their impact on the management of skid resistance.

This report presents a research study that investigated different approaches of assessing short- and long-term climatic impacts on skid resistance variation on the Strategic Road Network (SRN) in England. As part of the project, a machine learning based model for skid resistance relationship with weather conditions was developed. For that purpose, skid resistance data from multiple sideway-force skid resistance measurement devices covering the period 2013-2019 were used. These data were combined with relevant historical texture data and weather data from nearby weather stations. Promising results suggested to extend the model to a selection of benchmark sites with the aim to adapt the model to a wider range of surfaces and locations across the English SRN.

Overall, the developed machine learning model showed potential to predict skid resistance values, but further model improvement would be needed in order to provide more consistently accurate results. The inclusion of traffic information was suggested as a way to improve the model's accuracy as the skid resistance variation would then be taking account of both changes in weather and traffic conditions.

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