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Review

A comprehensive review on rubber wear modeling with focus on tire applications

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https://doi.org/10.1016/j.isci.2026.114755

SUMMARY

Tire wear arises from coupled viscoelastic deformation, interfacial friction, temperature, and material fatigue, with growing relevance for performance, durability, and environmental impact. This review synthesizes the main families of tire-wear models, including empirical, analytical, numerical, and data-driven approaches, and examines their physical assumptions, predictive range, computational cost, and applicability to realistic tire road conditions. Emphasis is placed on friction and wear interactions, rubber specific complexities, and the absence of a common tribological framework. This work offers three key contributions: a systematic classification of modeling approaches and their assumptions; integration of environmental and regulatory drivers relevant to tire wear assessment; and an evaluation of model applicability across validation contexts, from laboratory tests to indoor rigs and real world conditions. Remaining challenges include transient dynamics, thermo-mechanical coupling, and model generalization. Future directions highlight the need for physically grounded and efficient models able to bridge scales, materials, and applications.

INTRODUCTION

Wear is a fundamental degradation phenomenon affecting materials across various applications, from industrial machinery to transportation systems. It results from the complex interaction of surfaces under mechanical stress and manifests through abrasion, adhesion, fatigue, tribo-chemical wear, and fretting.[1,2] This deeply interlinked physical, chemical and thermodynamic framework results in an environmental imperative, largely absent from previous tire wear reviews, driving the authors' emphasis on model requirements in terms of predictive capability, computational efficiency and regulatory compliance.

The history of wear modeling reflects a progressive integration of theoretical insights, experimental findings, and multidisciplinary approaches. In the mid-20th century, foundational studies laid the groundwork for understanding wear as a result of energy dissipation at the contact interface. Finnie and Sheldon underscored the significance of both abrasive and adhesive mechanisms, demonstrating that wear rates are closely related to the energy dissipated in frictional processes.[3,4] Rabinowicz[5] further advanced the field by introducing a criterion for adhesive wear, linking elastic energy and adhesion to wear particle formation.[6] Experimental research by Schallamach provided deeper insights into rubber abrasion, revealing wave detachment phenomena during sliding, which highlighted the complexity of wear in viscoelastic materials.[7,8]

Further developments in wear modeling saw the introduction of analytical and numerical approaches to describe the localized forces and deformations occurring at the interface. Early models relied on simplified assumptions to estimate wear rates, but with advancements in computational methods, finite element models (FEMs) and tribological simulations became more prevalent, allowing for a more detailed analysis of material behavior under different loading conditions.[9,10] Studies incorporating dynamic parameters such as sliding velocity and normal loads, as well as surface characteristics like roughness, have improved the predictive capabilities of these models.[11,12]

The integration of tire-wear models into vehicle-level applications represents a critical frontier in automotive engineering, as advanced driver assistance systems (ADASs), autonomous vehicle controllers and vehicle dynamics management systems increasingly depend on accurate tire state estimators, including wear progression, to ensure safety and performance.[13,14] In this context, two main approaches have emerged: the first leverages physical smart tire technologies, where embedded sensors combined with machine learning algorithms enable real-time monitoring of wear and predictive maintenance capabilities[15]; the second relies on pure virtual sensing, utilizing standard vehicle-mounted sensors to indirectly evaluate tread depth without physical contact.[16] Furthermore, hardware-in-the-loop (HIL) simulation platforms now also address the increasing requirement to incorporate physically detailed tire models (e.g., weaRIDE,[17] CDTire[18]), facilitating real-time testing of electronic stability control (ESC) and anti-lock braking systems (ABSs) under scenarios previously inaccessible to empirical tire models, including pressure loss events and complex vibrational behaviors on uneven surfaces with coupled wear effects.[19,20] These integrations enable a new frontier of closed-loop analyses in which evolving tire properties,[21] such as grip degradation and stiffness modification, directly impact vehicle handling and control

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performance, and should be addressed already starting from the vehicle design phases.[22]

While extensive research has examined wear in metals and ceramics, where failure primarily results from plastic deformation and fracture, polymeric materials such as rubber exhibit distinct behavior due to their viscoelasticity, temperature dependence, and complex energy dissipation mechanisms.[23,24] The viscoelastic nature of polymers introduces additional complexities, as demonstrated by researchers like Persson, who showed how temperature and surface roughness influence wear behavior in soft materials.[25] These findings highlighted the need for models that incorporate time-dependent material responses, thermal gradients, and environmental interactions to accurately capture wear phenomena.[9,26]

Despite these advancements, most current literature addresses individual wear mechanisms in isolation,[27,28] and only a limited number of studies attempt integration into unified frameworks, as, for example, proposed in Sakhnevych and Genovese[17] Furthermore, much of the existing research relies on empirical or semi-empirical approaches, which may lack generalization and do not adequately capture the complexity of the processes involved.[29,30] Bridging microscale studies of material deformation with macroscale investigations of wear patterns is essential for advancing predictive models. Emerging computational tools, including machine learning and advanced finite element (FE) simulations, offer new opportunities for achieving this integration, though their full potential has yet to be realized.[31,32]

Within the broader study of wear modeling, tire wear represents a particularly complex case due to its dynamic contact conditions, high deformations, and interaction with rough road surfaces.[33,34] Beyond performance and safety implications,[35,36] tire wear is a major contributor to non-exhaust particulate emissions, driving increasingly stringent environmental regulations.[37,38] Despite the extensive research in this field, a generalized model integrating all primary wear mechanisms—abrasive, adhesive, erosive, corrosive, fatigue, and fretting wear—remains elusive. These mechanisms often coexist and interact, influenced by material properties, operational conditions, and environmental factors.[39,40] While some phenomena, such as fretting wear, may have a localized or less pronounced impact, prioritizing the most relevant mechanisms is essential for effective modeling. The growing demand for predictive models has driven a shift from empirical approaches to simulation-based methods,[41] enabling manufacturers to optimize tire design while reducing reliance on physical prototypes. The V-cycle development process, widely adopted in the automotive industry, underscores this transition by integrating simulation and validation at different design stages. In this context, digital twins have emerged as powerful tools, allowing for the virtual replication of real-world tire behavior. However, the accuracy of these simulations hinges on the robustness of tire-wear models, which must integrate wear mechanisms, emissions dynamics, and environmental factors.[42,43] Although many prior reviews summarize model classes, relatively few critically examine key representative works in relation to their validation scope and hidden assumptions. For example, laboratory-scale microscale analyses and macroscale FEM investigations are often presented alongside one another without discriminating which model assumptions break when moving from controlled tests to full-tire, outdoor service.

Within this framework, this review aims to synthesize existing knowledge on wear mechanisms and modeling approaches, establishing a solid foundation for understanding tire wear. While numerous studies have addressed individual wear processes or specific modeling techniques, a unified, predictive framework that integrates physical wear mechanisms with real-world tire behavior remains lacking. This review addresses this gap by critically assessing existing approaches, highlighting their assumptions, strengths, and limitations, and identifying key areas where integration and generalization are needed. This work distinguishes itself from previous reviews through three key contributions: (1) a systematic classification enabling direct comparison across modeling approaches and underlying hypotheses, (2) integration of environmental and regulatory drivers previously overlooked in tire-focused reviews, and (3) critical assessment of model applicability across validation contexts from laboratory to real-world conditions.

By bridging insights from materials science, mechanical engineering, and computational modeling, it provides researchers and practitioners with a comprehensive reference to support the development of robust, predictive, and environmentally aware tire-wear models.

METHODOLOGY

Database search strategy

The literature search was conducted across major scientific databases, including *IEEE Xplore*, *Scopus*, *Web of Science*, and *Google Scholar*. The search mainly relied on keywords such as *"tire-wear modeling," "rubber abrasion," "wear formulation,"* and *"tire tribology,"* combined with logical operators to refine results. The time frame considered was 1960–2025, in order to include both the classical foundations of wear modeling and the most recent developments in physics-based and data-driven approaches.

Inclusion criteria required that studies were peer-reviewed and provided either a theoretical contribution, experimental validation, or numerical implementation. Conference proceedings and technical reports were considered when they presented novel models or large-scale experimental datasets relevant to tire wear. Relevant review papers were also analyzed to identify prevailing perspectives and research gaps, to offer an updated synthesis and highlight complementary viewpoints. Articles not directly focused on tire or rubber materials were excluded unless they provided fundamental insights (e.g., Archard's law, Reye's hypothesis) that underpin modern formulations.

Classification framework

To enable a systematic comparison, the reviewed models were grouped into five main categories (Figure 1), based on their physical assumptions, level of abstraction, and computational implementation.

1. Empirical models: data-driven and regression-based, efficient but poorly generalizable.

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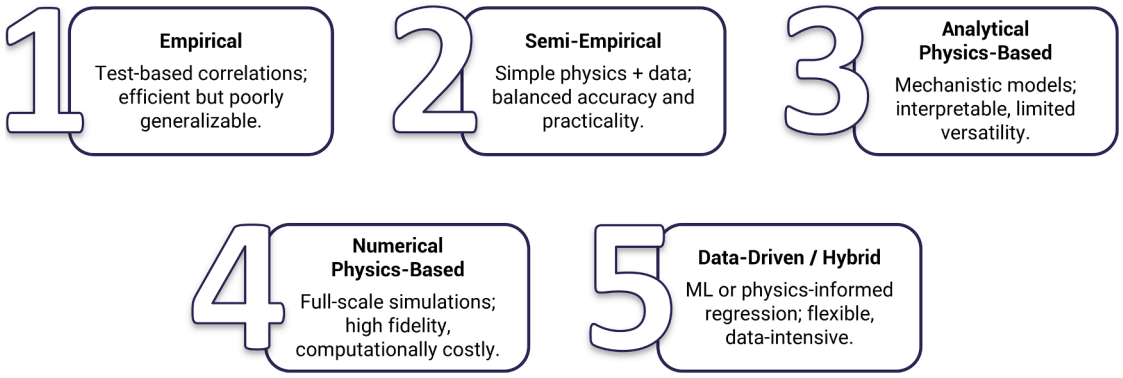


Figure 1. Classification of tire-wear modeling approaches

The figure groups the main tire-wear modeling frameworks into empirical, semi-empirical, mechanistic, multiscale, and data-driven categories.

2. Semi-empirical models: combine experimental trends with simplified physics, e.g., Archard-type formulations.
3. Analytical physics-based models: based on fundamental laws (e.g., viscoelasticity, crack growth), offering deeper insight but requiring strong assumptions and detailed inputs.
4. Numerical physics-based models: FEM, DEM, or FDM simulations resolve stresses and damage in 3D but are computationally expensive.
5. Data-driven and hybrid models: use machine learning or surrogate models, optionally constrained by physics, and are promising for digital twins and real-time applications.

The proposed classification framework enables systematic comparison of models based on three dimensions: physical fidelity, computational tractability, and practical applicability, providing the basis for the structured discussion in the following sections. This multidimensional assessment addresses a critical gap in existing reviews that typically focus on a single criterion.

FUNDAMENTALS OF WEAR MECHANISMS

Wear is a dissipative and irreversible process that arises from the relative motion of solid surfaces under load, leading to the progressive loss of material and permanent alterations in topography and surface properties. While closely related to friction, wear involves cumulative damage and is influenced by mechanical, thermal, and chemical factors.

From a physical perspective, wear is a multiscale phenomenon,[44] originating at the microscale through asperity deformation and fracture, and evolving into macroscale damage as material is removed, compacted, or restructured (Figure 2). The wear rate reflects a balance between removal, hardening, debris formation, and self-healing effects.

Multiple mechanisms may act simultaneously, including micro-cutting, ploughing, crack propagation, melting, or tribochemical reactions, with their prevalence depending on load, velocity, temperature, and material pairing.[45,46] This complexity challenges experimental quantification, as wear is stochastic, localized, and history-dependent. Additionally, standardized tests are sensitive to surface finish and test setup, which limits their generalizability.

Despite decades of studies, formulating predictive, general-purpose wear models remains difficult, especially for viscoelastic or heterogeneous materials, due to time-dependent and energy-dissipative behavior.

General classification of wear mechanisms

Tribological wear can be grouped into six main categories,[47,48] summarized in Figure 3.

- Abrasive wear involves material removal by hard asperities or particles via cutting or ploughing.[49]
- Adhesive wear occurs when junctions form and rupture due to localized bonding, often under high pressure or clean metallic surfaces.[50]
- Fatigue wear results from repeated cyclic loading, causing crack initiation and spalling.[51]
- Chemical wear: includes two distinct mechanisms:
- *Corrosive (oxidative)*: surface degradation caused by environmental agents (e.g., oxygen and humidity), producing brittle films removed during contact.[52]
- *Tribo-chemical*: mechanically activated reactions at the interface, driven by friction or pressure, often involving local heating or film formation.[53]
- Erosive wear is driven by high-velocity solid or liquid particle impacts causing micro-fracturing.[54]
- Fretting wear appears in micro-oscillatory contacts, often in joints or interfaces.[55]

While these categories apply broadly, rubber introduces additional complexity due to its viscoelastic and thermally sensitive nature.

Tribological behavior of rubber materials

Rubber exhibits time- and temperature-dependent viscoelasticity governed by molecular mobility, fillers, and crosslinking.[56] Unlike metals, rubber dissipates energy internally, leading to localized heating ("flash temperature") during sliding,[57] which in turn accelerates wear through softening and oxidation. In particular, Persson's microscale crack-propagation view[25]

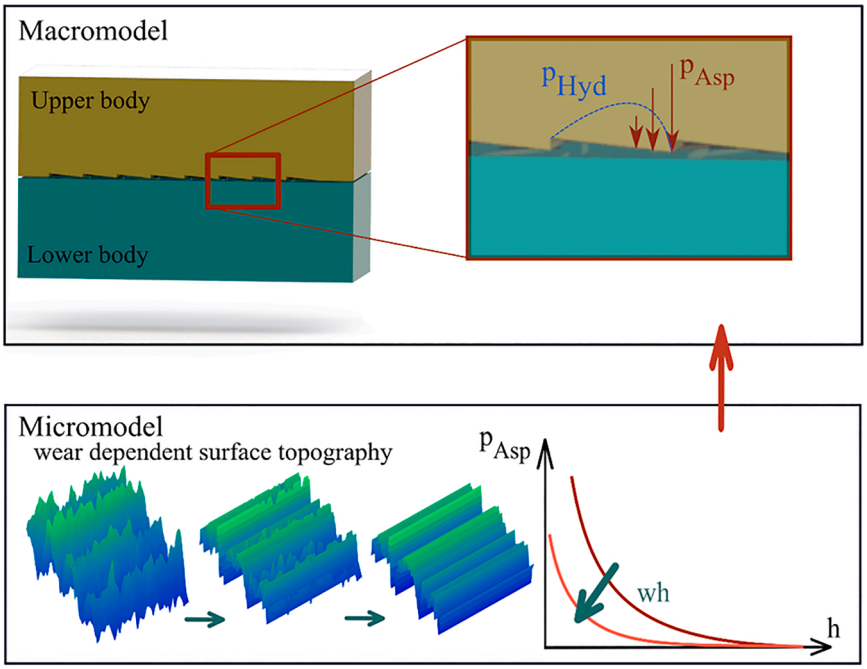


Figure 2. Multiscale nature of wear phenomena

The figure illustrates the interplay between hydrodynamic pressure (p_{Hyd}), asperity contact pressure (p_{asp}), the local lubrication gap (h), and the resulting local wear height (W_h). Adapted from Grigoratos et al.,[44] licensed under CC BY 4.0 (https://creativecommons.org/licenses/by/4.0/).

provides deep physical insight into asperity-level detachment and fracture-controlled particle release; however, its assumptions (single-asperity or sparse-asperity contacts, low sliding speeds) limit direct applicability to rolling-sliding footprints under realistic vehicle speeds and textured pavements. Thus, while Persson is indispensable for understanding mechanistic drivers of wear and related thermal effects at small scales, the model requires careful upscaling and additional hypotheses to support full-tire predictions. Authors and readers should therefore treat Persson-type models as mechanistic micro-references rather than plug-and-play predictive tools for service conditions.

Rubber friction involves both *hysteresis*, energy loss during deformation over surface roughness; and *adhesion*, due to molecular contact[58] (Figure 4). In tire-road interaction, wear mechanisms shift dynamically with variations in slip, contact pressure, and compound temperature. Under predominantly rolling conditions, the repeated cyclic deformation of tread elements generates subsurface stress

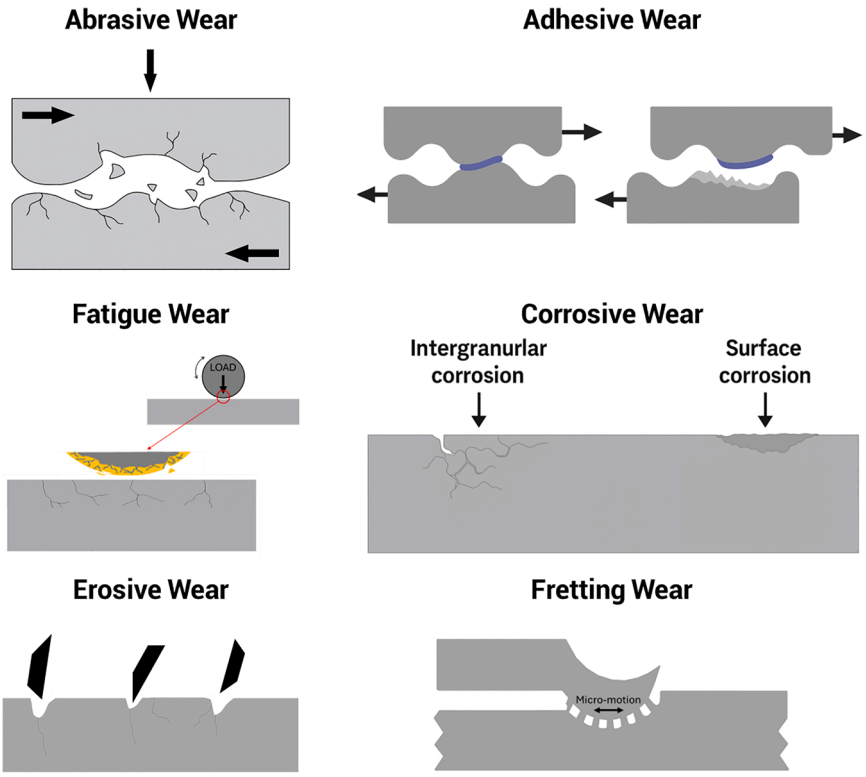


Figure 3. Classification of the main wear mechanisms

The figure summarizes the principal wear mechanisms, including abrasive, adhesive, fatigue-related, and corrosive processes, each illustrated through their characteristic material removal patterns.

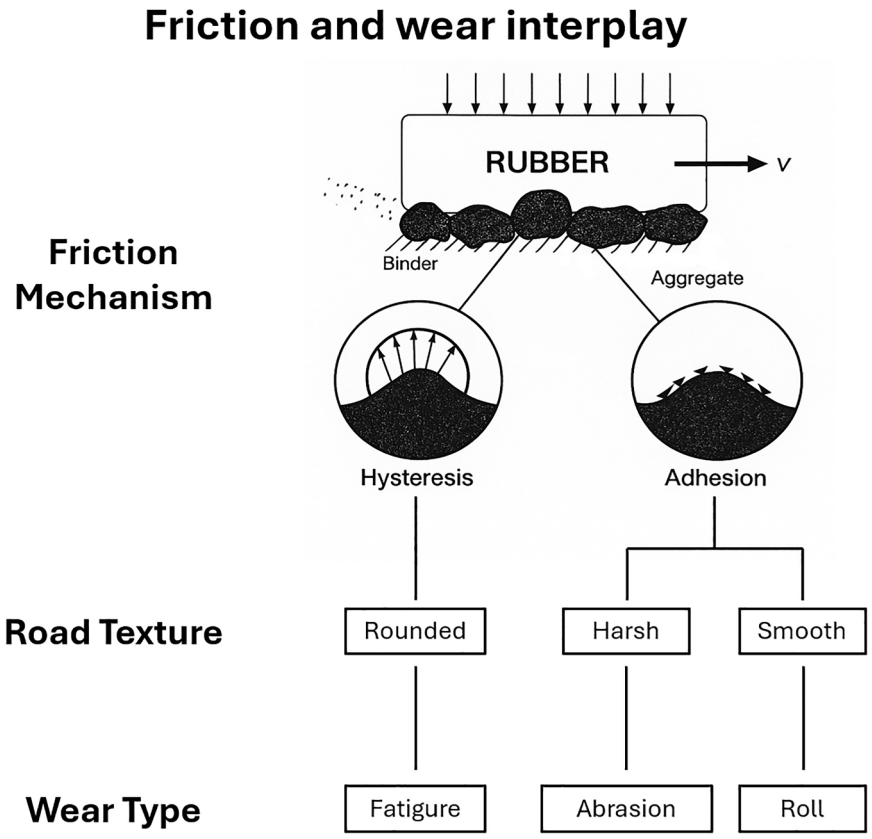


Figure 4. Schematic illustration of rubber-road friction mechanisms

The figure illustrates how viscoelastic hysteresis and interfacial adhesion combine to generate rubber–road friction and wear.

oscillations that may initiate and propagate micro-cracks, leading to fatigue wear.[59] In contrast, higher sliding levels increase the tangential force and interfacial shear stresses, intensifying the removal of material through abrasive wear, often accompanied by localized tearing of the rubber matrix and disruption of surface asperities.[33] On wet surfaces, the loss of adhesion further amplifies abrasive effects, often exacerbated by local temperature rise.

The frequency-dependent nature of rubber also shifts the position of friction peaks: adhesion dominates at low speeds (0.01–0.1 m/s), while hysteresis prevails at higher speeds (40–50 m/s).[60] This behavior can be interpreted in the framework of the time–temperature superposition principle,[61] which states that viscoelastic functions such as the complex modulus $E^*(\omega, T)$ obtained at different temperatures can be superimposed along the frequency axis by applying a shift factor $a_T(T)$. In dry sliding, the relevant excitation frequency (ω) is linked to the sliding velocity (v) through the surface roughness spectrum $\omega \approx v/\lambda$, where λ is the wavelength of the surface roughness component. Thus, variations in temperature, including local "flash temperature" rises, result in horizontal shifts of the friction curve along the velocity axis. In tire applications, empirical shift laws such as the Williams-Landel-Ferry[62] equation are often employed to determine a_T and construct master curves, enabling predictions of frictional behavior over broad ranges of speed and temperature. Compound formulation, through the selection of polymers, fillers, and additives, further shapes the viscoelastic spectrum; and thus, influences both frictional response and wear resistance, making universal modeling inherently challenging.

Wear mechanisms in tire-road interaction

Tire wear does not result only from high-load events but al Sakhnevych, A., and Genovese so from persistent micro-slip during rolling. Although a tire is a predominantly rolling object, real tire–road contact is never purely rolling: the non-uniform pressure and shear distribution across the footprint generates zones of stick, partial slip, and full slip. This means that rolling and sliding wear coexist, with rolling wear mainly driven by cyclic viscoelastic deformation and subsurface crack growth, and sliding wear governed by interfacial shear and cutting at the rubber–asperity interface. The balance between these mechanisms varies with operating conditions, pavement texture, and compound stiffness. This explains the initial "run-in" phase with high wear rates, followed by stabilization (Figure 5). This early-stage evolution and the associated material removal are primarily driven by local sliding phenomena, in which multiple wear processes are activated and modulated by interfacial shear,[63] although cyclic rolling deformation also contributes to the transient stabilization of wear.

From a physical perspective, tire wear arises from the interdependence of mechanical, thermal, and chemical processes at the tire-road interface. Given the viscoelastic behavior of rubber and the rolling-sliding contact over textured pavements, a limited set of mechanisms dominates, with abrasive and fatigue wear being the most relevant in pneumatic tires.[64]

Abrasive wear results from high-slip interactions with pavement asperities, where cutting and ploughing remove material, typically assessed using drum or pin-on-disk tests.[65] Fatigue wear, by contrast, stems from repeated cyclic deformation during rolling, causing internal crack initiation and growth, and is characterized using flexometers, DMA analysis, or endurance testing.[66]

Other relevant mechanisms include the following:

- *Tribo-chemical/oxidative wear* from flash temperatures and environmental agents.
- *Adhesive wear*, relevant on smooth dry surfaces.

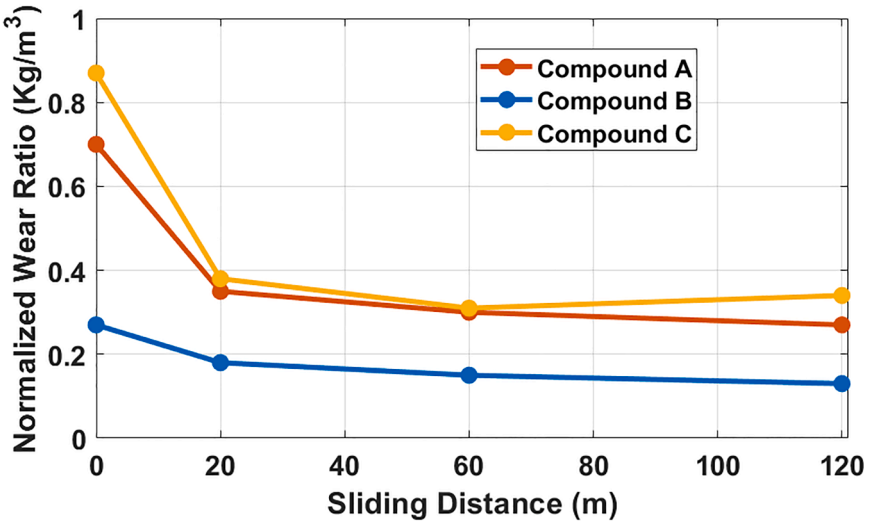


Figure 5. Normalized wear ratio as a function of sliding distance

The figure shows the normalized wear ratio for three tread compounds (A–C) as a function of sliding distance. The wear ratio is computed as the mass removed divided by the worn volume, estimated from the contact area and sliding distance. All compounds display a pronounced run-in phase with rapidly decreasing wear, followed by stabilization into a steady-state regime. Data originate from linear sliding tests on tread-compound specimens (0.2 m per stroke).

- *Fretting*, typically affecting internal tire interfaces under micro oscillations.
- *Graining* and *blistering*, phenomena involving localized tread surface damage: graining refers to the formation of small rubber agglomerates on the tread surface due to repeated shear and tearing under specific thermal-mechanical conditions, while blistering denotes the appearance of surface bubbles or voids caused by rapid vaporization or gas expansion within the compound under severe thermal stress or fatigue overload.[67]

Surface geometry further modulates wear: asperity shape and distribution affect stress concentration and damage patterns. Irregularities in wear, such as graining, often indicate underlying operational imbalances.

In conclusion, tire wear results from an intricate coupling of mechanical, thermal, and chemical phenomena, shaped by compound formulation, usage conditions, and surface texture. Understanding these mechanisms is essential for the development of accurate and generalizable wear models.

MODELING APPROACHES FOR TIRE WEAR

Tire wear has been modeled using a variety of strategies, ranging from empirical laws to physics-based and data-driven formulations. The complexity of tire–road interaction, together with the viscoelastic nature of rubber and varying operational conditions, makes wear prediction a multidisciplinary challenge involving tribology, contact mechanics, and materials science.

Previous reviews have addressed specific aspects. Persson[68] offers a deep theoretical treatment of rubber wear at the microscale, focusing on multiscale contact mechanics and fatigue-driven abrasion. Others[8,69] revisit classical wear laws (Archard, Reye, and Rabinowicz), while one study[70] analyzes modern extensions of Archard's equation. However, these works do not fully capture the peculiarities of rubber or tire-specific wear dynamics. Reviews such as Veith[71] emphasize operational factors influencing tire wear, while[48] provides a broad classification across materials, but not tailored to tires. More recently, Springis and Boiko[72] offered a comparative analysis of wear models across tribological systems. Their perspective, however, remains strongly rooted in Archard-type formulations and incremental extensions, giving a general overview but with limited relevance for rubber. This approach overlooks tire-specific mechanisms, does not systematically distinguish validation contexts (laboratory vs. indoor vs. outdoor tires), and neglects regulatory and environmental drivers such as TWP emissions.

A common limitation is the absence of a unified framework for comparing models in terms of predictive accuracy, computational cost, and usability in tire development. As outlined in the previous classification framework (section methodology), this chapter addresses that gap by discussing the five categories of tire-wear models in detail and critically reviewing them based on physical assumptions, implementation, and engineering applicability, with emphasis also on hybrid and surrogate approaches that bridge interpretability and predictive power.

Empirical and semi-empirical models

Empirical and semi-empirical models represent some of the earliest and most enduring strategies to characterize tire wear, particularly valuable during preliminary design phases or regulatory assessments. These approaches relate wear, typically expressed as volume, mass, or depth loss, to operational variables such as normal load, slip, speed, or roughness.

Energetic foundations

A cornerstone of empirical wear modeling is Reye's hypothesis,[73] which posits a direct proportionality between wear volume and the frictional energy dissipated:

$$\Delta V = k_{Reye} \cdot \int \mu \, p \, v_{slip} \, dt \quad (1)$$

where μ is the friction coefficient, p the normal pressure, v_{slip} the slip velocity, and k_{Reye} a material-dependent wear coefficient $\left[m^3/J\right]$. Hence, this formulation combines physically meaningful quantities (pressure, slip velocity, friction coefficient) with an empirical calibration factor k_{Reye}, which is why it is typically classified as a semi-empirical model. The model assumes uniform contact pressure and homogeneous energy dissipation, conditions that render it suitable only for idealized macroscale steady sliding.

Although originally conceived for metallic contacts, this energetic framework was later extended to rubber applications. For example, Villaggio[74] introduced elastic stress redistribution, deriving an analytical expression for local wear depth (m).

$$I_w = k_{\text{Reye}} \cdot \frac{p^2}{p_1 + 4\mu^2} \quad (2)$$

Despite such refinements, Reye's formulation is now recognized as an oversimplification: it neglects the strong heterogeneities of pressure and slip within real contact patches, ignores transient effects, and does not account for microscale and chemical wear mechanisms. As a consequence, while the hypothesis retains historical and conceptual importance and is still embedded in certain semi-empirical and FEM-based tire models,[75] modern predictive frameworks rarely apply it in its original form. Instead, it is often replaced or complemented by physics-based or data-driven approaches, where μ itself may be estimated via advanced constitutive laws or machine learning.[76] Moreover, recent nanoscale studies[77] have questioned the energetic basis altogether, showing that wear at small scales is dominated by atomistic processes such as bond rupture and tribochemical reactions, beyond the scope of Reye's energetic proportionality.

Parallel to this, erosive wear theories by Finnie and Sheldon[3,4] modeled particle-induced material loss via velocity- and flaw-dependent relations:

$$\Delta V = k \cdot r^{f_1(m)} \cdot U^{f_2(m)} \quad (3)$$

where k is a material-dependent constant, r is the particle radius, U is the impact velocity, and $f_1(m), f_2(m)$ are exponents determined by the flaw distribution. This approach successfully captured wear trends across a wide range of particle types and impact conditions.

Load-based scaling and material detachment

Archard's law[78] introduced a pragmatic relationship between wear volume and the product of normal force (F) and sliding distance (s), scaled by a hardness term (H):

$$V = k \cdot \frac{F \cdot s}{H} \quad (4)$$

Archard's law, though originally developed for metals, remains a baseline in tire-wear modeling due to its simplicity. It holds under moderate loads and low speeds,[25,79] but neglects viscoelasticity, roughness, and thermal effects, factors absorbed into the empirical dimensionless coefficient k. Extensions[70,80] aim to capture friction-induced material changes, making the model more suitable for rubber while preserving its tractability.[81] Archard's law can be considered as a simplified energetic wear relation, since the product $F \cdot s$ represents the mechanical work performed at the interface. Under steady sliding and nearly uniform pressure, this interpretation highlights that normal load, sliding distance, and hardness retain clear physical meaning, while the wear coefficient k is the only empirical term.

Archard/Reye-style energetic scalings remain attractive for their simplicity, but recent critiques and nanoscale studies show clear limitations. For instance, such formulations collapse surface chemistry, roughness spectrum, and viscoelastic dissipation into a single coefficient, which empirically works for fixed test rigs but fails to predict observed trends across compounds, road textures and temperatures. The literature, therefore, requires an explicit statement of the calibration domain when such laws are used, and dedicated sensitivity reporting (compound, temperatures, and roughness) that most surveyed papers do not provide.

Rabinowicz[82,83] shifted the perspective from energy dissipation to energy thresholds, introducing a criterion for wear particle detachment based on the Griffith fracture mechanics theory.[84] In his formulation, a wear particle detaches only if its size is large enough for the elastic energy stored during deformation to exceed the surface energy required to create new fracture surfaces. Assuming a hemispherical fragment, the balance between the residual elastic energy after unloading and the work needed to form new surfaces leads to the condition:

$$D_c \geq 30 \cdot \frac{W \cdot E}{\sigma_Y^2} \quad (5)$$

where D_c is the critical particle diameter (m) W is the specific surface energy (J/ m^2), E is the elastic modulus of the fragment (Pa), and σ_Y is the yield strength (Pa). Particles larger than D_c possess enough stored energy to detach once contact is lost, whereas smaller ones remain adhered or deform further. Importantly, Rabinowicz's criterion concerns the detachment of already fractured fragments rather than their formation. It predicts that a particle can leave the surface only if its residual elastic energy exceeds the work of adhesion or cohesion, regardless of whether failure is interfacial or internal. Although physically meaningful as a size-dependent detachment threshold, the model neglects indentation size effects and loses accuracy at micro- and nano-scale.[85]

A summary of the main early empirical/semi-empirical models is provided in Figure 6.

Popov et al.[86,87] later unified these formulations under a thermodynamic framework, reconciling Archard's and Rabinowicz's criteria through energy dissipation and real contact area evolution.

Rubber-specific extensions

Rubber materials prompted tailored adaptations of classical models. Lancaster[88] introduced viscoelastic correction factors to Archard's law for PTFE and filled polymers, while Cayer-Barrioz[89] proposed a quadratic load dependence to better capture abrasive wear in deformable polymeric fibers:

$$V \propto \frac{F_1^2 \cdot D}{M_n} \quad (6)$$

where V is the wear volume (m ^{3}), F_1 the applied tensile load (N), D the sliding distance (m), and M_n the molecular weight (kg/mol).

Rhee's power-law model[90] further generalized wear to arbitrary regimes:

$$\Delta W = K \cdot F^a \cdot V^b \cdot t^c \quad (7)$$

where ΔW is the mass lost due to wear, K is an empirical wear factor, F is the applied normal load, V is the sliding velocity, t is the sliding time, and a, b, and c are material- and condition-dependent exponents. These formulations offered flexibility but required empirical calibration for each compound and use case.

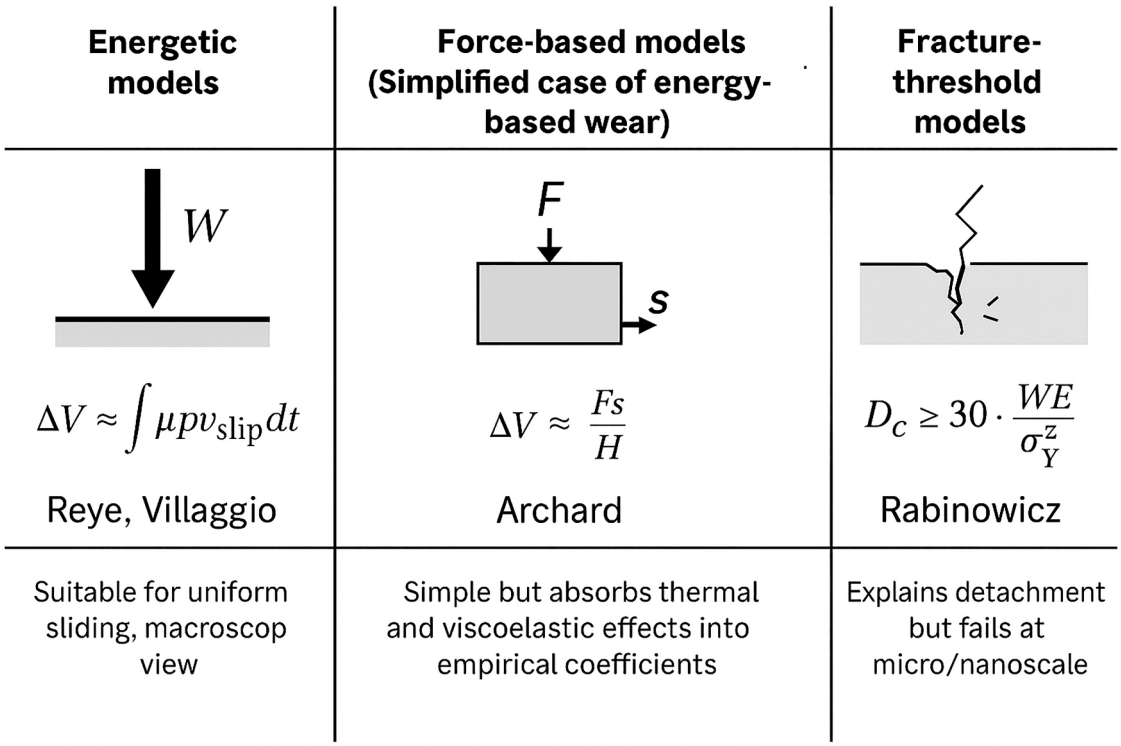


Figure 6. Conceptual comparison between wear model categories

The figure contrasts energetic, force-based, and fracture-threshold wear models. Simplified expressions (≈) are shown to emphasize their underlying physical principles, energy input, force-displacement work, and fracture criteria, without the full calibrated coefficients used in practical formulations.

Tire-focused models: From micro-slip to full-vehicle coupling

Schallamach was the first to demonstrate that rubber sliding does not proceed through uniform interfacial motion, but rather through the propagation of localized detachment fronts—now known as Schallamach waves. These slowly traveling "ruck-like" instabilities periodically break and restore adhesion within the contact patch, creating the characteristic wrinkle-like patterns often observed on worn elastomer surfaces. Building on this physical observation, Schallamach[7] formulated an energetic interpretation of rubber wear, identifying these detachment waves as the primary source of microscale energy dissipation:

$$A = \frac{\gamma \cdot \mu}{\nu} \int_x^a w \cdot p(x)\, dx \quad \Rightarrow \quad A = \gamma \cdot s \cdot F \tag{8}$$

where A denotes the abrasion per unit distance, γ the abradibility (abrasion per unit energy dissipation), μ the friction coefficient, v the velocity, a the contact length, and $w(x)$, $p(x)$ the local sliding velocity and pressure distribution along the longitudinal coordinate x. His investigations combined laboratory tests on rubber specimens with full-tire experiments; thus, bridging fundamental mechanisms with practical tire behavior.

Later, Shepherd[91] introduced a stress threshold for abrasive activation within the tread (Figure 7). Laboratory tests supporting this formulation were shown to be consistent with road experiments on full tires. When the threshold is exceeded, the wear volume is expressed as:

$$V = \frac{A}{k_{sh}} (\sigma_{lat} - \sigma_{th}) = \frac{A}{k_{sh}} (\sigma_{lat} - \mu_0 \cdot \sigma_z) \tag{9}$$

where A is the contact area, k_{sh} the shear-block stiffness, σ_{lat} the local tangential (lateral) shear stress at the tread–road interface, σ_{th} the threshold shear stress for abrasion activation, μ_0 a friction coefficient, and σ_z the local vertical pressure.

Sueoka[92] extended Shepherd's stress-threshold framework by introducing a semi-empirical model that links polygonal wear formation to the first vertical vibration mode of a rigid ring tire. The formulation, tested on a large-scale indoor wear rig with radial truck and bus tires, addresses a phenomenon (polygonal deformation) widely observed on full tires in real road service. The wear evolution is expressed through a time-delayed recursive law modulated by camber and toe angles:

$$U(t) = U(t - T) + \nu \cdot \beta^n \cdot P(t)^n, \text{with} \quad \beta = \left| C_\alpha \cdot \alpha + C_\gamma \cdot \gamma \right| \tag{10}$$

where $U(t)$ is cumulative wear, T is the delay associated with one tire revolution (i.e., the time needed for a given tread element to re-enter the contact patch), $P(t)$ the vertical load, and ν, n are empirical model parameters. The term β incorporates lateral effects via stiffness-weighted contributions of camber γ and toe α. By coupling dynamic load fluctuations and lateral slip, the model captures wear non-uniformities such as polygonal tread patterns and is calibrated through comparison with experimental profiles.

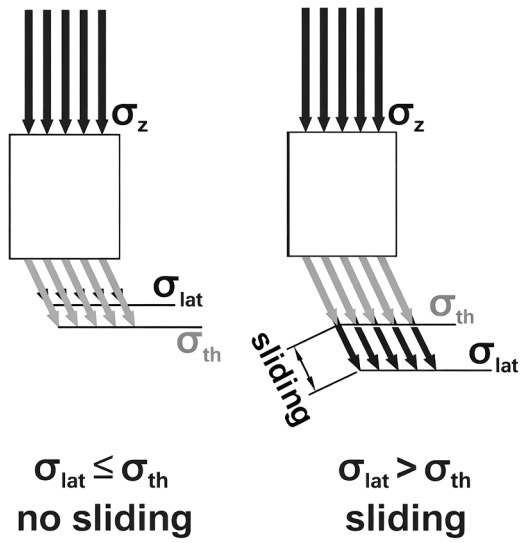


Figure 7. Shepherd's concept of stress threshold

The figure illustrates Shepherd's stress-threshold concept, where sliding occurs only when the lateral stress σ_{lat} exceeds the threshold σ_{th}, while no sliding is observed for $\sigma_{lat} \leq \sigma_{th}$. Reprinted from Genovese and Timpone[58] with permission from Springer Nature.

Veen[93] transitioned toward spatially resolved wear, integrating a brush model with the Magic Formula to accumulate wear from local force imbalances over time. The model was correlated with controlled experiments on a dedicated tire test rig using real slick tires, while addressing irregular wear patterns that are commonly observed in road service, especially on non-driven rear wheels of passenger cars.

Braghin[11] proposed a semi-empirical model grounded in both indoor and outdoor testing, linking tire wear to frictional power density. By normalizing dissipated energy with respect to contact area and scaling wear by traveled distance and contact width, he formulated:

$$\tilde{m} = k_{1,\mathrm{Braghin}} \cdot \tilde{w}^{k_{2,\mathrm{Braghin}}} \tag{11}$$

where $\tilde{m}$ is the mass loss per unit area, $\tilde{w}$ is the frictional power density, and $k_{1,\mathrm{Braghin}}$, $k_{2,\mathrm{Braghin}}$ are empirically tuned based on compound and conditions. Although calibrated experimentally, the model embeds a physically motivated structure by relating wear to energy dissipation, an approach that echoes foundational energy-based theories such as those of Reye and Schallamach, improving its generalizability across setups and compounds.

Expanding on this energetic approach, Radrizzani et al.[94] introduced a hybrid model aimed at closed-loop simulation. Wear rate is driven by local frictional power:

$$\frac{dm}{dt} = K_1 \left(\frac{|W|}{a_c} \right)^{K_2} \tag{12}$$

where W is the dissipated power, a_c the contact area, and m the local mass loss. K_1 is an empirical scaling factor with units consistent with a mass rate, while K_2 is a dimensionless exponent defining the sensitivity of wear to the local power density. Crucially, Radrizzani et al. embed tire wear directly into handling behavior by linking the local wear index $I_m = m/m_0$ (with m_0 the initial tread mass) to the Magic Formula parameters ($\mu_\lambda, \mu_\alpha, C_\lambda, C_\alpha$). In their formulation, these parameters are progressively updated as wear evolves, allowing the model to reproduce the gradual degradation of grip and stiffness observed in experiments.

Their implementation extends to two-wheeled vehicles with asymmetric wear indices (e.g., left, center, and right) and supports coupling with thermal models, making it suitable for real-time vehicle dynamics and control-oriented applications.

Building upon Schallamach's foundational insights on adhesion and micro-slip, Grosch conducted a comprehensive body of experimental work aimed at quantifying the influence of key variables, such as temperature, sliding velocity, normal pressure, and compound viscoelasticity, on tread wear.[95] His approach combined laboratory abrasion tests on rubber specimens or test wheels, outdoor road measurements on full tires, and simulation tools to bridge the two, showing that controlled indoor tests could be correlated with real tire service conditions. His studies revealed that wear is strongly correlated with hysteretic energy loss in the rubber bulk, which in turn depends on the loss tangent and the spectral characteristics of surface roughness.[33] This perspective effectively grounded wear modeling within the viscoelastic framework of rubber mechanics. By linking internal energy dissipation to observed wear rates, Grosch laid the experimental foundations for many modern formulations, including those based on Reye, Archard, or fatigue damage criteria. While differing in structure, these models share a common physical principle: wear arises from dissipative processes governed by stress, slip, and energy loss.

Analytical physics-based models

Physics-based analytical models aim to describe tire wear as a result of fundamental mechanisms such as energy dissipation, viscoelastic deformation, and fatigue-driven material removal. Compared to empirical models, these approaches provide deeper interpretative insight and generalization capacity, although they often require higher computational effort and reduced adaptability to noisy or limited experimental data.

Although not specifically focused on tires, the work by Muhr[8] provides a comprehensive overview of the fundamental mechanisms governing abrasion in rubber, emphasizing its origin in localized mechanical failure rather than bulk friction. He highlighted the role of viscoelasticity, surface roughness, and contact temperature, stressing the challenges in extrapolating laboratory test results to real wear conditions, an aspect still limiting several physical models today. These findings echo Grosch and Schallamach's view that wear stems from internal dissipation, with hysteresis and slip velocity playing a central role beyond mere pressure effects.

Polygonal wear and dynamic frameworks

Building on Sueoka's vibration-based formulation, Huang et al.[96] modeled polygonal wear patterns as the outcome of tread self-excited vibrations. In this context, the number of lobes N, i.e., the circumferential undulations or wear-induced polygons observed along the tread, is theoretically linked to the natural frequency f and rolling speed ω of the tire via

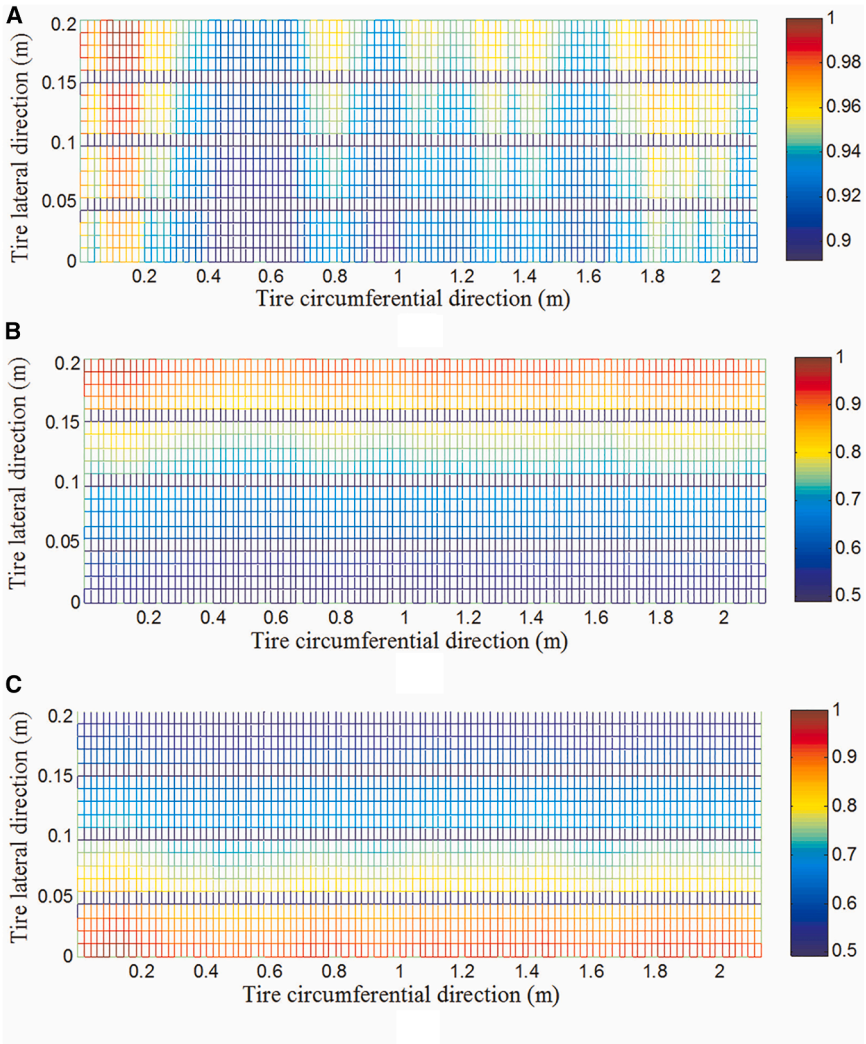


Figure 8. Global tire wear patterns at different camber angles

The figure shows the normalized wear distribution over the tire footprint for camber angles of (A) 0°, (B) 1.5°, and (C) 21.5°, highlighting the progressive shift and concentration of wear with increasing camber. Reprinted from Huang et al.,[10] with permission from SAGE Publications.

$$N \approx \frac{2\pi f}{\omega}, \text{with} \quad f \approx \frac{1}{2\pi}\sqrt{\frac{k_1+k_2}{m_1}} \tag{13}$$

where k_1 and k_2 are structural stiffnesses and m_1 the effective tread mass.

Wear evolution follows Schallamach-inspired laws modulated by camber and toe:

$$I(t) = \nu \cdot \beta^n \cdot [P(t)]^n, \beta(t) = a_\gamma \cdot \gamma(t) - a_\alpha \cdot \alpha(t) \tag{14}$$

where, ν (empirically calibrated) represents the reciprocal of the wear resistance of the tire, $P(t)$ the vertical load, and $n \approx 2$ reflects the nonlinearity of wear according to Schallamach's theory. The coefficients a_γ and a_α relate to camber and toe stiffness, respectively. The influence of camber on the global wear distribution is illustrated in Figure 8.

The coefficients a_γ and a_α relate to camber and toe stiffness, respectively. The influence of camber on the global wear distribution is illustrated in Figure 8. The plots show the normalized frictional dissipation energy (FDE) across the tread width (vertical axis) and along the circumference (horizontal axis) for a fixed toe angle of 1° and different camber angles. With zero camber (a), the wear distribution remains relatively uniform, whereas a positive camber angle of $+1.5°$ (b) induces pronounced wear on the outer shoulder and a negative camber angle of $-1.5°$ (c) shifts the maximum wear to the inner shoulder. This asymmetry reflects the lateral load transfer caused by camber and agrees with common experimental evidence. Vibration-induced wear requires a ν roughly ten times larger than uniform wear, to emphasize the irregularity.

To extend the dynamic-energy-based framework, Wang et al.[97] developed a 3D brush model discretized across the tread width. The model parameters were identified through laboratory tests on rubber samples, while validation was performed against published data from full-tire experiments. The local FDE is computed as:

$$w(i) = F_s(i) \cdot v_s(i), m = c_1 \cdot w^{c_2} \tag{15}$$

where $F_s(i)$ and $v_s(i)$ are the slip force and slip velocity vectors at the i-th slice; c_1 and c_2 capture compound and surface effects. Geometrical asymmetries from camber and toe are incorporated via a reference "middle plane," while footprint pressure is

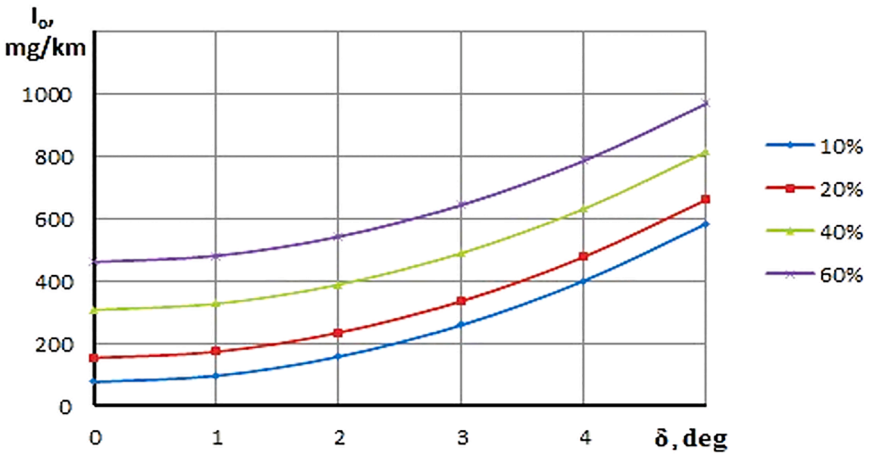


Figure 9. Specific tire wear versus sideslip angle

The figure reports the specific wear l_o as a function of sideslip angle δ under p = 0.6 MPa, Z = 12 kN, and α_0 = 0°. Curves are shown for longitudinal slip ratios of 10%, 20%, 40%, and 60%. Reprinted from Ivanov[28] licensed under CC BY 4.0 (https://creativecommons.org/licenses/by/4.0/), no changes were made.

obtained from a modified ring model accounting for inflation and belt stiffness. This structure enables detailed mapping of load and slip, echoing Braghin's[11] energetic scaling, but adds physical resolution across the contact patch. Sensitivity analyses show that wear depends not only on peak pressure, but on contact length, slip energy, and asymmetry, supporting earlier insights from Huang's polygonal wear modeling.

Energy-based fatigue and contact models

Ivanov[28] proposed a closed-form analytical law that combines abrasive and fatigue-related contributions to wear. The total wear intensity per kilometer, l_o (mg/km), is expressed as:

$$l_o = \left(A'_a S_o + \frac{A'_\delta k_\delta l \delta^2}{Z \varphi_y}\right) \cdot \frac{Z}{S_k} \quad (16)$$

where S_o is the longitudinal slip (–), δ the sideslip angle (rad), Z the vertical load (N), S_k the contact area (m^2), l the contact length (m), k_δ the sideslip coefficient (N/rad), and φ_y the lateral friction coefficient (–). The calibration coefficients A'_a and A'_δ account for compound and structural effects and are identified through two controlled laboratory tests on a real truck tire: one under pure longitudinal slip without sideslip (to extract A'_a), and one with an imposed sideslip angle (to extract A'_δ). This split calibration strategy makes the model experimentally tractable, while the explicit quadratic dependence on δ (Figure 9) reflects the strong nonlinear impact of lateral slip on wear, which increases with stronger growth at higher slip ratios, consistent with the findings of Sueoka and Huang.

Persson[25] instead focused on microscale mechanisms, modeling wear as crack propagation at asperities. A particle detaches when the elastic shear energy U_{el} exceeds the fracture threshold U_{cr}, yielding:

$$\tau > \tau_c = \beta\left(\frac{2E^*\gamma}{r_0}\right)^{1/2} \quad (17)$$

where $E^* = E/(1-\nu^2)$ is the effective elastic modulus of the rubber (Pa), r_0 is the radius of the asperity contact region (m), γ the fracture (tearing) energy per unit area $\left(J/m^2\right)$, and β a dimensionless geometric factor accounting for non-spherical particle shape. This mechanism is illustrated in Figure 10, which shows how wear area and particle detachment rate scale with particle size under a single-contact assumption.

This view reinforces Grosch's energy-based interpretation, framing wear as a fracture-controlled process governed by local stress and material toughness. Persson's experiments on carbon black-filled NR confirmed that wear rate scales with normal load but is nearly independent of sliding speed, and drops significantly under wet conditions. These trends diverge from macroscopic models (e.g., Ivanov, Wang), which emphasize dynamic load and velocity effects. As such, while physically grounded and predictive at the asperity scale, Persson's model is best suited for lab-scale investigations under controlled, low-speed conditions rather than for full-tire operational wear prediction. Moreover, analytical fatigue and vibration-driven approaches (Sueoka, Ivanov, Huang) explain specific phenomena such as polygonal wear and mode-coupled shoulder damage, but their validations are typically confined to indoor rigs or highly controlled tests. These models therefore illuminate mechanistic pathways (vibration-induced stress concentration, mode shapes) but do not by themselves resolve thermo-mechanical coupling or multi-mechanism coexistence in outdoor use. A critical takeaway is that analytical models are excellent for targeted phenomena explanation but must be coupled with either experimental field validation or higher-fidelity thermal coupling to claim broader predictive power.

Coupled thermo-mechanical formulations

Farroni and Sakhnevych[17,98] proposed a unified wear model incorporating viscoelasticity, transient temperature, and fatigue accumulation. The tire is discretized in layers, each governed by a Fourier-based thermal model:

$$\frac{dT}{dt} = \frac{1}{\rho c_v(T)}\left(\dot{q}_G + \nabla^2[k(T)T]\right) \quad (18)$$

where ρ, $c_v(T)$, and $k(T)$ are the local density, specific heat, and thermal conductivity, all temperature-dependent; $\dot{q}_G$ the volumetric heat generation [W·m^{-3}] due to hysteresis and frictional heating, modulated by $E^*(\omega, T)$.

The tread–road interaction is modeled as contact between a rough asperity distribution and a viscoelastic half-space. Each asperity imposes a local indentation and stress cycle, leading to cumulative damage. Wear is thus formulated as a fatigue-driven process, with damage evolving according to a miner-type law[99]:

$$\frac{dD}{dN} = \frac{1}{N_f(T,f)} \quad (19)$$

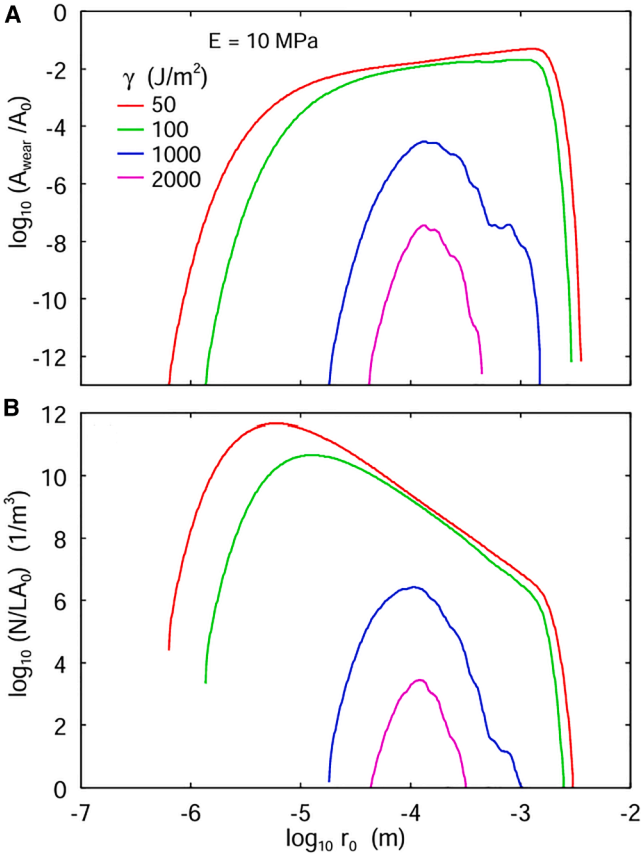


Figure 10. Wear statistics from Persson's model

The log-log plots show (A) the wear area A_{wear} and (B) the number of wear particles generated per unit sliding distance for a single contact ($N_{cont} = 1$). Reprinted from Persson et al.,[25] licensed under CC BY 4.0 (https://creativecommons.org/licenses/by/4.0/), no changes were made.

where D is the internal damage variable and $N_f(T, f)$ denotes the cycles to failure as a function of local temperature and frequency. Once $D = 1$ is reached in a given volume element, the corresponding material is considered detached, and wear is locally applied.

Sakhnevych and Farroni[17] introduced the Thermodynamic Tread Center of Gravity (TTCG), a metric that identifies the baricenter of the tread temperature field. The TTCG tracks how the depth of maximum dissipation shifts with wear, linking thermal gradients, viscoelastic losses, and material removal. This provides a compact descriptor of the evolving thermo–mechanical state and establishes a feedback loop between wear and contact mechanics. Figure 11, adapted from one study,[17] shows the predicted tread evolution, with validation on motorsport, passenger, and truck tires yielding deviations below 5%. While some effects, such as intralayer inhomogeneities or brake-induced heating, are simplified, and chemical aging is not explicitly included, the model's modular and physically grounded design ensures applicability for both offline studies and real-time digital twin frameworks.

Advanced anisotropic and directional wear

Nguyen et al.[27] proposed a wear model capturing directional fatigue and flash temperature effects via a damage vector D (dimensionless), aligned with the sliding direction:

$$\dot{D} = (1 - \| D \|)\,\alpha \left(\frac{P}{P_0}\right)^{\beta} \left(\frac{\| v_s \|}{v_0}\right)^{\gamma} \frac{v_s}{\| v_s \|} - \tau \dot{w} D \qquad (20)$$

with $\dot{D}$ being the dissipation rate of frictional energy, P the contact pressure (Pa+), P_0 a reference pressure (Pa); v_s is the local sliding velocity [m/s], v_0 a reference speed [m/s]. Then, α is a (temperature-dependent) growth rate [s^{-1}], τ is a damage-relaxation factor [m^{-1}] so that $\tau\,\dot{w}$ has units [s^{-1}]; $\dot{w}$ is the wear depth rate [m/s]; β, γ are model constants, depending on rubber compound and road sharpness characteristics.

The model was primarily implemented through FE simulations, with validation based on laboratory experiments using the Grosch wheel (a small rubber tire pressed against an abrasive disk under controlled load, slip, and temperature). This formulation reproduces the rise in wear under rapidly changing slip directions, as observed by Grosch, and offers a high-fidelity though computationally expensive reference framework.

In summary, empirical and semi-empirical models, despite their different forms, are based on similar ideas: wear is mainly driven by energy dissipation, contact pressure, and material limits. The early models by Reye, Archard, and Rabinowicz provided the basic rules, later refined by Schallamach, Shepherd, Sueoka, and Braghin to better capture rubber-specific behavior. Recent hybrid and simulation-based models build on these concepts, improving prediction and making them more useful in real tire development.

Numerical physics-based models

FEMs offer a high-fidelity thermomechanical description of tire behavior, capturing spatial gradients, compound heterogeneity, and viscoelastic heating. Although computationally demanding, they serve as reference frameworks for validating reduced-order estimators and for calibrating otherwise inaccessible variables such as internal temperature and frictional power.

Becker and Seifert[100] developed an early FEM wear model under steady-state rolling, combining a full 3D tire structure with a regularized Coulomb friction law. The study was primarily computational, but validation relied on comparisons with physical wear data from both laboratory tests (on rubber samples and full tires under controlled conditions) and also outdoor highway abrasion tests on real tires. By resolving local slip and energy dissipation in the footprint, the model reproduced lateral wear profiles and highlighted the influence of structural features (e.g., belt angles) on wear distribution.

To overcome the steady-state assumption, Braghin et al.[9] developed a dynamic FEM framework where wear is explicitly linked to local frictional energy dissipation in the contact patch. The core wear law follows the power relationship described in Equation 11. This formulation is implemented in the PaRRT (physical rigid ring tire) model (Figure 12), which uses the sliding velocity and tangential traction at each brush element to evaluate wear incrementally. The cumulative mass loss at position (i, j) is

$$M_{ij} = \sum_k \tilde{m}_{ij}(k) \cdot \Delta y_{ij} \cdot v_{x_{ij}}(k) \cdot \Delta t \qquad (21)$$

where $v_{x_{ij}}$ is the local longitudinal sliding speed and Δy_{ij}, Δt are the spatial and temporal discretization steps.

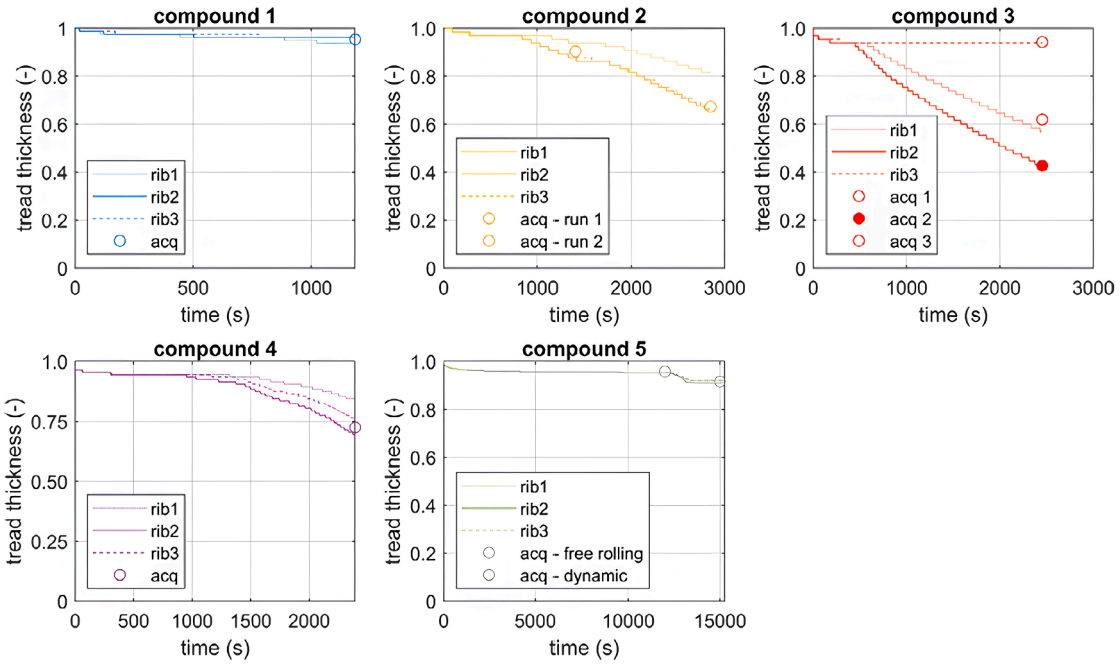


Figure 11. Simulated and experimental tread wear comparison

Simulated and experimental tread wear comparison. Reprinted from Sakhnevych and Genovese,[17] licensed under CC BY 4.0 (https://creativecommons.org/licenses/by/4.0/), no changes were made.

Validated through outdoor tire wear tests, the model captures the effects of inflation pressure, camber, tread stiffness, and compound properties on wear evolution. However, it still assumes a direct energy-mass loss link, neglecting flash temperature, directional fatigue, and transient thermomechanical feedback, limiting its applicability across variable driving conditions or compound formulations.

It has moreover to be said that high-fidelity FEM frameworks (Becker & Seifert, Braghin) act as industry-level references because they resolve contact fields and energy dissipation; nonetheless, their predictive accuracy is constrained by three recurring practical issues documented across studies: (i) incomplete thermo-mechanical coupling in many implementations, (ii) sensitivity to uncertain material characterization (viscoelastic spectra, temperature dependence), and (iii) heavy computational cost limiting scenario coverage. Consequently, while FEM studies should serve as benchmark references, they cannot alone justify claims of generalizability unless accompanied by systematic uncertainty quantification and demonstration across multiple compounds and outdoor validation cases.

Schütte et al.[101] coupled FTire with multibody suspension models to investigate wear sensitivity to camber and toe. Using both Fleischer's linear law,[102] where the total wear volume V_w is proportional to the frictional work W_f ($V_w = e_f^* W_f$), and Braghin's model[9] (Equation 11), they showed that optimized settings can reduce wear by over 50%, reinforcing the importance of suspension design. However, the analysis is restricted to straight-line driving.

The non-linear wear formulation as a function of frictional energy dissipation is also central in the work of Hartung et al.[30] They applied FEM to tread block samples reconstructed from tire images, supported by laboratory tests on both tread specimens and homogeneous rubber coupons for material characterization. The focus was on developing a simulation framework to predict wear and thereby reduce the reliance on costly full-scale physical tests. While results matched experimental mass loss and profiles, thermal coupling was absent, suggesting future refinements.

Liu and Cebon[103] introduced a 2D "string" model for truck tires under high slip, extending brush theory with lateral coupling between bristles. The local wear law is expressed as:

$$\frac{w}{w_0} = k_1 \frac{p}{p_0}\left(1 + k_2 \frac{v}{v_0}\right) \tag{22}$$

where w is the wear rate $\left(\mathrm{kg/m^3}\right)$, p the vertical pressure (Pa), v the sliding velocity (m/s), and $w_0 = 1\ \mathrm{kg/m^3}$, $p_0 = 1$ MPa, $v_0 = 1$ m/s are reference values. The coefficients k_1 and k_2 are dimensionless empirical parameters identified from laboratory data (both tread rubber coupons and full-tire static measurements), while the model was validated through outdoor track tests. Despite its simplicity, the model reproduced track wear data with good accuracy, allowing faster calibration compared to full finite-element simulations.

Other numerical models[104,105] adopt discretized wear formulations but are tailored to other fields (e.g., implants) and lack adaptations for rubber mechanics or tire-road contact.

In summary, numerical models have evolved from quasi-static FEM to more dynamic and hybrid formulations, progressively incorporating anisotropy,[27] fatigue,[98] and experimental calibration. Yet, limitations remain in modeling transient heating, aging,

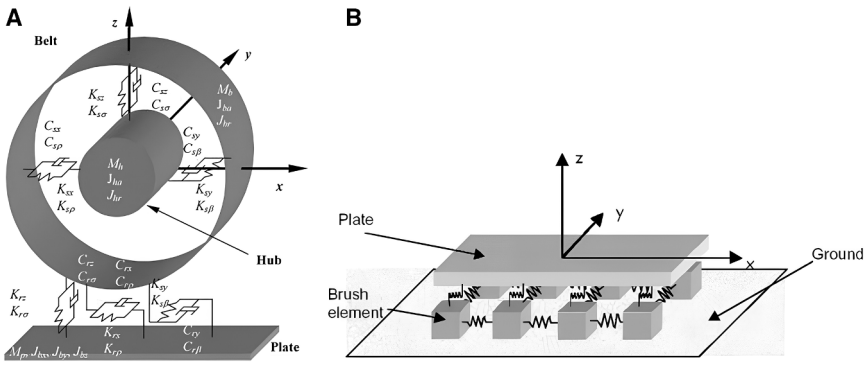


Figure 12. Structural and contact model of the PaRRT tire

The figure shows the PaRRT tire formulation, with panel (A) illustrating the structural model of the carcass-belt system and panel (B) the corresponding contact model. Reprinted from Braghin et al.,[9] with permission from Springer Nature.

and compound generalization, prompting integration with data-driven or symbolic approaches.

Data-driven and hybrid models

Data-driven approaches have gained momentum in tire-wear modeling, offering flexibility in capturing nonlinear input-output relationships without the need for explicit physical laws. Depending on the level of physical integration, these models span from purely statistical to physics-informed and hybrid strategies.

Among early efforts, Le Maître[106] proposed a statistical model describing tread wear variability via log-normal distributions, emphasizing the role of usage patterns (vehicle type, season, and road). The study was based on outdoor data collected from production tires mounted on 25–100 vehicles in real customer use, highlighting key influencing factors in real-world conditions, though lacking predictive capabilities.

Olazagoitia et al.[107] shifted toward model parameter estimation using deep feedforward neural networks (ANNs), showing sub-5% error in identifying Magic Formula coefficients from synthetic datasets. This reduced computational effort compared to classical optimization, enabling faster simulation loops.

A more physically grounded strategy was adopted in[32] by Napolitano Dell'Annunziata et al., who integrated telemetry, viscoelastic properties, and road roughness into a hybrid model for performance vehicles. Among various machine learning schemes, physics-informed linear regressors based on dissipated energy yielded the best compromise between accuracy and interpretability, as shown in Figure 13. Data-driven and hybrid strategies (Napolitano Dell'Annunziata et al., symbolic regression studies), moreover, show promise in reconciling interpretability and predictive capability, but available datasets are often proprietary or limited in operational envelope. Papers that report excellent performance typically evaluate on synthetic or narrow telemetry datasets; only a few combine telemetry with full-tire outdoor wear measurements. Therefore, the current literature tends to overstate the operational readiness of machine learning models: rigorous cross-compound and cross-environment transfer tests remain a key missing element.

Recent advances in intelligent tire systems have demonstrated the effectiveness of 1D Convolutional Neural Networks (1D-CNN) with bottleneck feature extraction for tire wear prediction, based on the availability of internal tire acceleration signals, that was validated through extensive experimental campaigns across multiple tire specimens and wear levels.[15,108]

An emerging frontier involves symbolic regression techniques that automatically discover interpretable mathematical expressions from data while respecting physical constraints, as polyconvexity, thermodynamic consistency and dimensional homogeneity, during the search process.[109] Applied to tire wear datasets incorporating frictional work, temperature, slip ratios and road texture effects, symbolic regression methodologies have identified compact wear laws with 3–5 terms that actually outperform traditional empirical models, providing a promising potential toward bridging the gap between data-driven flexibility and physics-based interpretability.[110]

In synthesis, the field is transitioning from empirical or purely statistical tools toward hybrid models that embed physical priors, aligning with earlier energy-based wear theories (e.g.,

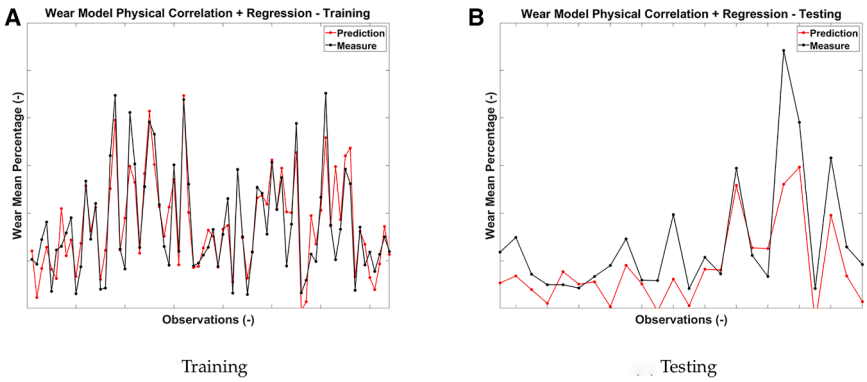


Figure 13. Hybrid physical-statistical approach to tire wear

The figure reports results from a hybrid approach that combines physical indicators—friction power, temperature, and road roughness—with a multiple linear regression model to predict tire wear. Panel A shows the model performance on the training dataset, while panel B reports the corresponding results on the testing dataset, comparing predicted and measured mean wear percentage. Reprinted from Napolitano Dell'Annunziata et al.,[32] licensed under CC BY 4.0 (https://creativecommons.org/licenses/by/4.0/), no changes were made.

Grosch, Braghin). This hybrid approach enhances generalization and minimizes the risk of extrapolation beyond training domains, in contrast with purely data-driven models that may violate physical principles. Yet, most existing models operate offline and lack dynamic adaptation to evolving tire states or environmental variations accountable for real-world deployment. Future research must address online learning, transfer learning across tire families and integration with digital twin frameworks able to fuse simulation, sensing and adaptation.[111,112]

DISCUSSION AND SYNTHESIS

This section offers a critical assessment of the wear models previously reviewed, focusing on their assumptions, predictive power, computational tractability, and applicability to real-world tire scenarios. Rather than listing features, the aim is to explore common themes and divergences, aiming to outline a path toward a more predictive, unified, and environmentally responsible framework for tire-wear modeling. A synthetic overview of the main modeling approaches is provided in Table 1, which contrasts their physical assumptions, expected accuracy, implementation costs, and illustrative references drawn from the literature.

Limits and common ground across models

Despite their diversity, the reviewed wear models share a handful of recurring assumptions. Nearly all empirical and semi-empirical laws, from Reye's energy balance to Archard's force-based scaling, rely on integral quantities and often neglect the transient, multi-scale nature of tire–road contact. Analytical and FEM-based approaches offer greater resolution, but are typically constrained to steady-state or simplified dynamic conditions, making it difficult to account for viscoelastic hysteresis, evolving contact geometries, or thermomechanical coupling without significant computational cost. Data-driven models, including neural networks and hybrid approaches, bring high flexibility and fast inference, but can suffer from poor generalization if not grounded in physical laws. Physics-informed machine learning, i.e., data-driven methods guided by physical principles, can mitigate this, though its application in tire wear prediction is still in its early stages.

A central element across all modeling strategies is energy dissipation, which often acts as a unifying descriptor of wear, either as a direct input or as a consequence of predicted stress and slip fields. Yet, focusing on energy alone is insufficient; to ensure predictive capability, models must resolve interfacial stresses accurately, as wear and friction are inherently coupled.[120] Reliable wear predictions depend heavily on the quality of the underlying friction model, especially when extrapolating to different compounds, surfaces, or driving conditions.

This interdependence becomes even more critical when modeling rubber, which presents unique challenges due to its large-strain behavior, strong rate and temperature dependence, and nonlinear contact mechanics. In real tire applications, phenomena such as transient loading during braking or cornering, local frictional heating, and internal hysteresis dominate the wear process. However, many existing models simplify or neglect these factors, limiting their generalization across usage scenarios. Even high-fidelity FEM formulations often rely on isothermal or linear viscoelastic assumptions, which fail to capture the behavior of high-performance or winter compounds under real-world conditions.

Crucially, the interaction between stress, temperature, and wear forms a nonlinear feedback loop: frictional work raises the temperature, which alters material properties, modifying both friction and wear in turn. Most current models treat these effects in isolation, and rarely close the feedback loop, leading to discrepancies between predicted and observed wear, especially under severe operating conditions where thermal and mechanical effects are tightly coupled.

Given this complexity, FE formulations remain the most dependable approach for quantitative tire wear prediction. FE models compute wear by resolving the local fields that govern abrasion, contact pressure, slip velocity, frictional work, temperature, and dissipated energy, allowing incremental wear depth to be evaluated at each point of the tread. This capability is essential in industrial design, where decisions must rely on high-fidelity predictions that empirical or data-driven models, although extremely useful for rapid assessments and optimization tasks, cannot yet provide. For this reason, FE-based wear computation remains the reference method in tire development workflows, with reduced-order and data-driven approaches used as complementary tools rather than replacements. In particular, Becker & Seifert's early steady-rolling FEM[100] and subsequent PaRRT/PaRRT-type implementations[9] demonstrate useful reproduction of footprint slip and lateral profiles but differ markedly in validation strategy: they compared with highway abrasion tests, while many later dynamic FEM studies validate primarily on indoor rigs or synthetic traces. This inconsistency in validation datasets creates a potentially misleading impression of methodological convergence; a model validated only on rigs should not be equated with a model validated on outdoor, full-service tires.

In addition to physical assumptions and computational aspects, the robustness of each model also depends on its validation context. As summarized in Table 2, validation spans from laboratory coupons to indoor rigs and full outdoor road tests. Lab tests are useful to isolate mechanisms, but they cannot capture the full complexity of tire behavior, which depends on road texture, temperature, and viscoelastic state. For this reason, validation on real tires, especially in outdoor conditions, remains essential, despite the high cost and effort required, making it a major challenge for predictive wear modeling. Comparing across model families highlights a recurring reporting shortfall: many papers do not publish the detailed calibration protocol, the domain of applicability, or a sensitivity analysis of the critical coefficients (e.g., wear constant k, thermal diffusion rates). Without these elements, present in only a minority of works such as Braghin's outdoor-validated studies, readers cannot ascertain whether reported agreements are robust or accidental. We therefore recommend that all future model publications include a standardized "validation dossier" detailing datasets, speed/load ranges, temperature windows, and uncertainty bounds.

Need for a unified predictive framework

Tire-wear modeling remains fragmented, with most approaches tailored to specific compounds, test setups, or vehicle classes. By contrast, fields such as bearing design or metallic wear have long benefited from consolidated tribological theories that

Table 1. Comparison and validation context of tire-wear model categories

Model Category	Physical assumptions	Predictive capability	Computational cost	Limitations	Related works
Empirical semi-empirical	Force or energy-based scaling, sometimes corrected with compound/load terms	Low-medium	Low-medium	Neglects transient and thermal co-dynamics and multiscale contact heterogeneity. Limited generalization across compounds, operating conditions and road textures. Calibration constants lack physical meaning and require extensive experimental calibration for each application context. Fails to predict TWP size distributions or emission rates.	Sheldon and Finnie,[3] Finnie and McFadden[4], Schallamach[7], Braghin et al.,[11] Grosch[33], Delaney et al.,[70] Reye[73], Villaggio[74], Archard[78], Steiner et al.,[80] Zhang et al.,[81] Rabinowicz et al.,[82] Rabinowicz and Tanner[83], Popov[86,87], Lancaster[88], Rhee[90], Shepherd[91], Sueoka et al.,[92] Veen[93], Radrizzani et al.,[94] Grosch[95], Liu et al.,[113] Lancaster[114], Rhee[115], Viswanathan and Chandrasekar[116], Grosch[117]
Analytical physics-based	Contact mechanics plus viscoelastic hysteresis. Typically steady-state assumptions.	High	Medium	Simplified geometry and loading scenarios. Restrict applicability to controlled laboratory conditions, with limited validation on full-scale tires under real driving cycles. Limited ability to handle dynamic or transient effects. Linearization or small-strain assumptions incompatible with large tire deformations.	Muhr and Roberts[8], Huang et al.,[10] Braghin et al.,[11] Sakhnevych and Genovese[17], Persson et al.,[25] Nguyen et al.,[27] Ivanov[28], Huang et al.,[96] Wang et al., Farroni et al.[98]
Numerical physics-based	Full thermomechanical and contact field resolution, including heat generation and large strains.	High	High	Prohibitive computational cost, precluding real-time or iterative design use. Requires detailed material characterization. Mesh sensitivity and convergence challenges for evolving contact boundaries. Scalability issues for transient or full-vehicle scenarios. Validation typically restricted to specific test conditions.	Braghin et al.,[9] Hartung et al.,[30] Becker and Seifert[100], Fleischer[102], Wang et al.[118]
Data-driven hybrid	Machine learning or symbolic regression, possibly combined with physics-informed constraints.	Medium-high (strongly dependent on data quality)	Low-medium	Requirement of extensive high-quality training datasets spanning the operational envelope. Extrapolation risks. Requires large datasets and physical insight for interpretability. Lack of established validation protocols and benchmarking. Online adaptation and transfer learning across tire families still open challenges.	Napolitano Dell'Annunziata et al.,[32] Le Maitreet al.,[106] Olazagoitia et al.,[107] Wang et al.[119]

Table summarizes the assumptions, capabilities, costs, and limitations of the main tire-wear modeling families.

Table 2. Validation context of main tire wear studies

Study	Year	Validation context	Reference
Schallamach	1968	Lab coupons + outdoor trailer/road tests	Schallamach[7]
Shepherd	1986	Lab tests validated against outdoor tire data	Shepherd[91]
Sueoka et al.	1997	Indoor rig (truck/bus tires) + field evidence	Sueoka et al.[92]
Becker & Seifert	1997	FEM simulation validated with lab coupons, indoor rigs, and highway abrasion tests	Becker and Seifert[100]
Le Maître et al.	1998	Outdoor data from production tires (25–100 vehicles)	Le Maitre et al.[106]
Grosch	1992–2008	Lab coupons (Akron, LAT) + outdoor road tests	Grosch[33,95,117]
Braghin et al.	2005–06	Lab coupons + indoor rigs + outdoor tests	Braghin et al.[9,11]
Veen	2007	Indoor rig (slick tires) + road-service comparison	Veen et al.[93]
Wang et al.	2017	Lab coupons for parameter ID + validation with literature outdoor data	Wang et al.[97]
Farroni et al.	2017	Lab tests on tread layers, indoor rigs; validated also on motorsport tires	Farroni et al.[98]
Nguyen et al.	2018	FE simulations + validation with Grosch wheel lab tests	Nguyen et al.[27]
Ivanov	2016	Controlled lab tests on full truck tire; no outdoor	Ivanov[28]
Hartung et al.	2021	Lab coupons and tread-block FEM validation	Hartung et al.[30]
Schütte et al.	2021	Simulation validated vs. published outdoor road/track data	Schütte and Sextro[101]
Napolitano et al.	2023	Lab coupons + telemetry datasets	Napolitano Dell'Annunziata et al.[32]
Sakhnevych et al.	2024	Lab tests + outdoor validation (passenger, truck tires)	Sakhnevych and Genovese[17]
Persson et al.	2025	Lab coupons (asperity-scale); no full-tire tests	Persson et al.[25]
Liu & Cebon	2025	Lab coupons + static tire data + outdoor track tests	Liu and Cebon[103]

Validation context of main tire wear studies in chronological order. Lab = coupon or tread-block tests; indoor = tire rigs/drums; outdoor = road or track tests on full tires.

provide a shared foundation across applications.[46] Such general principles, e.g., Hertzian contact, Archard's law, or elasto-hydrodynamic lubrication, facilitate model transfer and harmonization, a goal still largely unmet in the context of rubber and tire wear, due to their high compliance, large deformations, and viscoelastic nature.

Only a few recent works have attempted to define adaptable wear models that can bridge across materials or contact types. Efforts based on energy dissipation, frictional work, or multiscale asperity interactions show promise,[25,32,39] especially when coupled with machine learning or symbolic regression to incorporate material-dependent parameters. Nevertheless, the field still lacks a fully general framework capable of describing diverse material classes under variable thermomechanical regimes without sacrificing predictive power or computational feasibility.

The challenge lies in achieving a balance between generality and specificity: building modeling architectures flexible enough to accommodate materials with widely different behaviors, such as rubber, composites, and metals, yet grounded in physically interpretable mechanisms. Despite recent advances, the road toward such a predictive and unified wear model remains open and requires tighter integration between tribological theory, experimental validation, and data-driven adaptation. A pragmatic intermediate solution emerging from the surveyed literature is the modular hybrid: combine (a) micro-mechanistic modules (Persson-type or Schallamach-informed adhesion/fracture submodels) for particle generation, (b) a meso-scale energetic or damage integrator for block/tread evolution (Braghin, Radrizzani), and (c) a reduced-order thermo-mechanical correction calibrated from targeted FEM runs. Several recent contributions (Sakhnevych & Farroni, Radrizzani) have followed parts of this recipe, indicating that unification is feasible if future work standardizes interfaces and validation protocols between modules. This concrete modular path narrows the gap between purely descriptive reviews and operational predictive frameworks.

Tire-wear modeling remains largely fragmented, with most approaches developed for specific compounds, experimental setups, or vehicle classes. In contrast, fields such as bearing design or metallic wear have long benefited from unified tribological theories that offer consistent foundations across

applications.[46] Concepts like Hertzian contact mechanics, Archard's law, and lubrication have enabled broad transferability and regulatory coherence. Such harmonization is still lacking in the domain of rubber wear, primarily due to the material's high compliance, nonlinear viscoelasticity, and large-strain behavior, which challenge traditional modeling assumptions.

In synthesis, a systematic assessment of the reviewed literature reveals several critical deficiencies that actually constrain progress toward predictive tire-wear modeling.[15,121,122]

- validation heterogeneity remains pervasive, as most modeling approaches are validated solely on laboratory data and cannot be reliably extrapolated to full tires under real driving conditions;
- TWP emission modeling is almost entirely absent from existing frameworks despite growing regulatory pressure, where the majority of models predict only bulk mass loss, insufficient for environmental compliance assessment needing particle size distributions and emission rates;
- thermo-mechanical coupling is oversimplified or neglected in most approaches, treating temperature as a post-processing output rather than a coupled state variable and systematically underestimating wear in high-energy scenarios;
- data scarcity and proprietary barriers severely limit data-driven model development, forcing researchers to rely on synthetic data or highly constrained experimental scenarios;
- standardization of testing protocols and reporting metrics is lacking, with wear often reported as mass loss, volume loss or depth reduction without standardized normalization, which precludes quantitative inter-model comparison and meta-analysis across studies.

Only a limited number of recent studies have attempted to establish adaptable wear frameworks capable of spanning different materials and contact regimes. Approaches grounded in interfacial energy dissipation, multiscale asperity interactions, or frictional work, often inspired by generalized contact mechanics,[25,39] have shown encouraging potential. In particular, the integration of these physical principles with data-driven techniques, such as machine learning or symbolic regression, has been proposed to embed material-specific behavior while preserving interpretability and scalability.[32]

Nevertheless, the development of a general, predictive and computationally viable wear model remains an open challenge. Striking a balance between generality and specificity requires flexible modeling architectures that can adapt to diverse material behaviors, ranging from metals and composites to rubber, while remaining grounded in physically meaningful mechanisms. Progress toward this goal will depend on closer integration between tribological theory, experimental validation, and data-driven model refinement.

Environmental imperatives and regulatory pressure

Tire wear's environmental consequences are increasingly recognized, with TWPs, also referred to as tire and road wear particles (TRWPs) when combined with road surface material, constitute a major source of microplastic pollution and non-exhaust particulate emissions from road transport, contributing to both PM10/PM2.5 pollution and microplastics in water bodies.[123–125] Understanding TWP characteristics, as size distribution, morphology, count, and topography, is essential both for environmental risk assessment and for validating predictive wear models that must estimate emission rates under regulatory frameworks.[126] However, TWP are complex to monitor as their release depends on factors such as compound characteristics, vehicle behavior and road properties, since size, morphology and magnitude of emitted TWP are directly governed by the dominant wear mechanisms and operational conditions (e.g., abrasive wear under high-slip conditions generates larger irregularly shaped particles through cutting and ploughing of the tread surface by road asperities; fatigue wear from cyclic loading produces smaller more elongated particles resulting from subsurface crack initiation and propagation; flash temperature effects and tribo-chemical reactions contribute to the formation of ultra-fine particles through thermal decomposition and oxidation). Indeed, it is not a case that recent studies and funded projects often employ machine learning analysis of tire wear emissions data to understand and identify key influencing factors, including vehicle type, tire characteristics (compound, tread pattern, and inflation pressure), driving behavior (acceleration, braking, cornering intensity), road surface type and texture, and environmental conditions.[127,128]

The environmental imperatives outlined in this review (especially focused on the predictability in terms of TWP emission) mark a paradigm shift in models' design requirements, enabling addressing predictive environmental impact.

This growing concern is reflected in emerging regulations: ECHA has targeted high-emission additives like 6PPD,[129] Euro 7 will introduce TWP emission limits and testing protocols,[130] and regulatory action is underway in California.[131] These pressures underscore the need for predictive wear models that are compound-sensitive, thermo-mechanically robust, and efficient enough for integration into design processes or digital twin systems. Models must resolve both driving pattern effects and microscale contact phenomena to produce reliable emission estimates, critical for informing regulatory compliance. Thus, life cycle assessment (LCA) frameworks are being expanded to include non-exhaust emissions,[132] reinforcing the central role of predictive modeling in sustainable tire design and regulatory strategy.

Future directions: Testing, modeling, and integration

To meet these needs, testing protocols must evolve alongside modeling. Current drum-based wear tests, while standardized, are limited in scope, often performed under constant load or speed. Future experimental setups should explore wider thermal gradients, surface textures, and transient contact scenarios. Embedded sensing (e.g., strain gauges, infrared, and telemetry) can support real-time calibration and monitoring, bridging the gap between test data and model input.

From a modeling perspective, the path forward will likely require a hybrid strategy in the broadest sense, not merely mixing machine learning and physics, but combining detailed

Table 3. Influence of wear model categories on key application requirements

Model Category	TWP Estimation	Thermal Coupling	Real-Time Use	Regulatory Fit	Multi-Material	Scalability
Empirical Semi-Empirical						
Analytical Physics-Based						
Numerical Physics-Based						
Data-Driven Hybrid						

Color code: green = good suitability, yellow = moderate or partial suitability, red = poor suitability or lacking feature. The evaluation is qualitative and reflects the synthesis provided in Section discussion and synthesis.

simulations, interpretable laws, and targeted learning. Rather than assuming hybrids as a universal solution, their role should be viewed as part of a modular toolbox, tailored to the specific level of fidelity and application. Robustness and explainability must remain central to avoid black-box models that lack generalization.

Finally, models must be designed with usability and interoperability in mind. Creating standard datasets, open benchmarking protocols, and modular model architectures will be the key to accelerating progress and adoption across industry and academia. These must resolve the full friction-wear temperature interaction, adapt to diverse compounds and driving scenarios, and remain usable for design and regulatory applications. Achieving this balance, between generality, accuracy, and tractability, is the central challenge that the field must now address.

To better visualize the suitability of each model category with respect to practical and regulatory constraints, Table 3 summarizes their relative strengths and weaknesses. The color code follows the classification proposed in the discussion (section discussion and synthesis), reflecting expert judgment on each criterion based on the reviewed literature.

Summarizing the targeted critique of the above table, the central gap is not merely the absence of another catalog of models but the lack of cross-validated model hierarchies: micro-scale fracture theories (Persson, Schallamach) are insufficiently connected to mid-scale energetic and fatigue laws (Braghin and Ivanov) and to full-tire thermo-mechanical FEM benchmarks (Becker & Seifert, Braghin). Filling this gap requires (i) explicit multi-level validation campaigns reported with standardized metrics, (ii) openness of datasets (telemetry + outdoor wear), and (iii) modular model interfaces that allow direct coupling of micro, meso and macro representations. Until these steps are adopted by the community, claims of generalizability should be presented with careful qualification.

Limitations of the study

This review provides a structured synthesis of tire-wear modeling approaches, but some boundaries of the analysis must be acknowledged. First, although a broad set of empirical, analytical, numerical, and data-driven models is surveyed, the heterogeneity of validation practices across the literature limits the possibility of a fully uniform comparison. Many studies do not report complete calibration procedures, operating ranges, or uncertainty estimates, making direct benchmarking difficult. Second, the assessment is constrained by the limited availability of publicly accessible datasets, particularly outdoor wear measurements and compound-specific tests, which restricts the depth of evaluation for models requiring high-fidelity inputs. Third, while environmental and regulatory aspects are discussed, the review does not include a quantitative analysis of TWP emissions, as standardized measurements are not yet widely available. Finally, although conceptual pathways toward unified frameworks are identified, the review does not propose a single predictive model; achieving such integration will require coordinated progress in experiments, simulation tools, and data infrastructure.

CONCLUSIONS

This review has presented a comprehensive analysis of the current modeling strategies for tire wear, categorizing them into empirical, semi-empirical, analytical, numerical, and data-driven approaches. Each class was assessed in terms of physical assumptions, predictive capability, computational tractability, and adaptability to real-world tire–road interactions. Particular attention was given to the distinct characteristics of rubber wear, such as viscoelasticity, large deformations, and thermal feedback, which pose substantial challenges compared to traditional wear modeling domains.

Despite the variety of available models, tire wear prediction remains hindered by fragmentation and a lack of generalization. Most existing approaches are tailored to specific compounds, contact regimes, or testing conditions, limiting their transferability and long-term applicability. Furthermore, the strong interdependence between friction and wear is frequently underrepresented, weakening model accuracy when extrapolated to new materials or usage scenarios. While advances in FEM and machine learning offer promising tools, their integration into unified, predictive, and interpretable frameworks is still in an early stage.

Crucial gaps persist regarding the treatment of transient effects, the coupling between mechanical and thermal fields, and the incorporation of evolving material properties during wear. Additionally, the environmental impact of tire wear, especially the TWP emission, requires models that are both physically sound and compatible with emerging regulatory standards.

Addressing these limitations calls for the development of tribologically consistent, multi-scale, and computationally efficient models capable of adapting to diverse tire architectures and operational profiles. Establishing common modeling frameworks and standardized testing methodologies would represent a significant step toward harmonization across research and industry. The insights synthesized in this review aim to support the design of next-generation tire-wear models that are not only predictive and robust, but also environmentally and computationally sustainable.

ACKNOWLEDGMENTS

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

AUTHOR CONTRIBUTIONS

Conceptualization, A.S.; methodology, R.M., A.G., and A.S.; investigation, R.M. and G.N.D.'A.; data curation, R.M. and G.N.D.'A.; formal analysis, A.G. and F.T.; visualization, A.G. and F.T.; resources, F.F. and G.N.D.'A.; writing – original draft, R.M.; writing – review & editing, R.M., F.F., A.G., G.N.D.'A., and A.S.; supervision, F.F., F.T., and A.S.; project administration, A.S.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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