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CALIBRATED DIGITAL TWINS AND GEOMETRY-BASED PERCEPTION FOR AUTOMATED DRIVING IN HEAVY RAIN AND SNOWFALL: EVIDENCE FROM RESEARCH TESTING IN CHINA AND IMPLICATIONS FOR KAZAKHSTAN.

Abstract: Automated driving systems that perform reliably under clear conditions exhibit substantial degradation in heavy rain and snowfall. Precipitation attenuates and scatters LiDAR returns and generates spurious near-range points, water and spray impair camera imagery, whereas 4D radar has proved more robust than LiDAR in fog, rain and snow. Validation through public-road driving alone is impractical for these conditions, because severe weather events are infrequent, seasonal, hazardous for test personnel and not reproducible. This study examines whether a calibrated digital twin, understood as a virtual representation of the vehicle, its sensor suite and the meteorological environment that is iteratively corrected against physical measurements, constitutes a necessary component of severe-weather validation. The analysis is based on a structured narrative review of experimental testing conducted in China between 2009 and 2026, including the Intelligent Vehicle Future Challenge, virtual–real parallel testing, closed test fields that simulate rain, fog and other weather in Changsha, Wuhan and Chongqing, the cold-region proving grounds of Heihe, and recent studies that calibrate simulated rainfall and snowfall noise against field measurements. The results indicate that each testing modality addresses only part of the validation problem. Closed-field rainfall systems are repeatable but spatially non-uniform, so that nominal rainfall intensity overstates test realism; cold-region proving grounds provide natural snow and ice but are available only from November to March; and simulated rainfall is scalable and fully controllable but becomes credible only when parameterised with measured drop-size distributions and sensor responses. A digital twin that integrates these modalities converts scarce physical tests into calibration points and enables year-round exploration of the scenario space. The study further specifies a geometry-first machine-learning layer within the twin, supported by camera and LiDAR models adapted to heavy rain and snow, that infers the drivable corridor from road-surface elevation, road edges, snow banks, the tracks of preceding vehicles and three-dimensional occupancy rather than from painted markings or road

signs, and that triggers a minimal-risk manoeuvre when geometric confidence is insufficient or a road is officially closed. The framework is applied to Kazakhstan using data from RSE Kazhydromet, which recorded 190 hazardous meteorological events in 2024, including 28 severe blizzards with visibility as low as 50 m, and which reports road closures among the consequences of strong winds. The study proposes a weather transfer gap, $G = |P_{real} - P_{twin}| /$

P_{real}, as an acceptance criterion for substituting virtual for physical evidence, and specifies the data that test facilities and regulators would need to report for its application.

Keywords: *automated driving; adverse weather; heavy rainfall; snowfall; digital twin; parallel testing; closed-field testing; LiDAR; sensor simulation; scenario-based validation; 3D occupancy; road closures; Kazakhstan*

Калиброванные Цифровые Двойники для Валидации Автоматизированного Вождения в Условиях Сильного Дождя и Снегопада: Результаты Исследовательских Испытаний в Китае и Выводы для Казахстана

Аннотация: Системы автоматизированного вождения, надежно функционирующие в благоприятных погодных условиях, демонстрируют существенное снижение эффективности при сильном дожде и снегопаде. Осадки ослабляют и рассеивают сигналы лидара, порождая ложные отражения вблизи датчика; вода и брызги ухудшают качество изображения камер, тогда как 4D-радар показал более высокую устойчивость к туману, дождю и снегу, чем лидар. Валидация исключительно на дорогах общего пользования в таких условиях практически неосуществима, поскольку опасные погодные явления редки, сезонны, связаны с риском для испытателей и невоспроизводимы.

В исследовании рассматривается, является ли калиброванный цифровой двойник (виртуальное представление транспортного средства, его сенсорного комплекса и метеорологической среды, итеративно корректируемое по результатам физических измерений) необходимым элементом валидации в сложных погодных условиях. Анализ основан на структурированном нарративном обзоре экспериментальных испытаний, проведенных в Китае в 2009–2026 гг., включая конкурс Intelligent Vehicle Future Challenge, параллельное виртуально-реальное тестирование, закрытые полигоны с имитацией дождя, тумана и других погодных условий в Чанше, Ухане и Чунцине, полигоны холодного климата в Хэйхэ, а также недавние исследования, в которых имитированный дождь и снежный шум

калибруются по натурным измерениям.

Результаты показывают, что каждый вид испытаний охватывает лишь часть задачи валидации. Системы искусственного дождя на закрытых полигонах обеспечивают воспроизводимость, однако пространственно неоднородны, вследствие чего номинальная интенсивность осадков завышает реалистичность испытаний; полигоны холодного климата обеспечивают естественные снег и лед, но доступны лишь с ноября по март; имитационный дождь масштабируем и полностью управляем, но приобретает достоверность только при параметризации по измеренным распределениям размеров капель и откликам датчиков. Цифровой двойник, интегрирующий эти виды испытаний, превращает ограниченные физические испытания в точки калибровки и позволяет исследовать пространство сценариев круглогодично. Дополнительно предложен геометрически ориентированный слой машинного обучения в составе двойника, который опирается на модели камер и лидаров, адаптированные к сильному дождю и снегу, определяет полосу движения по рельефу дорожного покрытия, кромкам дороги, снежным валам, колеям впереди идущих транспортных средств и трехмерной занятости пространства, а не по дорожной разметке и знакам, и инициирует маневр минимального риска при недостаточной уверенности геометрической оценки или официальном закрытии дороги. Подход применен к условиям Казахстана на основе данных РГП

«Казгидромет», зарегистрировавшего в 2024 г. 190 стихийных метеорологических явлений, в том числе 28 случаев сильной метели с видимостью до 50 м, и отметившего закрытие автодорог в числе последствий сильного ветра. Предложен критерий погодного разрыва переноса $G = |P_{real} - P_{twin}| / P_{real}$ для обоснования замены физических данных виртуальными, а также определен перечень данных, которые испытательные центры и регуляторы должны раскрывать для его применения.

Ключевые слова: *автоматизированное вождение; неблагоприятные погодные условия; сильный дождь; снегопад; цифровой двойник; параллельное тестирование; испытания на закрытом полигоне; лидар; моделирование датчиков; сценарная валидация; трехмерная занятость пространства; закрытие дорог; Казахстан.*

Нөсер Жаңбыр мен Қар Жауу Жағдайында Автоматтандырылған Жүргізуді Валидациялауға Арналған Калибрленген Цифрлық Егіздер: Қытайдағы Зерттеу Сынақтарының Нәтижелері және Қазақстан Үшін Тұжырымдар

Аңдатпа: Қолайлы ауа райында сенімді жұмыс істейтін автоматтандырылған жүргізу жүйелерінің тиімділігі нөсер жаңбыр мен қар жауған кезде айтарлықтай төмендейді. Жауын-шашын лидар сигналдарын әлсіретіп, шашыратады және датчикке жақын жерде жалған шағылыстар тудырады; су мен шашырандылар камера кескінінің сапасын нашарлатады, ал 4D радар тұман, жаңбыр және қар жағдайында лидарға қарағанда тұрақтырақ екенін көрсетті. Мұндай жағдайларда тек жалпы пайдаланымдағы жолдарда валидациялау іс жүзінде мүмкін емес, өйткені қауіпті ауа райы құбылыстары сирек, маусымдық, сынақшылар үшін қатерлі және қайталанбайды.

Зерттеуде калибрленген цифрлық егіз (физикалық өлшемдер бойынша итеративті түрде түзетілетін көліктің, оның сенсорлық кешенінің және метеорологиялық ортаның виртуалды көрінісі) күрделі ауа райы жағдайындағы валидацияның қажетті құрамдас бөлігі болып табыла ма, сол мәселе қарастырылады. Талдау 2009–2026 жылдары Қытайда жүргізілген эксперименттік сынақтарға құрылымдалған нарративтік шолуға негізделген: Intelligent Vehicle Future Challenge жарысы, виртуалды-нақты параллель тестілеу, Чанша, Ухань және Чунцин қалаларындағы жаңбырды, тұманды және басқа да ауа райы жағдайларын имитациялайтын жабық полигондар, Хэйхэдегі суық климат полигондары, сондай-ақ имитацияланған жаңбыр мен қар шуын далалық өлшемдер бойынша калибрлейтін соңғы зерттеулер.

Нәтижелер сынақтың әр түрі валидация міндетінің тек бір бөлігін ғана шешетінін көрсетеді. Жабық полигондардағы жасанды жаңбыр жүйелері қайталанатын болғанымен, кеңістік бойынша біркелкі емес, сондықтан номиналды жаңбыр қарқындылығы сынақтың шынайылығын асыра бағалайды; суық климат полигондары табиғи қар мен мұзды қамтамасыз етеді, бірақ тек қарашадан наурызға дейін қолжетімді; ал имитацияланған жаңбыр масштабталатын әрі толық басқарылатын болғанымен, тамшы өлшемдерінің өлшенген таралуы мен датчиктердің жауаптары бойынша параметрленгенде ғана сенімді болады. Осы сынақ түрлерін біріктіретін цифрлық егіз шектеулі физикалық сынақтарды калибрлеу нүктелеріне айналдырып, сценарийлер кеңістігін жыл бойы зерттеуге мүмкіндік береді. Сонымен қатар егіз құрамында жол таңбалары мен белгілеріне емес, жол бетінің бедеріне, жол жиектеріне, қар үйінділеріне, алдағы көліктердің

ізіне және кеңістіктің үшөлшемді толтырылуына сүйене отырып жүру дәлізін анықтайтын геометрияға негізделген және нөсер жаңбыр мен қарға бейімделген камера мен лидар модельдеріне сүйенетін машиналық оқыту қабаты ұсынылады; геометриялық бағалаудың сенімділігі жеткіліксіз болғанда немесе

жол ресми түрде жабылғанда бұл қабат ең аз тәуекел маневрін іске қосады. Тәсіл Қазақстан жағдайына «Қазгидромет» РМК деректері (2024 жылы 190 дүлей метеорологиялық құбылыс, соның ішінде көрінуі 50 м-ге дейін төмендеген 28 қатты боран) негізінде қолданылады; бұл деректерде автожолдардың жабылуы қатты желдің салдары ретінде көрсетілген. Мақалада физикалық деректерді виртуалды деректермен алмастыруды негіздеу үшін ауа райы бойынша көшіру алшақтығы критерийі $G = |P_{real} - P_{twin}| / P_{real}$ ұсынылады және оны қолдану үшін сынақ орталықтары мен реттеушілер жариялауы тиіс деректер тізбесі анықталады.

Түйін сөздер: *автоматтандырылған жүргізу; қолайсыз ауа райы; нөсер жаңбыр; қар жауу; цифрлық егіз; параллель тестілеу; жабық полигондағы сынақ; лидар; датчиктерді модельдеу; сценарийлік валидация; кеңістіктің үшөлшемді толтырылуы; жолдарды жабу; Қазақстан.*

1. Introduction (Literature Review)

Adverse weather is a recurrent condition of road transport rather than an exceptional one. In the United States, approximately 12% of the roughly six million crashes recorded annually, close to 745,000, occur under adverse atmospheric conditions, resulting in more than 3,800 fatalities per year; more than 77% of these crashes take place during rain or mist [1]. For automated vehicles, precipitation affects not only traction and visibility but also the sensing chain itself. Raindrops and snowflakes attenuate and scatter LiDAR pulses and generate spurious near-range returns, water films and spray degrade camera images, and accumulated snow alters both the road surface and its visual appearance [2]. Radar is comparatively resilient: using the K-Radar dataset, which includes fog, rain and snow, Paek, Kong and Wijaya found 4D radar to be a more robust sensor than LiDAR in adverse weather [3].

The validation of automated driving under such conditions poses a distinct methodological problem. Because safety-critical events are rare, validating automated vehicles through naturalistic driving carries prohibitive economic and time costs; Feng et al. showed that an intelligent testing environment, in which AI-trained background agents interact with a real test vehicle through augmented reality, can accelerate evaluation by three to five orders of magnitude [4]. Heavy rainfall and snowfall represent only a small fraction of real-world driving exposure. Such events cannot be scheduled, they increase the risk to safety drivers, and an identical weather event cannot be reproduced for repeated testing. Evidence obtained from open-road driving is therefore insufficient for establishing performance boundaries in severe weather. The problem is particularly acute in Kazakhstan,

where prolonged snow cover, recurrent blizzards and icing regularly lead to the closure of national roads (Section 3.6).

Literature review. Relevant research has developed along three largely separate lines. The first concerns the robustness of perception. Beyond the radar evidence noted above [3], the Boreas dataset provides more than 350 km of driving on a repeated route over a full year, including rain and falling snow, recorded with LiDAR, radar and camera [5], and snowfall noise has been quantified directly: Cao, Huang and Yu recorded LiDAR data during snowfall in Beijing and compared denoising filters [6], whereas Sun, Zhao and colleagues examined LiDAR performance under snowfall and developed an adaptive filter for snow-induced noise [7], [8]. The second line concerns weather simulation. A recent review of open-source driving simulators notes growing concern about the validity of algorithms developed and evaluated in simulators [9], and a comprehensive survey notes that many driving simulators now provide adjustable rain, snow and fog [2]. Physics-based approaches extend this capability by introducing simulated snowfall into real LiDAR scans [10] or by rendering physically based rainfall within reconstructed three-dimensional driving scenes [11], [12]. The third line concerns digital twins and parallel intelligence. Hu et al. surveyed how simulation supports automated driving through sim-to-real transfer, digital twins and parallel intelligence [13], and Ai et al. developed PMWorld, a parallel testing platform for autonomous driving in mines [14].

Research gap. Although each of these lines is well established, the connections between them remain limited. Studies of weather simulation rarely report how simulated rainfall or snowfall was validated against a physical reference. Descriptions of closed-field tests frequently characterise rainfall solely by its nominal intensity, whereas recent work in China demonstrates that this single value can conceal considerable spatial variation within the rain field [15]. Digital-twin research in automated driving has concentrated predominantly on traffic interaction rather than on the physics of weather–sensor interaction. In addition, most perception stacks continue to depend on painted lane markings and road signs, which snow and ice routinely obscure, and the question of what a vehicle should rely on once these cues disappear has received less attention than the question of how to restore them. Evidence from research testing in China, spanning competitions, virtual–real testing, weather laboratories and cold-region proving grounds, is dispersed across journal articles, regulatory documents, institutional reports and preprints and has not previously been synthesised as a single body of evidence.

Research questions. The principal research question is whether severe-weather validation of automated driving requires a calibrated digital twin, and what research testing conducted in China reveals about the design of such a twin. Four subsidiary questions are addressed: (RQ1) what each testing modality employed in China contributes to validation under heavy rain and snowfall, and what its limitations are; (RQ2) against which quantities a weather digital twin must be calibrated for its results to transfer to real roads; (RQ3) by what criterion engineers and regulators can determine that a twin-based result may substitute

for a physical test; and (RQ4) what additional machine-learning layer within the twin can support driving when road markings and signs are unavailable, and how such a layer should interact with weather-related road closures in Kazakhstan.

Scientific novelty. The novelty of the study lies in treating the testing ecosystem in China as an integrated evidence base and analysing it from the perspective of digital-twin calibration, rather than reviewing perception algorithms or simulation platforms in isolation. The study additionally proposes an acceptance criterion, the weather transfer gap $G = |P_{real} - P_{twin}| / P_{real}$, which links twin-based results to their physical calibration points, and a geometry-first perception layer that derives the drivable corridor from the three-dimensional structure of the scene rather than from markings or signs. The framework is applied to the climatic and operational conditions of Kazakhstan.

Contributions. The principal contributions of the study are as follows:

- a structured review of research testing conducted in China that is relevant to heavy rain and snowfall, covering competitions, virtual–real parallel testing, closed test fields and cold-region proving grounds;
- a comparative assessment of what public-road, closed-field and virtual testing can and cannot establish under severe weather;
- a twin-calibrated testing loop in which scarce physical tests serve as calibration points for year-round virtual testing;
- the weather transfer gap metric G, together with a specification of the data that test facilities and regulators would need to report for its application;
- a geometry-first machine-learning layer that infers the drivable corridor from road-surface elevation, road edges, snow banks, vehicle tracks and three-dimensional occupancy, and that triggers a minimal-risk manoeuvre when confidence is insufficient or a road is closed;
- an application of the framework to Kazakhstan based on data from the national hydrometeorological service and the national road operator.

The remainder of the paper is organised as follows. Section 2 describes the review design, the analytical framework and the geometry-first perception layer. Section 3 presents the evidence from research testing conducted in China, the conditions prevailing in Kazakhstan and the evidence on marking-independent perception. Section 4 discusses the findings in relation to the research questions, and Section 5 concludes the paper.

2. Materials and Methods

The study adopts a structured narrative review design focused on experimental testing of automated driving under severe weather conducted in China between 2009 and 2026; international studies are used for context and comparison. The evidence base comprises peer-reviewed journal articles and conference papers, preprints (identified as such in the reference list), official regulatory documents of the People's Republic of China, and institutional or state-media reports describing test facilities. For the application to Kazakhstan, the study additionally draws on the 2024 climate review of RSE Kazhydromet,

which is based on observations from the national meteorological network, on statements by the national road operator KazAvtoZhol and the Ministry of Transport, and on official road-safety statistics reported by the Ministry of Internal Affairs. The geometry-first perception layer (Section 2.4) is informed by published studies of perception on snow-covered roads and of three-dimensional occupancy prediction. Searches were conducted in English and Chinese,

combining terms for automated and intelligent connected vehicles (智能网□汽□) with rain, snow, fog, ice, closed-field testing, winter testing (冬季□□), simulation and digital twin.

Sources were included if they described a controlled test conducted outside open public traffic, or the regulatory framework governing such tests, and if they addressed rain, snow, fog or ice or the infrastructure used to reproduce these conditions. Each source was assigned to one of five testing modalities: competition-based field testing; virtual–real parallel testing; closed-field weather facilities; cold-region proving grounds; and calibrated virtual weather. For each modality, the review recorded the weather conditions covered, the repeatability and realism of those conditions, the period of availability and the quantities measured. Sources were weighted according to evidential strength. Peer-reviewed findings received the greatest weight, followed by preprints and official documents, whereas facility capabilities reported only by operators or the media were treated as claims rather than as measured results.

2.1 Scope of controlled testing

In this study, controlled testing refers to any test in which the scenario is deliberately configured away from open public traffic, whether on a closed test field, in a weather laboratory, in a simulator, on a competition course or in a combination of these settings. It is distinguished from public-road testing and demonstration, which in China is governed by national and local rules on intelligent connected vehicles. The national pilot programme on vehicle–road–cloud integration launched in January 2024 explicitly calls for building a scenario database and for strengthening simulation, closed-field and real-road testing and validation capabilities [16]; most weather-related controlled tests take place in the closed-field part of this system.

2.2 Twin-calibrated testing loop

The evidence is organised by means of the conceptual loop shown in Figure 1. A physical test conducted on a rainfall rig or at a cold-region site yields measurements of both the meteorological field and the sensor response. These measurements are used to calibrate a digital twin comprising a weather model and a sensor model. Once the twin reproduces the physical results within an acceptable tolerance, it is used to explore a considerably larger scenario space than the physical facility can accommodate. Scenarios in which perception or planning fails within the twin are then returned to the physical facility for confirmation, and the cycle is repeated.

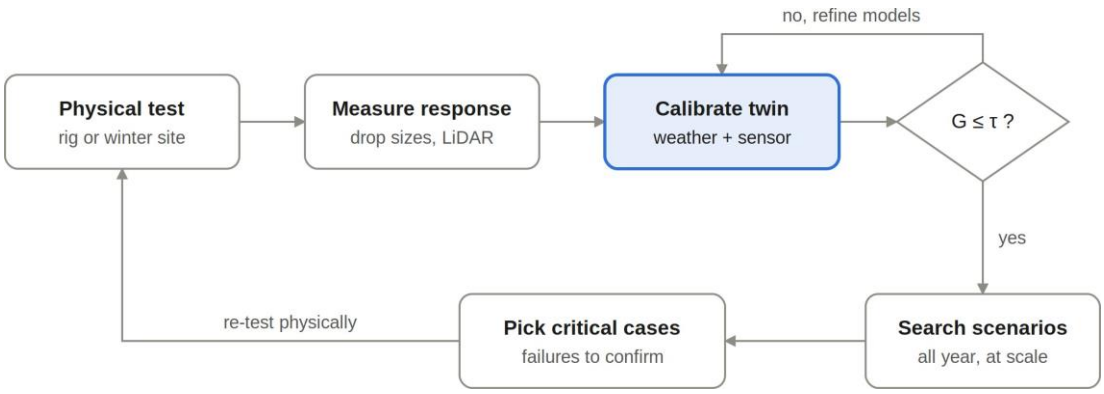


Figure 1. Twin-calibrated testing loop

Within this arrangement, each physical test becomes a calibration point, and each virtual exploration identifies the physical test that is most informative to conduct next.

2.3 Weather transfer gap

To determine whether the twin is sufficiently accurate, the study proposes the weather transfer gap G, defined for any selected performance measure P under matched weather conditions:

$$G = \frac{|P_{real} - P_{twin}|}{P_{real}}$$

The measure P may be defined at sensor level, for example as the number of LiDAR returns on a target or its mean reflectivity, or at task level, for example as detection recall at a fixed range or the minimum time-to-collision in a cut-in manoeuvre. Matched weather denotes an equivalent condition in both domains, such as an identical path-equivalent rainfall intensity rather than an identical nominal setting of the rainfall system [15]. A twin-based result is accepted for a given measure when $G \leq \tau$, where the threshold τ is derived from the safety case for that measure. The study does not propose a numerical value for τ, which is properly a matter for testing standards.

2.4 Geometry-first perception layer

In addition to the weather and sensor models, the study specifies a machine-learning layer that operates within the twin and is intended for conditions in which painted lane markings and road signs cannot be relied upon. The layer does not attempt to recover obscured markings or read signs. Instead, it infers the drivable corridor directly from the three-dimensional geometry of the scene: the elevation profile of the road surface, the edges formed by kerbs, barriers and snow banks, the tracks left by preceding vehicles, and the occupancy of the surrounding space by static and moving objects. Each cue is estimated together with its uncertainty, and the fused estimate is passed to a decision gate. When the confidence of the geometric corridor falls below a threshold, or when an external notice indicates that the road has been closed, the gate instructs the vehicle to leave its operational

design domain and to execute a minimal-risk manoeuvre. Figure 2 summarises this architecture.

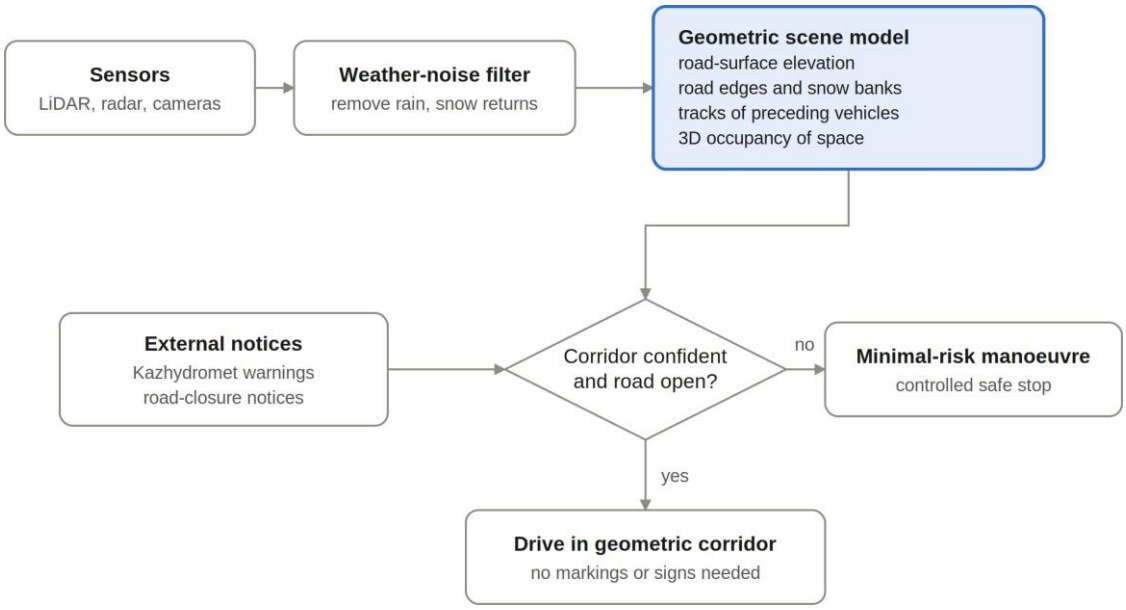


Figure 2. Geometry-first perception layer and closure-aware decision gate

Within the twin, the layer is trained and evaluated on scenes from which markings and signs have been deliberately removed or covered, so that its performance does not depend on cues that winter conditions routinely erase. The camera and LiDAR inputs to the layer are themselves adapted to heavy rain and snow: the perception models are trained and tested on images and point clouds rendered under calibrated rainfall and snowfall within the twin, and sensor fusion reduces reliance on the sensors most affected by the prevailing precipitation. Its evaluation uses the same weather transfer gap G, with P defined, for example, as the lateral error of the estimated corridor or as the proportion of correct decisions to leave the operational design domain.

3. Results

The scale of public-road testing in China provides a point of reference. In July 2026, the Ministry of Industry and Information Technology reported that more than 20,000 test and demonstration licences had been issued nationwide, more than 57,000 km of roads opened for testing and demonstration, and more than 220 million km of testing accumulated [17]. Although substantial, this exposure accrues mainly in ordinary weather, and because safety-critical events are rare, naturalistic driving alone remains an inefficient route to validation [4]; only a small proportion of these kilometres can be assumed to have been driven in heavy rain or snow. Controlled testing is the principal means by which developers and test facilities in China address this shortfall. Table 1 summarises the contribution of each testing modality.

Table 1. Testing modalities in China relevant to heavy rain and snowfall.

Testing modality	Example in China	Weather conditions	Repeatable	Availability	Measured quantities	Refs.
Competition-based field testing	Intelligent Vehicle Future Challenge, held since 2009, recently in Changshu	Incidental; whatever occurs on the days of the event	No	Annual event	Team performance on defined driving tasks	[18]–[20]
Testing modality	**Example in China**	**Weather conditions**	**Repeatable**	**Availability**	**Measured quantities**	**Refs.**
Virtual–real parallel testing	Parallel testing platforms such as PMWorld	Conditions specified by the tester in the virtual component	Yes	Year-round	Performance in coupled virtual and physical tests	[13], [14]
Closed-field weather facilities	Changsha test zone; Wuhan Economic and Technological Development Zone platform; Chongqing laboratory	Rain, fog and lighting; wind and lightning reported in Wuhan	Yes, with a spatially non-uniform rain field	Independent of natural weather	Sensor and function response in staged scenarios	[15], [21]–[23]
Cold-region proving grounds	Heihe, Heilongjiang Province	Natural snow and ice, frequently below −20 °C	No	November to March	Vehicle dynamics, braking, battery performance	[24], [25]
Calibrated virtual weather	GSRAIN; RainyGS	Rainfall of controlled intensity, 0–13 mm/h in GSRAIN	Yes	Year-round	Detection confidence, closed-loop collisions	[11], [12]

Result 1 (Table 1) corresponds to Contribution 2: no single modality is simultaneously repeatable, realistic and available throughout the year, and the two fully repeatable modalities, parallel testing and calibrated virtual weather, are both virtual.

3.1 Competition-based field testing

The Intelligent Vehicle Future Challenge was launched in 2009 by the National Natural Science Foundation of China [18]. The 13th edition, held in Changshu in 2023,

focused on driverless passenger services [18]; the 14th was held in Changshu on 22–23 November 2024 under the auspices of the Foundation's Department of Information Sciences and the Chinese Association of Automation [19]; and the 15th, held in December 2025, brought together 14 university teams and focused on multi-agent embodied interaction [20]. The competition format enables the comparison of teams under common rules. With respect to weather, however, it is opportunistic: participants encounter whatever precipitation occurs on the days of the event, at an uncontrolled intensity and without the possibility of repetition.

3.2 Virtual–real parallel testing

The coupling of virtual and physical testing has been formalised through the concept of parallel intelligence, which Hu et al. review alongside sim-to-real transfer and digital twins [13]. Ai et al. subsequently built PMWorld, a parallel testing platform for autonomous driving in mines [14]. Functionally, such platforms constitute digital twins employed for testing. As their scope indicates, however, the emphasis lies on the testing architecture rather than on weather-specific sensor physics; this component is supplied by the facilities and studies described in Sections 3.3–3.5.

3.3 Closed-field weather facilities

Several test zones in China now incorporate weather simulation into their infrastructure. The national test zone in Changsha covers more than 80 hectares, includes a 3.6 km two-way expressway and in 2023 introduced a testing system based on hazardous scenarios that include rain, fog, dust and lighting conditions [21]. A platform in the Wuhan Economic and Technological Development Zone contains an extreme-environment area that, according to its operators, can simulate wind, rain and lightning and switch from clear conditions to a downpour within seconds [22]. In early 2026, a laboratory of more than 5,000 m² began operating in Chongqing, combining vehicle motion control, rain–fog–light simulation and traffic-flow simulation within a single facility [23]. These capabilities are reported by operators and state media and have not been independently measured.

The fidelity of artificial rainfall is therefore the critical question, and a 2026 study by researchers from Tongji and Tsinghua universities provides quantitative evidence on this point [15]. Xia et al. used approximately 10,000 real-rainfall raindrop-spectrum samples as a reference and sampled 45 points within a 2.4 m × 7.2 m simulated-rainfall area. The rain field remained spatially non-uniform under a single nominal setting, indicating that one intensity value cannot characterise the entire test area. The proposed method identified two preferred test paths with equivalent intensities of 11.54 ± 0.31 mm/h and 8.28 ± 0.34 mm/h [15]. It follows that an identical rig setting may expose different vehicles, or different paths of the same vehicle, to materially different rainfall.

3.4 Cold-region proving grounds and measured snowfall

Because snowfall is more difficult to reproduce artificially than rainfall, winter testing in China continues to rely on geography. Heihe, located on the border with Russia in Heilongjiang Province, experiences snow cover for approximately 140 days a year, and its testing season extends from November to March [24]. During the 2024–25 season it hosted

147 companies and research institutions and more than 4,000 test vehicles, and local reports attribute to it approximately 85% of the Chinese cold-weather testing market [25]. Test tracks are laid out on the frozen Heilongjiang River [24], [25]. Although these conditions are highly realistic, the testing window is limited to about five months a year, conditions cannot be controlled, and the reported focus is on vehicle dynamics, braking and battery performance rather than on perception.

Measured snowfall data illustrate why perception requires dedicated evidence. Cao, Huang and Yu recorded 3,000 LiDAR frames during snowfall in Beijing using a 40-line sensor operating at 10 Hz [6]. Table 2 reports their principal results alongside other recent quantitative findings.

Table 2. Quantitative findings from recent rainfall and snowfall studies.

Study	**Setting**	**Principal reported result**
Cao, Huang, Yu, 2022 [6]	Real snowfall, Beijing; 40-line LiDAR at 10 Hz	DSOR filter precision 74.63% vs 48.22% for DROR; mean processing time 130.11 ms vs 706.97 ms per frame
Zhao, Sun, Sun, 2026 [8]	Public snowfall datasets CADC, Boreas and WADS	F1-score above 90 on all three datasets; detection accuracy improved by 5.9, 9.7 and 6.4 percentage points for three detectors
Xia, Zhao, Ye, Chen, 2026 [15]	Closed-field simulated rainfall; 45 points in a 2.4 m × 7.2 m area	Non-uniform field under one nominal setting; preferred paths at 11.54 ± 0.31 and 8.28 ± 0.34 mm/h
Wang, Zhang, Chen, 2026 [11]	Virtual rainfall of 0–13 mm/h in reconstructed 3D scenes	Collisions in a cut-in scenario at 8.5 and 12.0 mm/h; truck detection confidence reduced from 0.63 to 0.41

The timing results from Beijing are particularly relevant. At 10 Hz, a new LiDAR frame arrives every 100 ms, and both filters exceeded this interval on a desktop processor [6]. Snowfall therefore poses a real-time engineering problem in addition to an accuracy problem. The filter proposed by Zhao et al. was evaluated on Canadian and US winter datasets [8], which illustrates how few openly available snowfall datasets exist.

3.5 Calibrated virtual weather

Recent research transfers weather conditions into the virtual domain while retaining a link to measurement. GSRAIN derives its raindrop model from measured rainfall and introduces rainfall of controllable intensity, from 0 to 13 mm/h, into 3D Gaussian Splatting reconstructions of real driving scenes [11]. The generated images achieved a Fréchet Inception Distance of 149.09, lower than that of CycleGAN-Turbo (155.71) and WeatherEdit (157.94). Of greater relevance to safety, closed-loop simulations produced collisions in a cut-in scenario at 8.5 and 12.0 mm/h, and the confidence of one detector for a nearby truck decreased from 0.63 to 0.41, with the truck misclassified as a car at 8.5 mm/h [11]. RainyGS, developed at Peking University, follows a related approach by adding

physically based raindrops, splashes and reflections to reconstructed scenes with adjustable intensity [12].

Result 2 (Tables 1 and 2) corresponds to Contributions 1 and 3: the rainfall intensities at which collisions occurred in the virtual study, 8.5 and 12.0 mm/h [11], fall within the range of equivalent intensities delivered by a calibrated closed-field rig, approximately 8.3–11.5 mm/h [15]. Because the two studies employed different vehicles and experimental configurations, this correspondence does not validate either result. It does, however, demonstrate the practical feasibility of the loop in Figure 1, since a twin can identify a failure at a rainfall intensity that an existing closed-field rainfall rig is able to reproduce and verify.

3.6 Severe weather and winter road operations in Kazakhstan

Kazakhstan combines a sharply continental climate with a long and sparsely populated road network, which makes the questions examined in this study directly relevant to its transport system. The national hydrometeorological service, RSE Kazhydromet, recorded 190 hazardous meteorological events in 2024, compared with 203 in 2023 [26]. Table 3 lists these events by type together with the long-term changes reported by Kazhydromet.

Table 3. Hazardous meteorological events in Kazakhstan in 2024 and long-term change, according to RSE Kazhydromet [26].

Phenomenon	**Cases in 2024**	**Change, 2008–2024 vs 1991–2007**
Strong wind (30 m/s or more)	115	Increase by a factor of 1.9 (reported jointly with heavy snowfall and hail)
Heavy rain	32	Increase by a factor of 1.5
Severe blizzard	28	Decrease of 8%
Heavy snowfall	8	Increase by a factor of 1.9 (reported jointly with strong wind and hail)
Hail	4	Increase by a factor of 1.9 (reported jointly with strong wind and heavy snowfall)
Wet-snow deposition	2	Not reported
Very dense fog	1	Decrease of 26%
Total	190 (203 in 2023)	—

Counts for 2024 are taken from the summary table of hazardous events in the source, whose rows sum to the reported total of 190.

The severe blizzards of 2024 were concentrated in the northern and western regions. Aktobe Region alone recorded 13 of them, lasting 13–28 hours with visibility of 50–500 m, and the event with the poorest visibility, at the Kos-Istek station on 7 February 2024, lasted 25 hours with wind speeds of up to 21 m/s [26]. Kazhydromet lists road closures among the

consequences of strong winds in 2024 [26]. The winter of 2023/24 was the wettest on record since 1941, with 144.5% of the national norm of precipitation, and a cold wave between 15 and 24 February 2024 brought temperatures of −35 to −45 °C to northern and eastern regions, including a station record of −44.5 °C at Kokpekty on 21 February [26]. Snow cover remains long-lasting in the north: at Petropavlovsk it persisted for 149 days in the 2023–24 season and reached a maximum depth of 53 cm [26].

Road operations respond to these conditions primarily through closure, although closure does not remove risk entirely. On 3 January 2025, after traffic on the Astana–Petropavlovsk road had been restricted because of snowfall, blizzard, strong wind, poor visibility and ice, a mass collision involving approximately 95 vehicles occurred near Zhanatalap while traffic was moving under escort; the national road operator KazAvtoZhol attributed the collision to drivers failing to observe the speed limit and a safe distance [27]. Winter maintenance capacity is a further constraint. In September 2023, the Ministry of Transport reported that 838 of the 1,050 units of equipment assigned to the winter maintenance of national roads, approximately 80%, were in working order, and that a tender was under way to rent a further 214 units [28]. These conditions add to an existing road-safety burden: in November 2024 the Committee of Administrative Police of the Ministry of Internal Affairs reported about 2,000 road deaths in Kazakhstan since the start of that year and noted that out-of-town highways accounted for half of all fatal crashes [29].

3.7 Evidence for marking-independent, geometry-based perception

Winter conditions directly undermine perception that relies on painted markings. Goberville, Kadav and Asher report that a leading automotive vision system detected both the left and the right lane lines in only 21.8% of winter driving, and that only 0.9% of these detections had sufficient confidence for safety-critical driver-assistance functions; as an alternative, they identify the drivable region from the tyre tracks left by preceding vehicles [30]. Ariram et al. constructed LiDAR maps of a Finnish urban road in January and showed that road width can be estimated from the snow banks at the road edges even when lane markings are covered, after which lanes can be inferred from the estimated width and the known number of lanes [31].

At the level of complete scene representation, researchers at Tsinghua University have shown that three-dimensional semantic occupancy, which describes which parts of the space surrounding the vehicle are occupied, can be predicted from surround-view cameras; their TPVFormer model achieved performance comparable to that of LiDAR-based methods on the nuScenes LiDAR segmentation task [32]. Such representations encode the drivable surface and obstacles geometrically rather than through markings or signs. Finally, ISO 34503:2023 specifies a taxonomy for defining the operational design domain, that is, the operating conditions within which an automated driving system is designed to function [33]. In these terms, an official road closure in Kazakhstan places the affected road explicitly outside the operational design domain.

Result 3 (Table 3 and Sections 3.6–3.7) corresponds to Contributions 5 and 6: winter conditions in Kazakhstan produce frequent and prolonged losses of visibility and of road-surface cues, closures are the principal operational response, and published methods already demonstrate that a drivable corridor can be inferred from scene geometry without reliance on markings or signs.

4. Discussion

The evidence supports the conclusion that severe-weather validation requires a digital twin. The principal reason is not that simulation is less costly, but that the twin is the only setting in which the realism of a cold-region proving ground, the controllability of a rainfall rig and the scale of virtual testing can be combined. The twin acquires this role, however, only when it is calibrated against the physical tests it is intended to extend.

RQ1 concerned the contribution and limitations of each testing modality employed in China. Competitions such as the Intelligent Vehicle Future Challenge provide common rules and public comparison, but the weather conditions they present are incidental [18]–[20]. Parallel testing supplies the methodological basis, namely a closed loop between virtual and physical tests [13], [14], but its published form addresses weather physics only marginally. Closed-field facilities offer control and repeatability [21]–[23], yet their rainfall is spatially non-uniform [15], and none of the reviewed facilities reports artificial snowfall. Cold-region proving grounds provide natural snow and ice for approximately five months a year, without control over conditions and with a reported emphasis on vehicle dynamics rather than on perception [24], [25]. Calibrated virtual weather offers scale and full controllability [11], [12] but derives its credibility entirely from the measurements on which it is based. Because each modality compensates for a limitation of another, the evidence favours their integration rather than the selection of any single modality.

RQ2 concerned the quantities against which a weather twin must be calibrated. The reviewed studies suggest three layers of calibration. The first is the weather field itself, including drop size, drop velocity and spatial variation across the test area, since a nominal intensity conceals this variation [15]. The second is the sensor response to that field, such as LiDAR returns and reflectivity on targets [15] and the spatial distribution of snowfall noise [6], [8]. The third is task-level performance, namely detection and closed-loop behaviour [11]. The distinction is important because image-quality measures such as the Fréchet Inception Distance quantify the visual appearance of rainfall rather than its effect on LiDAR returns. A twin that is accurate at the first two layers and verified at the third produces failures that merit physical confirmation.

RQ3 concerned the criterion under which a twin-based result may replace a physical one. The weather transfer gap G provides a workable criterion subject to two conditions: weather must be matched in equivalent terms rather than by rig settings [15], and the same measure P must be recorded in both domains. Neither condition is currently standard practice in the facility reports reviewed, which describe capabilities rather than measured fields [21]–[23].

RQ4 concerned the additional machine-learning layer that can support driving when markings and signs are unavailable, and its interaction with road closures in Kazakhstan. The evidence indicates that such a layer should be geometry-first. Marking-based lane detection fails in most winter driving [30], whereas road width can be recovered from snow banks [31], the drivable region from the tracks of preceding vehicles [30], and the full occupied space from three-dimensional occupancy prediction [32]. None of these cues depends on the visibility of paint or signs, and each can be trained and stress-tested within the twin by removing markings and signs from otherwise realistic scenes. Cameras remain valuable within this layer, but only if their models are trained and tested on imagery degraded by calibrated rain and snow: detection confidence falls measurably as simulated rainfall intensifies [11], while radar provides a comparatively robust complement in fog, rain and snow [3]. The same layer provides a natural point at which to encode road closures. Because a closure places the road outside the operational design domain [33], an automated vehicle should treat a closure notice from the road operator, or a hazardous-weather warning from Kazhydromet, as a condition for executing a minimal-risk manoeuvre regardless of its own perception confidence. The Zhanatalap collision [27] shows that the period immediately after reopening, when traffic moves in convoy on a surface that remains snow-covered, is itself hazardous; an automated vehicle should therefore resume normal operation only when both the closure has been lifted and its geometric corridor estimate has regained sufficient confidence.

The hypothesis that severe-weather validation requires a calibrated digital twin is therefore supported, with the qualification that the twin complements rather than replaces physical testing. Three developments may be anticipated if this approach is adopted more widely. First, closed-field reports are likely to move from nominal to measured, equivalent descriptions of eather, as Xia et al. already propose [15]. Second, the principal function of physical rigs is likely to shift from serving as the test itself to calibrating and confirming the twin. Third, cold-region sites are likely to combine seasonal campaigns with year-round work; in early 2025, a new facility in Heihe was expected to open by May of that year to enable testing throughout the year [24]. These expectations are inferred from the evidence and should not be interpreted as empirical findings.

Practical implications

Test facilities should report, for each weather condition, the measured drop-size spectrum, a spatial map of the rain field and the equivalent intensity along each test path. Developers should record identical sensor-level and task-level measures in physical and virtual runs so that G can be computed, and should evaluate perception on scenes in which markings and signs are absent. Camera-based perception, in particular, should be trained and validated on imagery degraded by calibrated rain and snow rather than on clear-weather data alone. Regulators that accept simulation-based evidence could require G to be reported alongside it.

For Kazakhstan, four implications follow. First, Kazhydromet warnings and KazAvtoZhol closure notices should be made available in a machine-readable form, so that automated vehicles and fleet operators can apply them as hard operational-design-domain boundaries rather than as advice to drivers. Second, the reopening of a closed road should be treated as a distinct operational phase with its own speed and spacing rules for automated vehicles, given the risk demonstrated by the Zhanatalap collision [27]. Third, winter maintenance vehicles, which already traverse the network during and after snowfall, could carry low-cost LiDAR or camera units to record the post-clearing geometry of the road, including the position of snow banks; these observations would keep the geometric layer of the twin current and would be particularly valuable where maintenance capacity is limited and markings remain covered for extended periods [28]. Fourth, the northern regions, where snow cover lasts for about five months, could host a national cold-weather calibration site whose measurements feed the twin, rather than relying on short seasonal campaigns abroad [26].

Limitations of the study

Several limitations should be acknowledged. First, the study is a review rather than an original experiment; neither the metric G nor the geometry-first layer has yet been tested empirically. Second, the evidence base combines peer-reviewed articles, preprints, regulatory documents and media reports, and facility capabilities drawn from the last category represent operator claims. Third, the correspondence between the collision intensities observed in simulation and the equivalent intensities of the physical rig derives from two independent studies and is illustrative only. Fourth, the cited rainfall rig delivered approximately 8–12 mm/h on its preferred paths [15], whereas natural downpours can be considerably more intense; the heaviest rainfall therefore remains insufficiently covered. Fifth, evidence on snowfall is weaker than evidence on rainfall, since none of the reviewed facilities in China reports controlled snowfall. Sixth, the Kazakhstan data cover a single climatological year, and the account of the Zhanatalap collision and the 2024 road-death figure are drawn from official statements reported in the media rather than from official statistical series. Finally, the searches covered English- and Chinese-language sources available online, and literature accessible only through subscription databases may have been omitted.

5. Conclusion

The central conclusion of this study is that automated driving in heavy rain and snow cannot be validated on public roads alone and should first be developed and tested in a calibrated digital environment. Physical tests in China provide either realism or control, rarely both, and never throughout the year; virtual tests provide scale and control but are credible only when calibrated against measurements. The digital twin is the only setting in which these strengths can be combined. Four specific conclusions follow from the evidence.

1. **Test in the digital world first.** Severe-weather scenarios should be generated, run and repeated in a digital twin that is calibrated against physical rainfall rigs and

winter proving grounds. Physical tests should be used to calibrate the twin and to confirm the failures it identifies, and a twin-based result should be accepted for a given measure only when the weather transfer gap G falls below a threshold set in the safety case.

2. **Build the drivable corridor from road geometry.** In heavy rain and snow, the vehicle should determine where it can drive from the three-dimensional geometry of the road: the elevation of the road surface, road edges and snow banks, the tracks of preceding vehicles and the occupancy of the surrounding space.
3. **Adapt cameras and other sensors to heavy rain and snow.** Camera and LiDAR models should be trained and validated on data degraded by calibrated rainfall and snowfall rather than on clear-weather data alone, and sensor fusion should reduce reliance on the sensors most affected by the prevailing weather.
4. **Disregard road signs and lane lines in severe weather.** Because snow and heavy rain routinely obscure painted markings and signs, the perception layer should not depend on them. When the geometric estimate is not sufficiently confident, or when the road has been officially closed, the vehicle should execute a minimal-risk manoeuvre.

For Kazakhstan, where Kazhydromet recorded 28 severe blizzards in 2024 with visibility falling to 50 m, and where road closure is the principal operational response to severe weather, these conclusions are of direct practical relevance. Closure notices and hazardous-weather warnings should be treated by automated vehicles as hard boundaries of the operational design domain.

The scientific novelty of the study lies in analysing research testing in China as an integrated body of evidence through the lens of digital-twin calibration, in proposing the weather transfer gap G as an acceptance criterion, and in specifying a geometry-first perception layer that operates without reliance on road markings or signs. Future research should evaluate G using paired physical and virtual runs at a single facility, extend weather-field calibration from rainfall to snowfall and road spray, and test the geometry-first layer on roads in northern Kazakhstan, including data recorded by winter maintenance vehicles after snow clearing.

Author Contributions

Conceptualization: Y.K.; Methodology: Y.K.; Investigation: Y.K.; Formal Analysis: Y.K.; Writing – Original Draft Preparation: Y.K.; Writing – Review and Editing: Y.K.; Visualization: Y.K.

Conflicts of Interest

The author declares no conflict of interest.

Data Availability Statement

No new datasets were generated during this study. The research is based on publicly available scientific literature, preprints, government documents and public reports cited in the manuscript.

List of Supplementary Materials

No supplementary materials are associated with this study.

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