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Review

Contact and Weight-Based Yield Monitoring Technologies for Major Root and Tuber Crops in Korea

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Abstract

Root and tuber vegetables, including potatoes, radishes, sweet potatoes, and carrots, are important components of Korean upland agriculture, yet harvesting and yield determination remain less mechanized and digitally integrated than cereal production. This review integrated contact- and weight-based yield measurement technologies applicable to Korean root and tuber crop harvesting, with emphasis on load-cell systems, conveyor weighing, hopper/bin weighing, impact-force sensing, and integrated multi-sensor approaches. Korean and international studies were checked in relation to sensing principles, harvester integration, calibration, dynamic measurement, spatial yield mapping, and field applicability. The literature shows that direct load-cell-based measurement provides the most physically interpretable basis for harvested mass estimation, while conveyor systems are particularly suitable for continuously conveyed crops such as potatoes and radishes. Hopper and cart weighing provide practical alternatives for semi-mechanized operations, including sweet potato harvesting, whereas impact sensing offers compact measurement but is more sensitive to crop trajectory, vibration, inclination, and mechanical damage. Korean studies have demonstrated promising sensor-level performance for potatoes and radishes; however, field-scale implementation remains constrained by vibration, slope, soil and debris contamination, tare drift, crop transport delay, limited standardization, and differences in harvester architecture. Integration of direct mass sensing with GNSS, IMU, belt-speed sensing, machine-state information, and machine vision provides a promising pathway toward reliable yield mapping. The synthesis indicates crop-specific pathways: continuous conveyor weighing after soil separation for potatoes; dynamically compensated event/impact sensing for radishes; low-impact hopper, cart, or batch weighing for sweet potatoes; and post-cleaning weighing for carrots. The main remaining gap is integrated field validation under realistic throughput, vibration, slope, headland transitions, and field-scale conditions. Future studies should report accuracy together with throughput, calibration burden, spatial-lag error, contamination effects, cost, and field repeatability.

Keywords: precision agriculture; yield mapping; root and tuber crops; load cell; conveyor weighing; impact plate; Korea

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1. Introduction

Root and tuber vegetables constitute an important component of agricultural production, food consumption, processing industries, and rural economies in Korea. Major crops include the Korean radish (*Raphanus sativus* L.), potato (*Solanum tuberosum* L.), sweet potato (*Ipomoea batatas* L.), and carrot (*Daucus carota* L.), which are cultivated under diverse soil, climatic, and topographic conditions. These crops support both fresh-market consumption and processing industries and are closely associated with traditional Korean food systems. The Korean radish is particularly important as a principal ingredient of kimchi and other fermented foods, whereas the potato and sweet potato contribute to fresh consumption, starch-based foods, snacks, and other processed products [1–3]. National production statistics indicate that these crops continue to occupy substantial cultivated areas and contribute significantly to Korean upland agriculture [1]. Potato production occurs under geographically diverse conditions ranging from spring cultivation to highland and summer production systems, making productivity sensitive to regional soil and climatic variation [2–4].

The term root and tuber vegetables is used in this review for crops whose economically important harvested organs develop below the soil surface and consequently share comparable harvesting and yield-sensing constraints [2,3]. The principal technical focus is on radishes, potatoes, sweet potatoes, and carrots. Other underground-harvested field crops are considered where their harvesting or sensing technologies provide transferable engineering knowledge. This operational classification is particularly relevant to yield monitoring because the mechanical requirements for measurement are determined not only by botanical classification but also by crop-flow characteristics during digging, lifting, soil separation, conveying, cleaning, and collection [5,6].

Korean upland agriculture is undergoing a gradual transition toward increased mechanization and digitalization. Agricultural labor shortages, aging of the farming population, increasing labor costs, and the need for greater operational efficiency have accelerated the development of small- and medium-sized agricultural machinery adapted to Korean fields [3,6]. Harvesting of root and tuber crops remains more difficult to mechanize than cereal harvesting because underground crops must first be detached or excavated from the soil and subsequently separated, conveyed, cleaned, and collected while minimizing physical damage. Korean farms are also frequently characterized by relatively small and fragmented fields, short operating rows, restricted headland space, ridge-based cultivation, and variable terrain. These conditions limit the direct application of large-scale harvesting machinery and increase the importance of compact and versatile equipment [5]. Korean research on underground-crop harvesters has consequently addressed digging and conveying mechanisms, operational loads, intelligent control, vibration compensation, and adaptation to diverse field conditions [6–8].

The Korean focus is not intended to imply that these constraints are unique to Korea. Comparable machinery-adaptation problems occur in other small-field and sloping agricultural systems. In Japan, aging farm populations, restricted field dimensions, and sloping production areas have motivated the development of compact and terrain-adapted mechanization systems [9], while studies in mountainous regions of Italy have similarly emphasized intermediate machinery suited to small farms and steep or fragmented fields [10]. These contexts provide more appropriate engineering comparators for Korea than large, relatively uniform commercial fields in North America. Nevertheless, crop type, harvesting architecture, and institutional conditions differ among countries; therefore, these international cases are used here as comparative engineering benchmarks rather than as direct evidence of Korean root-crop yield-monitor performance.

Despite progress in harvesting mechanization, measurement of the actual harvested yield has received comparatively less attention than mechanical harvesting performance. Farm-level yield is commonly determined through plot sampling, manual weighing, container or truck weighing, cooperative collection records, and post-harvest sales information. These approaches are effective for quantifying total production but provide limited information on when and where yield is generated within a field. Sampling-based estimates are also sensitive to sampling location because root and tuber productivity can vary substantially according to soil texture, moisture availability, nutrient status, topography, crop establishment, disease incidence, planting uniformity, and local environmental conditions. Consequently, field-average yield values can obscure important spatial variations in crop productivity.

Accurate yield information is important at multiple levels of agricultural management. At the farm level, measured yield facilitates comparisons among fields, cultivars, planting dates, fertilization strategies, irrigation practices, and harvesting conditions. At the operational level, information on harvested quantity supports scheduling of labor, collection containers, transport vehicles, storage facilities, grading operations, and processing capacity [2,6]. At the spatial-management level, georeferenced yield information enables identification of consistently high- and low-performing field zones and can be integrated with soil properties, topography, weather, crop growth, and management records. Yield maps therefore represent an important feedback layer in precision agriculture because spatial patterns in harvested production provide a direct basis for evaluating previous management practices [11].

Yield prediction and yield measurement represent related but distinct components of digital agriculture. Remote sensing, UAV imagery, satellite observations, crop models, and machine-learning approaches have demonstrated considerable potential for estimating crop yield before harvest. In Korea, UAV imagery has been applied to rice yield estimation [12], while satellite data, meteorological information, crop models, and deep-learning approaches have been used for pixel- and regional-scale yield prediction [13,14]. These methods are valuable for early forecasting, regional production assessment, and supply planning. However, they infer final yield from crop or environmental characteristics and require observed yield data for calibration and validation. In contrast, harvest-mounted yield-monitoring systems measure the crop physically recovered during harvesting and provide direct production information at the end of the cropping cycle.

Real-time yield monitoring was initially developed for mechanized grain production, where combine harvesters provide suitable locations for measuring grain flow, moisture content, travel speed, and geographic position. Yield-monitoring systems subsequently became a major technological component of precision agriculture because sensor measurements could be synchronized with positioning information to generate spatial yield maps [11,15]. Transfer of these concepts from grain to horticultural and underground crops is considerably more complex. Horticultural harvesting systems vary substantially in crop geometry, material flow, harvesting mechanism, throughput, mechanical-damage sensitivity, and degree of mechanization. Longchamps et al. [16] classified horticultural yield-sensing technologies according to direct and indirect measurements and proximal and remote sensing, highlighting the strong dependence of sensor performance on crop and harvesting-system characteristics.

For root and tuber vegetables, direct measurement during harvesting is particularly relevant because harvested material normally passes through a defined mechanical pathway after excavation or extraction [17]. Depending on machine design, potatoes, radishes, carrots, and sweet potatoes can pass through digging units, separation webs, conveyors, elevators, temporary hoppers, collection bins, and discharge points. These material-transfer

locations provide opportunities for integrating load cells, weighing frames, conveyor weigh sections, impact plates, pressure sensors, and instrumented collection containers. Mass-based systems can measure instantaneous crop mass-flow or accumulated crop mass and, when synchronized with travel speed and positioning information, can generate spatially referenced yield data. Reviews of non-grain and horticultural yield monitoring have identified load-cell weighing, impact-force sensing, volumetric sensing, machine vision, and integrated sensor systems as major technological approaches, with direct mass measurement providing one of the most physically interpretable measures of harvested production [16–18].

Historical studies demonstrated the feasibility of applying dynamic weighing to bulky agricultural crops. Rawlins et al. [19] developed a potato yield-mapping system in which potatoes were continuously weighed on a conveyor section and measured mass was related to harvester travel distance and effective harvesting width. The study also addressed spatial displacement between the original crop location and the position at which potatoes reached the yield sensor. Pelletier and Upadhyaya [20] subsequently developed a continuous yield-monitoring system for processing tomato based on a load-cell weighbridge, belt-speed measurement, angle sensing, differential GPS, and signal processing. These studies established that accurate dynamic weighing depends on the integration of crop-flow measurement with machine operating parameters and positioning information.

Korean research has provided an important foundation for adapting such technologies to compact root-crop harvesters. Kim et al. [21] evaluated load-cell-based mass sensing and CCD-camera-based volume sensing for small Korean potato harvesters. The load-cell system produced a coefficient of determination of approximately 0.95 with an RMSE of approximately 11 g, whereas the volume-based approach produced an (R^2) of approximately 0.91. Sensor performance was affected by machine vibration and inclination, illustrating the difference between laboratory calibration accuracy and field measurement performance. Jang et al. [22] subsequently evaluated impact load-cell and CCD-based sensing for potato yield monitoring and reported a strong mass-based calibration relationship (R^2 = 0.98) under selected operating conditions, while also demonstrating the dependence of measurement performance on crop-drop and sensing conditions. Jang et al. [23] later applied deep-learning-based machine vision to potato detection and tracking. These Korean studies are discussed in greater detail in Section 6.2.

Root and tuber vegetables nevertheless present several unique measurement challenges. A weight sensor mounted on a harvesting machine responds not only to crop mass but also to vibration, shocks, frame deformation, belt tension, inclination, and dynamic acceleration [24]. Harvested roots and tubers are also accompanied by variable quantities of adhering soil, clods, stones, plant residues, and foliage. The resulting gross mass can therefore differ from cleaned or marketable crop mass. Individual roots and tubers additionally vary in shape, size, orientation, surface moisture, and impact behavior, producing crop mass-flow that can consist of discrete objects, clustered groups, or intermittent pulses rather than a smooth continuous stream [24,25]. Furthermore, the time required for crop material to travel from the digging point to the sensing location introduces a spatial lag between crop origin and sensor measurement. Mechanical interaction between sensing devices and the harvested product also influences crop bruising, cracking, skin damage, and overall market quality [17].

These issues are particularly relevant under Korean harvesting conditions. Compact harvesters provide limited space for isolated weighing structures; short rows and frequent headland turns increase the frequency of transient operation; sloped upland fields alter the gravitational component acting on weighing sensors; and vibration generated by digging

blades, shaking webs, conveyors, engines, and track–soil interaction can obscure crop-induced force signals. Lim et al. [8] investigated vibration-error compensation for weight measurement in underground-crop harvesters, demonstrating the importance of separating crop-induced loads from machine-induced dynamic forces. Kiraga et al. [26] evaluated the effects of vibration and slope under laboratory test bench conditions. Accordingly, real-time yield monitoring for Korean root crops is fundamentally a system-level measurement problem involving mechanical sensor integration, calibration, signal processing, machine-state detection, belt and travel speed, inclination, positioning, and data management.

Although several reviews have addressed yield monitoring in non-grain and horticultural crops [16–18], a focused synthesis of contact- and weight-based yield measurement for root and tuber vegetables under Korean harvesting conditions remains limited. Existing reviews encompass broad groups of horticultural crops and diverse sensing technologies, whereas underground-harvested crops are characterized by a distinctive combination of soil contamination, discrete crop mass-flow, vibration, slope effects, mechanical-damage risk, and compact harvester architectures. Korean studies are additionally distributed across potato sensor development, harvester engineering, vibration compensation, machine vision, and precision-agriculture applications.

A recent Korea-focused review by Dey et al. [27] examined non-contact yield-measurement approaches for root vegetables, with emphasis on RGB/RGB-D imaging, LiDAR, ultrasonic, thermal, radar, hyperspectral sensing, machine learning, and image-based crop detection and geometric estimation. The present review is complementary but technically distinct. Its primary focus is the direct measurement of physically harvested material through contact- and weight-based sensing, including load-cell load transfer, conveyor weighing, hopper/bin and cart weighing, impact-force measurement, and mechanically derived crop-flow signals. Accordingly, the present synthesis emphasizes issues that are not central to the non-contact review, including load-path design, belt and weighing-section mechanics, vibration and inclination effects, tare drift, soil/debris contribution to measured mass, dynamic calibration, crop transport delay, sensor-placement-dependent definitions of gross, recovered, cleaned, and marketable yield, and the crop-specific integration of weighing systems with Korean harvesters. Multi-sensor integration is considered here primarily as a means of correcting and interpreting a direct mass reference, with GNSS, IMU, belt-speed, vibration, and vision sensors serving complementary functions rather than replacing direct weighing.

Accordingly, this review aimed to synthesize the principles, current development status, engineering limitations, and crop-specific applicability of contact- and weight-based real-time yield-monitoring technologies for major root and tuber crops relevant to Korean agriculture. Particular attention was given to sensor–harvester integration, dynamic measurement errors, calibration and field validation, spatial yield mapping, and transferable engineering approaches from Korean and international yield-monitoring research.

2. Review Approach and Methodology

2.1. Structured Narrative Review Scope and Literature Identification

This study was conducted as a structured narrative review rather than a systematic or scoping review. The objective was to synthesize engineering principles, crop-specific applicability, and practical limitations of contact- and weight-based yield-monitoring technologies relevant to Korean root and tuber crop harvesting. Google Scholar was used as the principal scholarly search source, supplemented by targeted journal/publisher searches and backward reference screening of relevant review and primary research articles. No lower publication-year restriction was imposed because several early studies established the

fundamental principles of potato conveyor weighing and non-grain yield monitoring; the literature search was updated through October 2026. Search terms were used individually and in combinations and included "yield monitoring", "yield mapping", "load cell", "conveyor weighing", "belt weighing", "impact plate", "hopper weighing", "bin weighing", "mass flow", "potato", "radish", "sweet potato", "carrot", "root crop", "harvester", and "Korea" or "Republic of Korea".

Peer-reviewed journal articles and relevant conference proceedings were included when they provided evidence concerning: (i) direct contact- or weight-based yield measurement; (ii) load-cell, conveyor, hopper, bin, cart, or impact-force sensing; (iii) harvesting and crop-flow characteristics affecting sensor integration; (iv) vibration, inclination, crop impact, tare drift, or other dynamic measurement errors; (v) calibration or field validation; or (vi) GNSS-based spatial yield mapping and crop-transport delay. Korean agricultural statistics and government reports were additionally used when describing production and mechanization conditions. Studies focused solely on pre-harvest remote sensing or yield prediction were excluded from the primary technological synthesis, except where they provided complementary evidence concerning crop/non-crop discrimination, mass estimation, or comparison with direct measurement.

Because relatively few Korean studies have evaluated complete contact-based yield-monitoring systems for root and tuber crops, selected international studies and Korean grain-monitoring studies were included when their sensing principles or engineering problems were directly transferable. These studies were used as engineering benchmarks rather than as direct evidence of crop-specific performance under Korean root-crop harvesting conditions. The review was intended as a structured engineering synthesis rather than a systematic meta-analysis. The previous Korea-focused non-contact review [27] was used as contextual literature; non-contact technologies themselves were not re-reviewed comprehensively in the present study and were considered only where they complemented direct mass measurement.

A total of 79 sources were retained in the final narrative synthesis, including peer-reviewed journal articles, relevant conference papers, and official Korean statistical or government sources. Because the review was not designed as a systematic review, a PRISMA-style record count of initial search hits and duplicate removal was not maintained. No formal language restriction was applied; both English- and Korean-language publications were eligible when they satisfied the review scope. No separate Korean bibliographic database was used; Korean-language publications were identified through Google Scholar, relevant journal/publisher websites, and backward reference screening.

2.2. Literature Classification and Information Extraction

The selected literature was organized according to both the sensing principle and the harvesting-system configuration. Contact- and weight-based technologies were classified into: (i) load-cell-based measurement; (ii) belt-conveyor weighing; (iii) hopper, bin, cart, and cumulative weighing; (iv) impact-force sensing; (v) other mechanically derived measurement approaches; and (vi) integrated multi-sensor monitoring systems. This classification reflects the principal technological architectures identified in the reviewed studies and enables comparison of measurement directness, temporal resolution, mechanical integration requirements, and sensitivity to field operating conditions.

For each relevant study, information was synthesized according to the crop, measurement principle, sensor configuration, experimental or field platform, major operating conditions, reported performance indicators, and principal sources of measurement error. Particular attention was given to vibration, inclination, belt-speed variation, crop clumping, soil and foreign-material contamination, tare drift, crop-impact characteristics, transport

delay, and field-position assignment because these factors repeatedly affected the performance of direct yield-measurement systems. Measurement performance was interpreted using reported indices such as coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), relative or percentage error, cumulative mass error, and field-scale yield error where available. The review also distinguished static sensor calibration from dynamic calibration and independent field validation because a strong laboratory calibration relationship does not necessarily indicate equivalent performance during harvesting.

The reviewed studies were conducted at substantially different experimental scales, including static sensor calibration, laboratory test benches, harvester prototypes, recorded-video evaluation, single-field testing, and field-scale validation. Reported performance values were therefore not treated as directly comparable measures of technological superiority. In particular, a high R^2, precision, recall, or mAP obtained during model calibration or within-domain validation does not represent complete field-level yield-monitoring accuracy. Where available, sample size, data partitioning, replication, validation level, and field independence were examined together with the reported metric. When confidence intervals, independent test sets, or replicate variability were not reported in the original study, these limitations were explicitly noted rather than inferred.

2.3. Synthesis Framework for Korean Applicability

The reviewed technologies were further evaluated in relation to Korean root- and tuber-crop harvesting conditions. The synthesis considered crop morphology, harvesting mechanism, degree of mechanization, crop-flow continuity, potential sensor location, machine size, field slope, vibration environment, and compatibility with spatial yield mapping. Particular emphasis was placed on whether the harvested material passed through a controlled and measurable crop-flow pathway, because this determines whether continuous conveyor weighing, event-based measurement, or cumulative batch weighing is most appropriate.

The applicability of each sensing approach was therefore interpreted on a crop-specific basis rather than assuming that a common yield-monitoring architecture could be applied to all root and tuber crops. Potatoes were evaluated primarily in relation to continuous conveyor-based sensing after soil separation; radishes in relation to discrete or event-based load and impact measurement; sweet potatoes in relation to hopper, cart, crate, or batch weighing compatible with semi-mechanized collection; and carrots in relation to conveyor or cumulative measurement after foliage and soil removal. These crop-specific recommendations are consistent with the harvesting architectures and future development priorities synthesized later in the manuscript.

Finally, the maturity of Korean yield-monitoring research was qualitatively assessed according to progression from sensor feasibility to dynamic-condition validation, crop or mass discrimination, GNSS integration, spatial yield mapping, and field-scale validation. This assessment was intended as a comparative synthesis of the reviewed literature rather than a formal Technology Readiness Level assessment. The resulting framework was used to identify remaining research gaps and to propose crop-specific development pathways for practical contact- and weight-based yield monitoring under Korean harvesting conditions.

For the qualitative maturity assessment demonstrated indicates that at least one peer-reviewed Korean study directly demonstrated the corresponding function with experimental or field evidence; partial implementation indicates that the function was incorporated into a prototype or limited field system but was not validated as a complete end-to-end yield-monitoring function; developing indicates that relevant experimental evidence exists but the function remains under investigation or has not yet been integrated into a complete

monitoring system; limited evidence indicates that only sparse, indirect, or transferable Korean evidence was identified without a dedicated demonstration for the crop; and not reported indicates that no peer-reviewed Korean study demonstrating the corresponding stage was identified in the literature reviewed. These categories represent a qualitative literature-based comparison and should not be interpreted as formal Technology Readiness Levels (TRLs).

2.4. Limitations of the Review Approach

Because this study was designed as a structured narrative engineering review, it did not employ a PRISMA-based systematic-review protocol, formal risk-of-bias assessment, or meta-analysis. The search and selection process was intended to identify the principal technologies and engineering evidence rather than to provide an exhaustive quantitative census of all published records. This approach is particularly relevant because the Korean literature on contact-based root-crop yield monitoring remains relatively small and heterogeneous, spanning laboratory sensor tests, harvester prototypes, machine-vision studies, conference papers, government statistics, and field validation. Consequently, conclusions concerning relative technology maturity and crop applicability were based on qualitative synthesis of the available evidence and should not be interpreted as pooled estimates of performance.

Several Korea-specific studies included in this review were authored or co-authored by members of the present review team. Their inclusion reflects the relatively limited published literature on Korean root- and tuber-crop yield monitoring rather than preferential selection. To reduce potential author-related selection and interpretation bias, the same topical inclusion criteria were applied irrespective of authorship; only publicly available peer-reviewed articles, conference publications, and official reports were used; no unpublished laboratory results or internal datasets were included; and findings from author-affiliated studies were interpreted alongside independent Korean and international studies. Performance values from these studies were reported together with their experimental scale and principal limitations rather than given greater evidential weight because of authorship.

3. Status of Root and Tuber Crop Harvesting in Korea

3.1. Production Context and Importance of Major Root and Tuber Vegetable Crops

Root and tuber vegetables occupy an important position in Korean upland agriculture because of their contributions to domestic food consumption, processing industries, regional agricultural economies, and diversified cropping systems. Potatoes (*Solanum tuberosum* L.), Korean radishes (*Raphanus sativus* L.), sweet potatoes (*Ipomoea batatas* L.), and carrots (*Daucus carota* L.) differ substantially in morphology and cultivation practice, but all require extraction of the marketable organ from or near the soil followed by separation, conveying, cleaning, and collection. These operations make harvesting mechanically more complex than above-ground cereal harvesting and directly influence the feasibility and performance of real-time yield sensing.

Potato production in Korea includes spring, summer, autumn, and highland cultivation systems. Highland potato production is particularly associated with cooler regions such as Gangwon Province, Korea, where altitude and temperature provide suitable summer production conditions [2,7]. Korean potato productivity is influenced by planting date, temperature regime, soil properties, water availability, and cultivation system, which also affect tuber size distribution, harvesting timing, soil adhesion, and machinery performance [2–4]. Statistics [28] reported approximately 126,700 t of highland potato production

from approximately 3835 ha in 2023, indicating the importance of geographically concentrated seasonal potato production.

Korean radishes are strongly associated with domestic food culture and the kimchi industry. Seasonal radish production systems differ in planting period, growing environment, plant dimensions, root size, and soil conditions. Statistics [29] reported approximately 486,700 t of autumn radish production from approximately 6207 ha in 2023. Unlike potatoes, Korean radishes develop a relatively large root that is often partly exposed above the soil surface. Its harvesting process therefore commonly involves foliage gripping, pulling, lifting, and subsequent conveying rather than the digging and sieving processes characteristic of potato harvesting.

Sweet potatoes are widely cultivated for fresh-market and processing purposes. Their harvesting process is complicated by irregular tuber morphology, clustered tuber formation, vine growth, skin sensitivity, and susceptibility to cutting, abrasion, and breakage. Mechanical harvesting therefore involves a balance between effective soil loosening and acceptable crop-damage levels. Kim et al. [30] demonstrated substantial labor savings from mechanized sweet potato harvesting compared with conventional manual harvesting, indicating the importance of mechanization in reducing dependence on seasonal labor.

Carrots represent another important root-vegetable harvesting system because their elongated root shape, foliage attachment, and dependence on soil resistance influence mechanical extraction. Choi et al. [31] investigated a harvesting system applicable to radishes and carrots, demonstrating the feasibility of integrating digging, lifting, conveying, and crop-separation functions for these crops. The recent Korean literature on carrot-specific yield monitoring remains relatively limited compared with potatoes, making carrots an important target for adaptation of technologies developed for other underground crops.

Garlic and onions are botanically classified as bulb crops rather than root or tuber vegetables and are not the principal crops considered in this review. Nevertheless, their mechanization provides useful context because their Korean production systems share several engineering characteristics with root and tuber crops, including ridge cultivation, soil-contact harvesting, high manual labor requirements, small-field operation, and the need for compact machinery. Their mechanization experience therefore provides complementary information on the broader development of upland-crop machinery in Korea.

3.2. Mechanization Status of Korean Upland Crop Harvesting

Mechanization has historically progressed more rapidly in Korean paddy rice production than in upland crop production. Rice cultivation benefits from relatively standardized production systems and mature machinery for tillage, transplanting, crop protection, and harvesting. Upland crops exhibit greater variability in row spacing, ridge geometry, crop morphology, harvest maturity, soil condition, and harvesting mechanism, resulting in lower overall mechanization levels.

According to the 2023 Agricultural Work Mechanization Survey published by the Rural Development Administration (RDA) [32], the overall mechanization rate was 99.7% for paddy rice and 67.0% for upland crops. Within upland-crop production, harvesting remained substantially less mechanized, at 42.9%, compared with tillage and land preparation (100.0%) and crop protection (96.2%), as shown in Figure 1. This operation-specific gap is particularly relevant to yield-monitor development because direct harvest-time sensing requires a sufficiently mechanized and controlled crop-flow pathway.

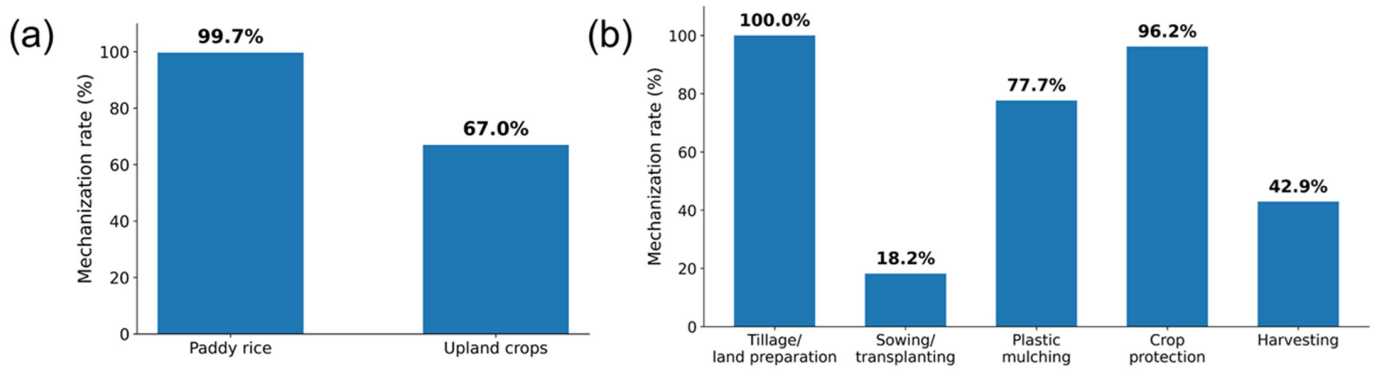


Figure 1. Mechanization status of Korean agriculture based on the 2023 Agricultural Work Mechanization Survey: (**a**) overall mechanization rates for paddy rice and upland crops; and (**b**) operation-specific mechanization rates for upland crops. Source: Rural Development Administration (RDA), 2024 [32].

The level of harvesting mechanization is directly related to the feasibility of real-time yield monitoring. A continuous yield-monitoring system requires a defined crop-flow path through which the harvested product consistently passes [17]. In grain combines, harvested material moves through a standardized internal flow path, allowing mass-flow sensors to be positioned at specific locations [17,18]. In Korean root- and tuber-crop production, harvesting can range from simple mechanized digging followed by manual collection to integrated systems incorporating digging, separation, conveying, cleaning, and collection. The available sensing location therefore varies according to machine architecture and degree of mechanization.

Korean mechanization programs have increasingly emphasized standardized cultivation models and integrated machinery systems rather than isolated machine development. The RDA [33] has promoted complete mechanization systems for major upland crops such as garlic and onions. This broader systems-oriented approach also provides an important technological context for root and tuber crops because standardized harvesting pathways facilitate integration of sensors, data acquisition, and automated control.

Farm structure is another major determinant of machinery development. Korean agriculture contains a large proportion of relatively small and fragmented fields, limiting the economic and operational suitability of large specialized harvesters. Kang et al. [5] emphasized the economic role of compact, versatile, and multifunctional agricultural machinery for small-scale Korean farms. These conditions favor compact sensing modules that can be integrated into small self-propelled machines, tractor-mounted harvesters, collection carts, and contractor-operated equipment.

Available studies provide additional quantitative context for these constraints. Kang et al. [5] evaluated machinery economics for small-scale Korean agriculture and found the benefits of versatile machinery to be particularly relevant for farms below 2 ha; annual machinery-use costs were reduced by approximately 63.54% for field-preparation operations and 71.71% for crop-season operations in the evaluated scenarios. For root-crop machinery, Lee et al. [34] evaluated a Korean gathering-type potato harvester at an operating speed of approximately 0.24 m s^{-1}. Kiraga et al. [26] evaluated radish yield sensing at conveyor speeds of 0.05–0.25 m s^{-1} and simulated slopes of 3°, 6°, and 9°, while noting 15° as the maximum recommended machinery slope considered in their experimental rationale. These values represent published study conditions rather than national operating ranges and should not be generalized to all Korean farms. Moreover, the reviewed Korean root-crop yield-monitoring studies rarely report installed sensor cost, calibration labor,

maintenance cost, or payback period; economic suitability therefore remains an important evidence gap rather than an established advantage.

3.3. Crop-Specific Harvesting Mechanisms and Material-Flow Characteristics

3.3.1. Potato Harvesting

Potato harvesting typically begins with destruction or removal of above-ground vegetation, followed by soil penetration using a digging blade or share. The resulting soil–potato mixture is transferred onto a web or conveyor, where soil and smaller debris are separated while tubers continue toward the collection or discharge section. Depending on machine configuration, potatoes are deposited onto the field, collected manually, transferred into containers, or accumulated in an integrated hopper.

Conventional Korean potato harvesting has often combined mechanized digging with manual collection. Lee et al. [34] developed and evaluated a gathering-type potato harvester that integrated digging, conveying, foreign-material separation, and collection. At an operating speed of approximately 0.24 m s^{-1}, the system achieved a digging rate close to 100%, while crop damage, foreign-material mixing, and crop loss remained relatively limited. Integration of crop collection also substantially reduced labor requirements compared with conventional harvesting.

Potato harvesters provide favorable mechanical conditions for conveyor-based yield sensing because harvested tubers pass through one or more conveying and separation stages. Potential sensing locations include load-cell-supported conveyor sections, weighing idlers, impact sensors at transfer points, and machine-vision units mounted above the conveyor [35]. Positioning the sensor after major soil separation reduces the influence of soil and stones on measured crop mass, although crop losses occurring before the sensing location are not represented in the final measurement [18,36]. This distinction separates biological yield from recovered yield. Biological yield represents the total crop produced within the soil, whereas recovered yield represents the quantity successfully delivered through the harvesting system to the sensing point [16,17,37]. A yield monitor located near the discharge section therefore reflects both agronomic productivity and harvester recovery efficiency.

3.3.2. Radish Harvesting

Radish harvesting differs from potato harvesting because extraction can be achieved through gripping and pulling the foliage while loosening the surrounding soil. Kook et al. [38] evaluated the pulling performance of a self-propelled radish harvester and reported variation in physical crop characteristics and required pulling forces. The harvesting system incorporated foliage handling, gripping, conveying, and crop-transfer functions. The relatively large size of Korean radish results in discrete crop mass-flow rather than the quasi-continuous material flow characteristic of grain. Individual roots or small groups of roots can generate distinct force or mass pulses on a conveyor-based weighing section [39]. Weight-based radish monitoring therefore differs dynamically from grain mass-flow sensing and is more closely related to event-based or intermittent weighing.

Potential sensing locations include the final transfer conveyor, a weighing platform positioned before loading, and load-cell-supported collection bins. Measurement after foliage removal represents root mass more directly, whereas measurement with foliage attached represents combined above- and below-ground harvested biomass [17,26,40]. Development of multipurpose driving platforms for radish and Chinese cabbage harvesting has further expanded the range of integrated self-propelled machinery available in Korea [41]. These platforms include controlled harvesting and conveying pathways that are compatible with future integration of yield-sensing devices.

3.3.3. Sweet Potato Harvesting

Sweet potato harvesting consists of several sequential operations, including vine management, plastic mulch removal where applicable, soil loosening, tuber lifting, soil separation, and collection [42]. Kang et al. [43] developed a vine crusher for sweet potato harvesting, demonstrating the importance of preparatory crop-residue management before underground harvesting. Won et al. [44] developed a double-conveyor sweet potato harvester and evaluated its digging performance and crop-damage rate. Kim et al. [45] reported substantial reductions in labor requirements through mechanized harvesting.

Full mechanization of sweet potato harvesting remains difficult because tubers are highly variable in size, orientation, and distribution around the plant. Their relatively delicate skin and irregular geometry increase susceptibility to cutting, abrasion, bruising, and breakage [46]. Kim et al. [45] compared sweet potato production and mechanization systems in Korea and the United States and emphasized substantial differences in cultivation scale and machinery requirements.

Yield-monitor integration is strongly influenced by the level of sweet potato mechanization. In systems where machinery only loosens the soil and workers subsequently collect exposed tubers, there is no continuous machine-controlled crop stream. Instrumented collection crates, weighing carts, or load-cell-supported bins are therefore more compatible with these semi-mechanized operations [27]. In more integrated harvesting systems, conveyors and temporary hoppers provide potential locations for continuous or batch-based mass measurement. The mechanical sensitivity of sweet potatoes also differentiates their sensing requirements from those of harder crops [42]. Impact-based sensing can introduce additional crop–sensor collisions, whereas conveyor and hopper weighing can measure mass without requiring high-energy impacts. Crop quality and sensing accuracy are therefore closely linked in the design of sweet potato yield-monitoring systems.

3.3.4. Carrot Harvesting

Carrot harvesting can use digging and lifting mechanisms or pulling systems that grip the foliage and extract the root from the soil. Choi et al. [31] investigated machinery for radish and carrot harvesting and demonstrated the feasibility of integrating digging, lifting, conveying, and separation within a mechanized system. Choi et al. [47] also tested the design factors of a developed carrot harvester.

The elongated geometry of carrots creates non-uniform orientation and loading on conveyors. Foliage can remain attached during the initial stages of handling, while adhering soil can contribute substantially to measured mass under wet conditions [27,48]. Measurements obtained immediately after extraction therefore represent a mixture of crop, soil, and foliage rather than cleaned marketable carrot mass. The relatively limited Korean literature on carrot-specific yield monitoring means that most applicable sensing concepts originate from other root crops. Conveyor weighing, collection-bin weighing, and vision-assisted crop/debris discrimination are particularly relevant because these methods can be integrated with carrot crop-flow pathways without requiring extensive changes in harvesting principles.

Because modern Korean field research on carrot-specific yield monitoring remains limited relative to potatoes, this crop represents an important future application for transferring technologies such as conveyor weighing, instrumented collection bins, and vision-assisted debris correction. The harvesting mechanisms and crop-flow characteristics of major root and tuber vegetables differ substantially, resulting in crop-specific requirements for sensor placement and yield measurement. Table 1 summarizes the principal harvesting characteristics, major measurement challenges, suitable sensing locations, and potential yield-monitoring approaches for potatoes, radishes, sweet potatoes, and carrots.

Table 1. Crop-specific harvesting characteristics and potential implications for yield-sensor placement in major Korean root and tuber crops.

Crop	Typical Harvesting Principle	Crop-Flow Characteristic	Major Measurement Issue	Suitable Sensing Location	Potential Sensing Approach	Reference
Potato	Digging + soil separation + conveying	Discrete tubers, relatively continuous flow at high throughput	Soil/clods, vibration, tuber loss	After soil separation or discharge conveyor	Conveyor load cell, impact sensor, vision	[2,6,21,34]
Radish	Foliage gripping/pulling + conveying	Large discrete roots	Tops, variable orientation, intermittent loading	After top removal or final conveyor	Load cell, event-based weighing, bin weighing	[31,38,41]
Sweet potato	Digging/loosening + collection	Irregular clustered tubers	High damage sensitivity, manual collection	Collection conveyor, crate, or hopper	Hopper/bin weighing, cart weighing	[30,43,45]
Carrot	Pulling or digging/lifting (harvesting machinery)	Elongated discrete roots	Soil adhesion, foliage, orientation	After cleaning/top removal	Conveyor weighing, bin weighing, vision-assisted system	[31]

References in this table support the harvesting architecture, crop-flow characteristics, and/or sensing concept. They do not necessarily represent crop-specific field validation of a yield-monitoring system.

3.4. Harvesting Process as the Basis for Yield Sensor Placement

The harvesting processes of potatoes, radishes, sweet potatoes, and carrots differ in their detailed mechanisms but can generally be represented by the sequence as shown in Figure 2.

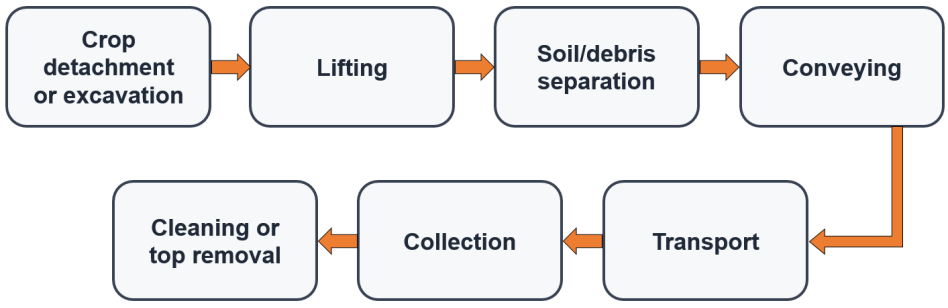


Figure 2. Generalized harvesting sequence and potential yield-sensing locations for the major root and tuber crops considered in this review.

This sequence provides a useful engineering framework for understanding yield-sensor placement. Measurement immediately after excavation captures a relatively complete material stream but includes substantial quantities of soil, stones, residues, and dynamic loads generated by the digging system [17,27]. Measurement after soil separation produces a cleaner crop signal but excludes material lost during earlier separation. Measurement near the final discharge section provides a closer representation of recovered crop mass but increases the transport delay between the crop's original field position and the sensing location [35]. Hopper or bin measurement provides relatively stable cumulative mass but integrates crop from larger field areas and therefore reduces spatial resolution.

The sensing position also determines the meaning of the resulting yield value. Depending on the measurement point and degree of crop cleaning, sensor output can represent

gross harvested mass, recovered yield, cleaned yield, or marketable yield [16]. These quantities are not interchangeable, particularly for root crops harvested with substantial quantities of adhering soil and plant material. Harvester crop-flow architecture therefore forms an integral part of yield-monitor interpretation. The crop entry point, transfer mechanisms, soil- and residue-separation stages, crop-loss locations, sensing position, and final collection point collectively determine which component of production is quantified by the sensor.

3.5. Yield Measurement Practices and Limitations

Yield determination in Korean crop production continues to rely substantially on manual sampling, direct weighing of harvested produce, farmer records, collection-center information, and statistical surveys. In research experiments, representative plots or row sections are commonly harvested and weighed, after which yield per unit area is calculated and extrapolated to the field or treatment level. At the commercial scale, harvested crops are generally quantified through bags, boxes, bins, pallets, storage records, or transport-vehicle weights.

These methods provide direct measurements and remain important as reference techniques for sensor calibration and validation. However, they provide relatively sparse spatial information. Manual sampling and weighing require considerable labor, limiting the number of measurements that can be collected across a field. Local variation in soil depth, compaction, drainage, moisture availability, nutrient status, ridge geometry, plant population, and disease incidence can therefore remain undetected when only a small number of representative plots are sampled.

Conventional post-harvest weighing also separates yield quantity from its original time and position of harvest. Accurate total field mass may be available without information on which areas produced high or low yield. Collection-center and market records additionally represent aggregated production after cleaning, sorting, grading, storage, or crop loss, making them unsuitable for reconstructing spatial patterns of harvested production. Remote sensing, UAV imagery, and crop models provide an alternative approach to spatial yield estimation. Korean studies have demonstrated strong predictive performance using UAV and satellite data [12,13]. Nevertheless, these techniques estimate final production indirectly and remain dependent on observed yield measurements for calibration, validation, and long-term model improvement.

3.6. Harvester Integrated Yield Measurement in Korea

The transition from partial mechanization toward integrated root-crop harvesting has created increasing opportunities for harvester-mounted yield measurement in Korea. Sensor integration converts harvesting from a purely mechanical operation into a simultaneous crop-measurement process in which mass, machine operating state, time, and geographic location can be recorded throughout field operations.

Korean potato research has demonstrated the feasibility of load-cell and image-based sensing on small harvesters [21,22]. However, sensor outputs were affected by vibration and inclination, demonstrating that field performance depends on the interaction between sensing hardware and machine dynamics. Lim et al. [8] specifically examined vibration compensation for underground-crop weighing, further illustrating the importance of dynamic correction in contact-based measurement.

Korean agricultural conditions create a distinctive operating environment for yield monitors. Small and fragmented fields result in frequent starting, stopping, and turning. Ridge cultivation creates crop mass-flow concentrated along narrow harvesting paths. Sloped upland areas alter machine inclination, while compact machinery provides lim-

ited space for mechanically isolated sensors. These factors distinguish Korean root-crop monitoring from conventional combine-yield-monitor applications developed for large, relatively uniform cereal fields. Three broad technological configurations are compatible with these production systems. Conveyor-integrated weighing systems are applicable to potato and radish harvesters with controlled crop transfer. Hopper-, bin-, and cart-based weighing systems are suited to intermittent and semi-mechanized collection systems, including sweet potato and carrot operations. Hybrid monitoring systems combine direct mass measurement with belt-speed sensing, GNSS, inertial measurement, vibration sensing, and machine vision to provide contextual information for compensation, spatial mapping, and crop/non-crop discrimination.

The development of Korean root- and tuber-crop mechanization therefore provides the mechanical basis for increasingly integrated yield sensing. As harvesting systems evolve from digging-only machines toward combined digging, separation, conveying, and collection platforms, crop mass-flow becomes more controlled and measurable. This transition provides the technological foundation for direct contact- and weight-based yield monitoring examined in the following sections.

4. Overview of Real-Time Yield Measurement

4.1. Definition and Functional Concept of Real-Time Yield Monitoring

Real-time yield monitoring refers to the acquisition, processing, and recording of crop-production information during harvesting rather than determining yield solely after harvest through sampling, truck weighing, storage records, or sales information. In mechanized production, a yield monitor is generally associated with harvesting machinery and quantifies crop mass-flow or accumulated crop mass while simultaneously recording information required to relate the measurement to the harvested field area [11,49,50].

The term real-time describes measurement and processing at a temporal resolution sufficient to follow ongoing harvesting operations. It does not imply that the calculated yield corresponds instantaneously to the current GNSS position because crop material often requires several seconds to travel from the original harvesting location to the sensing location [17,18].

A complete yield-monitoring system differs from an individual yield sensor. A yield sensor detects crop-related mass, force, volume, count, or another measurable property, whereas a yield-monitoring system combines the sensor with machine-motion information, positioning, calibration, signal processing, data acquisition, and software [17]. Typical components include a crop-flow or crop-mass sensor, travel-speed measurement, information on effective harvesting width, GNSS positioning, machine-state sensing, signal-conditioning electronics, data logging, and an embedded computing platform.

This system-level distinction is especially important for root crop harvesters because sensor output is strongly influenced by machine operation. A load cell that accurately measures known static masses can produce unstable readings when exposed to digging vibration or conveyor dynamics [24]. Similarly, machine vision can provide accurate crop detection under controlled conditions but experiences reduced performance when tubers overlap, rotate, become partially covered by soil, or move under changing illumination [39]. Real-time yield monitoring is therefore a combined sensor–machine–data integration problem rather than an isolated sensing task [16,17].

For consistency, yield refers to harvested crop mass per unit area unless otherwise stated; mass flow refers to crop mass passing a sensing location per unit time; yield monitoring refers to acquisition of yield-related measurements during harvesting; and yield mapping refers to the spatial assignment of these measurements to georeferenced field locations. Gross harvested mass includes all material passing the sensing point,

including crop and foreign material; recovered yield refers to crop successfully delivered to the sensing point after upstream harvesting losses; cleaned yield refers to crop mass after removal of soil, stones, foliage, and other foreign material; and marketable yield refers to the portion of cleaned crop meeting specified quality or grading criteria. In this review, "contact- and weight-based" is used as an umbrella term for harvest-time systems involving physical crop–sensor interaction, while direct gravimetric weighing and contact dynamic/impact-based mass estimation are distinguished according to their measurement principles in Section 4.3. Machine vision and remote sensing are treated as complementary indirect approaches rather than direct mass-measurement technologies.

4.2. Conversion of Sensor Measurements into Spatial Yield

In contact- and weight-based yield monitoring, conversion of a raw sensor response into spatially referenced yield requires more than a direct relationship between measured mass and harvested area. During field operation, the primary load or force signal can be affected by tare variation, machine vibration, inclination, conveyor dynamics, crop impact, and other transient disturbances. In addition, harvested material requires a finite transport time to move from the digging or extraction point to the sensing location. A practical formulation should therefore account for signal correction, sensor calibration, machine dynamics, and spatial lag. For a dynamic contact-based yield-monitoring system, the corrected crop mass-flow rate can be represented generically as Equation (1).

$$q_m(t) = G(F[S_{raw}(t) - S_{tare}(t)], v_b(t), \theta(t), a(t)) \quad (1)$$

where $q_m(t)$ is the corrected mass-flow rate, $S_{raw}(t)$ is the raw sensor signal, $S_{tare}(t)$ is the tare/baseline signal, F represents filtering, $v_b(t)$ is belt speed, $\theta(t)$ is inclination, $a(t)$ is dynamic acceleration/vibration, and G is the calibration/correction function that converts the compensated sensor response into crop mass-flow.

Equation (1) emphasizes that the relationship between sensor output and crop mass is condition-dependent. For load-cell-supported conveyors, the calibration function can incorporate belt speed, weighing-section geometry, and inclination correction, whereas impact-based systems additionally depend on crop velocity, impact angle, and collision characteristics. The appropriate form of G therefore differs among conveyor, hopper, bin, and impact-based systems and should be established under representative dynamic operating conditions rather than from static calibration alone.

Spatial yield assignment requires an additional correction because the crop measured at time t generally entered the harvester at an earlier time. The corresponding harvest-origin position can be expressed using Equation (2).

$$x_h(t) = x_{GNSS}[t - \tau(t)] \quad (2)$$

where $x_h(t)$ is the estimated original harvest position, x_{GNSS} is the GNSS-recorded position, and $\tau(t)$ is the deterministic crop-transport component and, where applicable, the known filter delay; crop mixing and dispersion represent additional spatial averaging that cannot generally be removed by a simple temporal shift.

Crop transport should not be interpreted solely as a fixed temporal shift. Three effects contribute to spatial misregistration. First, a deterministic transport delay arises from the travel distance between crop entry and the sensing point and varies with conveyor speed. Second, crop accumulation, transfer between conveyors, rolling, slippage, and mixing create a distribution of residence times, causing spatial dispersion that cannot be completely corrected using a single delay value. Third, causal low-pass filters and moving-average windows used to suppress vibration introduce additional signal delay

and temporal averaging. Accordingly, the effective synchronization procedure should distinguish physical transport delay from crop-flow dispersion and filter-induced delay. Where real-time causal filtering is used, its group delay should be included in spatial correction; where post-processing permits zero-phase filtering, phase delay can be avoided, although smoothing still reduces effective spatial resolution. The delay may be approximately constant in a mechanically stable system, but it can vary with conveyor speed, crop-flow rate, accumulation, or machine operating state. This correction is particularly important during row entry, row exit, stopping, and headland turning, where assigning sensor measurements to the instantaneous GNSS position can generate artificial spatial yield patterns.

After dynamic correction and spatial synchronization, the area-based yield can be calculated using Equation (3).

$$Y[x_h(t)] = \frac{10^4 q_m(t)}{v_g[t - \tau(t)]W_h} \quad (3)$$

where $Y[x_h(t)]$ is yield in kg ha^{-1}, v_g is harvester ground speed in m s^{-1}, and W_h is effective harvesting width in m represented by the harvested row.

These relationships demonstrate that spatial yield is not determined by crop mass measurement alone. Accurate mapping requires synchronization of the primary mass or force sensor with tare correction, filtering, conveyor or crop-flow information, machine inclination and vibration, ground speed, GNSS position, and crop-transport delay. The relative importance of these corrections depends on the sensor architecture. Conveyor systems are particularly sensitive to belt speed, tare drift, vibration, and inclination, whereas impact sensors additionally depend on crop trajectory and impact conditions.

For hopper-, bin-, cart-, or batch-based systems, the same principles apply to the accumulated crop mass. The corrected mass of each batch is related to the georeferenced field area represented by that batch rather than to an instantaneous mass-flow signal. Such systems generally reduce sensitivity to short-duration crop-flow fluctuations but provide lower spatial resolution because harvested material from a larger field segment is combined before the final mass is recorded.

For root and tuber crops, interpretation of the resulting yield also depends on the physical location of the sensor within the harvesting pathway. Soil, stones, foliage, vines, clods, and damaged produce may contribute to the measured load before adequate separation or cleaning. Consequently, the calculated value may represent gross transported mass, recovered crop yield, cleaned yield, or marketable yield. Sensor location and the degree of upstream crop cleaning should therefore be reported together with the yield value so that measurements obtained from different harvesting systems can be interpreted consistently.

4.3. Classification of Yield Measurement Approaches

Yield-measurement technologies can be classified according to both the physical quantity being measured and the degree to which harvested mass is obtained directly. For root and tuber crops, an important distinction is required between direct gravimetric weighing, in which crop mass is determined from gravitational loading of a calibrated weighing structure, and contact dynamic or impact-based mass estimation, in which mass is inferred from a force–time response generated during crop impact. Indirect proximal methods estimate mass from crop geometry or other measurable characteristics, whereas remote and pre-harvest methods predict yield from crop or environmental information without measuring the harvested material directly. This classification provides a more physically consistent basis for comparing load-cell weighing, impact sensing, machine vision, and remote sensing [16,17].

4.3.1. Direct Gravimetric Weighing

Direct gravimetric systems determine harvested crop mass from the gravitational force acting on a calibrated weighing structure. Representative configurations include load-cell-supported conveyor sections, instrumented idlers, weighbridges, hopper and bin weighing frames, weighing carts, collection platforms, and instrumented crates. Under known gravitational, geometric, and operating conditions, the measured load can be converted directly to crop mass.

The principal advantage of gravimetric weighing is its physical interpretability. A calibrated load cell converts mechanical loading into an electrical signal, and crop mass can be determined after accounting for tare, sensor orientation, and system calibration. Unlike methods based on crop geometry or image-derived volume, gravimetric weighing does not require an empirical relationship between crop dimensions and individual crop mass. It therefore provides an important reference measurement for calibration and validation of other yield-estimation methods [16,17,51].

Direct gravimetric weighing can be implemented in both continuous and cumulative configurations. Conveyor-based systems measure the load carried over a defined weighing section and combine this information with conveyor speed to estimate mass flow. Hopper-, bin-, cart-, and crate-based systems measure accumulated crop mass over a defined period or field area. These cumulative approaches are particularly relevant to partially mechanized harvesting systems where harvested material does not pass continuously through a single conveyor-based sensing point. Georeferenced weighing systems have also been applied to manually harvested crops, demonstrating that direct mass measurement can be combined with positioning even where crop collection remains partly manual [52].

Although gravimetric measurement provides the most direct relationship with crop mass, field accuracy remains affected by vibration, inclination, belt tension, tare drift, structural deformation, soil and residue accumulation, and dynamic acceleration. Consequently, direct gravimetric measurement should not be interpreted as automatically providing accurate field yield without appropriate dynamic calibration and compensation.

4.3.2. Contact Dynamic/Impact-Based Mass Estimation

Impact sensing is a direct contact-based measurement approach but differs fundamentally from gravimetric weighing. An impact sensor records the dynamic force–time response produced when harvested crop material strikes an instrumented plate or other sensing surface. The resulting signal reflects momentum transfer rather than gravitational loading alone. Crop mass is therefore estimated through calibration of the impact response rather than obtained directly from quasi-static weight.

For a moving crop object, the measured response depends not only on mass but also on impact velocity, trajectory, angle of incidence, restitution, contact duration, crop stiffness, orientation, rebound behavior, and the dynamic characteristics of the plate and supporting structure. Consequently, identical crop masses can produce different force profiles when impact conditions vary. This effect is particularly important for root and tuber crops because potatoes, radishes, carrots, and sweet potatoes vary substantially in geometry and orientation during handling.

Impact-based systems nevertheless offer several practical advantages. They can be compact, can be installed at existing transfer or discharge points, and do not necessarily require the conveyor itself to be supported by a weighing frame. Impact-type systems have been evaluated for horticultural crops and Korean radish monitoring [26]. However, calibration must represent the actual crop trajectory, conveyor speed, drop height, plate geometry, machine vibration, and slope conditions. At high throughput, simultaneous

impacts may also overlap, reducing the ability to relate individual force events to individual crop masses.

Impact sensing should therefore be interpreted as contact dynamic mass estimation rather than direct gravimetric mass measurement. This distinction is important when comparing reported performance because a strong calibration relationship between impact response and reference mass does not imply that the sensor is measuring mass independently of crop motion and collision mechanics.

4.3.3. Indirect Proximal Measurement

Indirect proximal methods estimate yield from measurable crop characteristics that are correlated with harvested mass. Common examples include machine vision, object counting, two- and three-dimensional image analysis, LiDAR, ultrasonic sensing, mechanical-volume measurement, and other crop-layer or volume-based approaches. Machine vision is particularly useful because it can simultaneously provide crop count, size, shape, surface condition, and crop/non-crop classification [16,18,27]. Jang et al. [23] demonstrated high potato-detection performance using deep-learning-based machine vision. However, accurate crop detection or counting does not directly correspond to accurate mass yield because individual roots and tubers can vary substantially in size and weight.

Volume-to-mass conversion requires the density definition to correspond to the type of volume being measured. For an individually reconstructed root or tuber, the relevant quantity is the individual-object density, defined from the object mass and reconstructed object volume; inter-object void space is not part of this volume. By contrast, when a camera, depth sensor, or other device estimates the volume of a bulk crop layer or accumulated pile, the appropriate quantity is bulk density, which includes interparticle voids and therefore varies with crop size distribution, orientation, packing, and compaction. Consequently, individual-object mass estimation may be affected by crop-specific density variation and geometric reconstruction error, whereas bulk-flow mass estimation is additionally affected by packing fraction and interparticle void space. These two volume–density relationships should not be treated interchangeably [27,53].

Indirect proximal sensing can nevertheless complement gravimetric and impact-based systems. Machine vision can identify crop and non-crop objects, characterize size distributions, and detect potentially damaged produce. However, classification alone does not determine the mass contribution of each material class. Quantitative partitioning of measured gross mass requires an additional validated relationship, such as individual-object mass estimation, volume–density conversion, class-specific calibration, or independent reference measurement. Accordingly, indirect sensing is particularly valuable as a complementary source of crop identity and quality information within hybrid yield-monitoring systems.

4.3.4. Remote and Pre-Harvest Yield Estimation

Remote sensing estimates crop yield without directly measuring harvested material. Satellite imagery, UAV imagery, multispectral and hyperspectral sensing, thermal imaging, crop models, and machine-learning methods have been widely used for yield prediction. Korean studies have applied UAV and satellite information to crop-yield estimation with high predictive performance [12–14]. UAV-based RGB imagery has also been investigated for growth-status assessment of Korean radishes [41,54], illustrating the complementary role of non-contact crop monitoring relative to harvest-time direct yield measurement.

The major advantages of remote approaches are their ability to provide early-season estimates, large-area crop assessment, spatial crop-condition information, and regional production forecasts. However, the resulting yield represents an estimate derived from crop

or environmental characteristics rather than a direct measurement of the material physically recovered during harvesting. Remote methods therefore remain dependent on reliable ground-reference yield measurements for model calibration and validation [12–14,37,54].

Harvest-time and pre-harvest approaches should consequently be regarded as complementary rather than interchangeable. Remote sensing can indicate expected spatial production before harvest, whereas contact-based yield monitoring records the crop actually passing through or being collected by the harvesting system. Direct gravimetric measurements can therefore provide valuable reference data for validating remote and indirect yield-estimation models. Table 2 summarizes the principal distinctions among direct gravimetric weighing, contact dynamic/impact-based mass estimation, indirect proximal measurement, and remote or pre-harvest yield estimation.

Table 2. Classification and characteristics of agricultural yield-measurement approaches relevant to root and tuber crops.

Category	Measurement Principle	Typical Sensors	Primary Output	Main Strength	Main Limitation	Reference
Direct gravimetric weighing	Physical mass or force measurement	Load cells, conveyor scales, hopper scales	Mass or mass flow	Direct and interpretable	Vibration, tare, soil contamination	[16–20]
Contact dynamic/impact-based mass estimation	Dynamic force or impulse generated by momentum transfer during crop impact	Impact plate, load-cell-supported impact surface, force sensor	Estimated crop mass or mass flow	Compact installation at crop-transfer points	Sensitive to velocity, trajectory, impact angle, crop orientation, vibration, and structural dynamics	[24,55]
Indirect proximal measurement	Crop characteristics related to mass	RGB/depth cameras, LiDAR, ultrasonic sensors	Count, area, volume	Can provide size and quality information	Requires calibration to mass	[16,18,23]
Remote/pre-harvest estimation	Crop/environment characteristics related to future yield	UAV, satellite, multispectral/hyperspectral sensors	Predicted yield	Large-area and early estimation	Does not directly measure harvested mass	[12–14]

4.4. Applications of Yield Information

Yield monitoring converts total crop production from a single field-average value into spatially and temporally resolved information. Georeferenced yield data can reveal high- and low-yielding zones and can be compared with soil properties, topography, irrigation, nutrient management, crop establishment, disease occurrence, and other field variables. Yield maps consequently provide an important feedback layer for site-specific management and evaluation of previous production practices [11].

Yield monitoring also has direct operational applications during harvesting. Cumulative crop mass can be used to estimate container fill level, coordinate transport vehicles, plan storage and grading operations, and document production by field, row, farmer, or harvesting lot. Changes in crop-flow measurements can additionally indicate irregular feeding, temporary blockage, or other abnormal machine operating conditions [15,22].

Direct harvest measurements are also important for calibrating and validating indirect yield-estimation methods. Remote sensing, machine vision, crop models, and machine-learning approaches depend on reliable ground-reference yield data. Contact- and weight-based measurement therefore has an important role not only as a standalone monitoring approach but also as a reference source within broader precision-agriculture systems. The quality of spatial yield information depends on both mass-measurement accuracy and correct assignment of measurements to field position. Errors associated with GNSS positioning, crop transport delay, headland turns, machine stopping, conveyor residual crop,

vibration, and changes in tare can create artificial spatial patterns even when cumulative crop mass is measured accurately [15].

4.5. Calibration, Validation, and Measurement Quality

Calibration is a fundamental component of contact- and weight-based yield monitoring. Static calibration uses known masses to characterize sensor zero offset, sensitivity, linearity, hysteresis, and repeatability. Although this establishes the basic response of a load cell or weighing system, static testing does not reproduce the dynamic operating environment of a harvester.

Dynamic calibration evaluates the installed system under representative crop-flow and machine conditions. Conveyor speed, crop-flow rate, vibration, inclination, crop size, and crop-impact behavior can all influence the relationship between sensor output and actual mass. Dynamic calibration therefore provides a more realistic assessment of sensor response during harvesting. Field validation compares yield-monitor measurements with independently measured crop mass obtained using calibrated reference scales. Field validation is particularly important because sensor response can differ substantially between controlled testing and commercial harvesting conditions.

Performance is commonly reported using the coefficient of determination (R^2), RMSE, MAE, bias, relative error, and percentage error. The (R^2) value describes the relationship between measured and reference values but does not independently characterize measurement error. Error-based indices provide complementary information on the magnitude and direction of deviations from reference measurements.

For spatial yield monitoring, cumulative mass accuracy represents only one component of system performance. Spatial lag, positioning error, crop mixing during conveying, and machine-state transitions also affect the accuracy of yield maps. Root-crop systems are additionally affected by variability in crop size, adhering soil, field moisture, harvester vibration, and slope, resulting in a need to evaluate sensor performance under representative operating conditions.

4.6. Relevance of Contact and Weight-Based Monitoring to Korean Root and Tuber Crops

Contact and weight-based yield measurement is particularly relevant to Korean root- and tuber-crop harvesting because crop production is commonly quantified commercially by mass and because many harvesting systems already contain suitable mechanical crop-transfer structures. Conveyors, elevators, discharge points, hoppers, bins, and collection carts provide potential locations for integrating direct weighing devices. Conveyor weighing is well suited to mechanized potato and radish harvesting systems in which harvested crops pass through a defined conveyor section. Hopper- and bin-based weighing can be applied to intermittent or batch collection, including partially mechanized sweet potato and carrot harvesting. Instrumented carts provide a related approach when manual collection remains part of the harvesting process. Impact-force sensors can provide rapid crop-flow measurements at transfer points but are more dependent on crop-handling characteristics and impact conditions.

Korean operating conditions amplify these measurement challenges because compact machinery, sloping upland fields, soil contamination, and frequent machine-state transitions affect both dynamic weighing and spatial assignment. These effects are examined in detail in Sections 5 and 7. Digging and soil-separation mechanisms also produce substantial machine vibration that can interfere with dynamic weighing. Previous international and Korean studies have demonstrated the feasibility of direct mass-based yield monitoring for potatoes and other horticultural crops [19,21,22]. Current technological development therefore extends beyond basic sensing feasibility toward improved field robustness, dynamic

compensation, crop-specific calibration, spatial accuracy, and integration with compact harvesting machinery. These developments provide the basis for the load-cell, conveyor, hopper, impact, and hybrid sensing technologies discussed in the subsequent sections.

5. Contact- and Weight-Based Yield Measurement Technologies

Contact- and weight-based yield-monitoring technologies quantify harvested material through direct measurement of mass, gravitational load, dynamic force, or mechanically related crop-flow responses. Compared with indirect approaches based on crop count, projected area, or volume, direct weighing provides a physically interpretable relationship between sensor response and harvested mass. This characteristic has made weighing-based systems an important reference technology for non-grain and horticultural yield monitoring [16–18,51].

The literature, however, shows that the performance of these systems is determined by considerably more than the nominal accuracy of the weighing sensor. Crop-flow characteristics, sensing location, harvester vibration, conveyor dynamics, inclination, foreign-material content, crop impact behavior, calibration procedure, and spatial synchronization all influence the final yield estimate. These effects are especially important for underground crops because roots and tubers enter the harvester together with soil, stones, clods, foliage, and other residues. Crop mass-flow is also highly discrete: individual potatoes, radishes, sweet potatoes, and carrots can roll, bounce, cluster, or change orientation during conveying. Consequently, contact-based yield monitoring is most appropriately interpreted as an integrated crop-flow–mechanical sensing–signal processing system rather than as an isolated sensor application.

Research has generally converged on four principal contact- and weight-based measurement architectures: continuous conveyor weighing, cumulative or batch weighing, impact-force measurement, and load-cell-supported collection systems. Several additional mechanical proxies, such as hydraulic pressure, paddle displacement, torque, and pressure distribution, have also been investigated. Their applicability differs according to whether the crop is continuously conveyed, intermittently collected, or manually transferred. This distinction is particularly relevant to Korean root-crop agriculture, where the degree of harvesting mechanization varies considerably among potato, radish, sweet potato, and carrot systems.

5.1. Load Cell-Based Method

Load cells form the sensing foundation of most direct mass-based agricultural yield monitors. Strain-gauge load cells are particularly common because mechanical deformation of the elastic sensing element produces a proportional change in electrical resistance that can be measured through a Wheatstone bridge. Following amplification, analog-to-digital conversion, and calibration, the electrical response is converted to force or mass. In agricultural yield monitoring, load cells have been incorporated beneath conveyor idlers, weighbridges, hoppers, collection baskets, trailers, and impact plates [16,51].

The literature indicates that sensor configuration is as important as sensor type. Durrence et al. [56] evaluated a load-cell-based peanut yield monitor and showed that machine vibration and crop mixing influenced the quality of instantaneous yield measurements. The later peanut yield monitoring system described by Vellidis et al. [57] demonstrated substantially better accuracy when crop mass was integrated over larger spatial or temporal intervals, with errors of approximately 2–3% at trailer-load scale and about 1% at field scale. These findings illustrate a recurring trade-off in dynamic weighing: averaging improves mass accuracy but decreases sensitivity to short-distance yield variation.

Root-crop studies demonstrate the same behavior. Kim et al. [21] reported a strong calibration relationship for a load cell-based potato mass sensor, but sensor performance changed with vibration, slope, and load cell configuration. Kiraga et al. [26] quantified these effects for radish mass measurement using load-cell-supported impact plates. Under controlled conditions without slope or vibration, standard errors were below 4 g; however, vibration and slope markedly increased measurement errors, while signal filtering reduced the combined-condition relative error from 9.13% to 5.42%. Thus, strong static or laboratory calibration does not necessarily imply equivalent dynamic field accuracy. Figure 3 illustrates the fundamental measurement chain of a load-cell system, from mechanical crop loading through strain conversion, signal conditioning, calibration, and digital mass estimation.

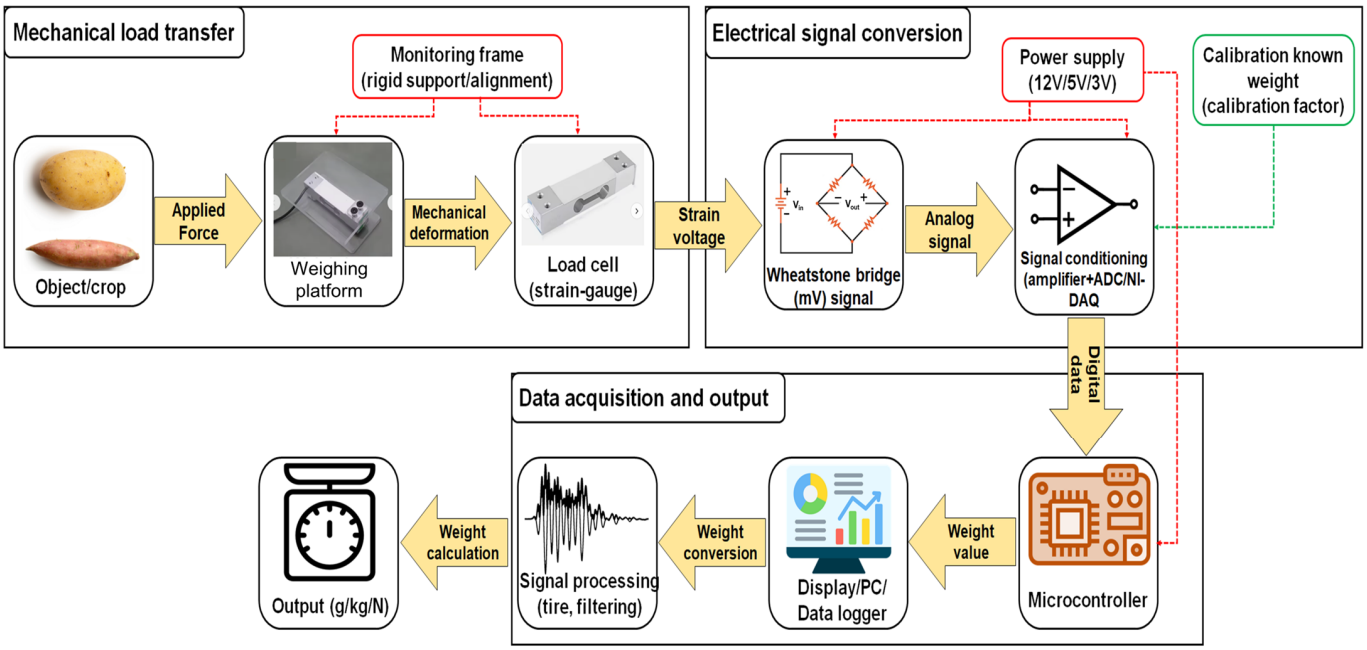


Figure 3. Load-cell-based measurement chain for contact- and weight-based crop yield sensing, showing mechanical load transfer, strain conversion, signal conditioning, calibration, data acquisition, and mass output. Conceptual illustration developed by the authors based on the literature synthesized in this review; not reproduced from a single cited study.

The load-transfer path represented in Figure 3 is central to measurement performance. A crop-induced force may be accompanied by belt tension, frame bending, side loading, machine acceleration, and impact forces. Consequently, the measured signal represents the resultant mechanical loading of the sensing structure rather than crop mass alone. This explains why mounting arrangement, structural stiffness, alignment, and mechanical isolation repeatedly emerge as critical variables in dynamic agricultural weighing studies.

Load-cell rated capacity should be distinguished from rated electrical output, measurement resolution, and overload tolerance. Strain-gauge load cells with different nominal capacities can have similar rated outputs, commonly expressed in mV/V; therefore, selecting a higher-capacity load cell does not necessarily reduce its rated electrical sensitivity. However, for a given signal-conditioning circuit and ADC range, a small crop load occupies a smaller fraction of full-scale output when an unnecessarily large capacity is selected. This can reduce resolution in mass units and lower the signal-to-noise ratio of the useful crop signal. Conversely, selecting a capacity too close to the nominal crop load increases the risk of overload from crop clumps, stones, shocks, and transient dynamic forces. Sensor selection should therefore consider rated capacity, rated output, ADC resolution, expected useful-load range, signal-to-noise ratio, and mechanical overload protection together.

Calibration approaches reported in the literature generally progress from static to dynamic testing. Static calibration establishes load-cell sensitivity, zero offset, linearity, and repeatability [26]. Dynamic calibration incorporates crop movement, machine vibration, impact, conveyor speed, and changes in loading rate. Field validation subsequently compares cumulative sensor output with independently measured harvested mass. Dynamic studies of potato harvesting by Mostofi and Minaei [58] demonstrated that the number and arrangement of instrumented conveyor idlers influenced weighing performance, emphasizing the interaction between transducer design and the crop-feed mechanism.

Signal processing represents the other major component of load-cell monitoring. Dynamic weighing studies commonly employ low-pass filtering, moving averages, or more advanced filtering to suppress vibration. However, vibration frequencies can overlap with crop-flow frequencies, and excessive filtering can attenuate genuine short-duration yield changes. Long et al. [59] obtained errors below 1% during static bale weighing but considerably larger errors during on-the-move weighing, demonstrating the importance of machine dynamics in load-cell applications. Taken together, previous studies indicate that load cells are technically mature sensing elements, but field performance depends principally on how the crop load is mechanically presented to the sensor. For root and tuber crops, their strongest role is therefore in systems where crop mass-flow is constrained through a defined weighing structure rather than applied directly to the general harvester frame.

Dynamic measurement performance also depends on the frequency response of the complete sensor–structure–electronics chain. Sampling frequency must be sufficiently high to resolve the useful crop-load or impact signal and should be selected with consideration of structural vibration frequencies and impact-event duration. Insufficient sampling can attenuate short impact events or produce aliasing, while structural resonance can amplify machine vibration even when the load cell itself has adequate bandwidth. The analog front end should therefore include appropriate anti-alias filtering, and ADC resolution should be sufficient to resolve the expected crop-load variation within the selected load-cell range. Filter cut-off frequency should be chosen from measured signal spectra where possible, rather than selected solely to maximize smoothness, because excessive attenuation can remove true crop-flow variation and reduce spatial resolution. These requirements are particularly important for impact plates, for which event duration and peak-force representation are strongly sampling dependent. Table 3 summarizes the principal engineering factors affecting load cell yield measurement.

Table 3. Design considerations for load cell yield measurement in root and tuber crop harvesters.

Design Issue	Recommended Practice	Reason for Recommendation
Capacity, resolution, and overload	Select rated capacity from maximum static and dynamic load; verify rated output, ADC usable range, mass resolution, and signal-to-noise ratio; include mechanical overload stop	Avoids overload while maintaining sufficient resolution for the expected crop-load range
Mounting stiffness	Use a rigid load path and isolate the weighing section from frame stress	Reduces parasitic forces and improves repeatability

Table 3. *Cont.*

Design Issue	Recommended Practice	Reason for Recommendation
Environmental protection	Use sealed sensors, waterproof connectors and protected cable routing	Root vegetable harvesting exposes sensors to mud, water, dust and plant residues
Calibration	Combine static weights, dynamic crop-flow calibration and field-scale validation	Static calibration alone may not represent belt motion and vibration
Signal processing	Measure vibration frequency; apply low-pass, moving average or model-based filtering	Improves signal-to-noise ratio while maintaining spatial resolution
User operation	Provide simple zeroing, calibration prompts and diagnostic warnings	Improves farmer acceptance and reduces false confidence in bad data
Sampling and ADC	Select sampling frequency from crop-signal/impact bandwidth; use adequate ADC resolution and anti-alias filtering	Prevents aliasing and loss of short-duration load events
Structural dynamics	Characterize natural frequencies and vibration spectrum of the installed weighing structure	Avoids resonance and helps select mechanically and digitally appropriate filtering

5.2. Belt-Conveyor Weight Measurement Methods

Among direct weighing approaches, belt-conveyor measurement has received the greatest attention for potatoes and other conveyor-harvested root crops. The concept is mechanically compatible with existing harvesters because crops already pass through conveying and soil-separation sections. A section of the conveyor, one or more idler rollers, or a dedicated weighbridge is supported by load cells; crop loading is then combined with conveyor velocity to derive mass flow.

Early potato yield-monitoring studies established the feasibility of this principle. Campbell et al. [60] and Rawlins et al. [19] developed systems in which a potato harvester conveyor section was supported on load-cell-equipped idlers and crop mass was combined with conveyor speed and GPS information. Rawlins et al. [19] reported yield measurement errors within approximately 5% for experimental and commercial harvesters. Subsequent work by Demmel et al. [61] evaluated a commercially available conveyor weighing system on a one-row bunker-hopper potato harvester and obtained a standard deviation of relative errors of approximately 4.1%. Panneton and St-Laurent [62] similarly investigated the performance of yield monitors specifically for root crops. Collectively, these studies established conveyor weighing as one of the earliest practical approaches to spatial yield measurement for potatoes.

Later studies shifted the focus from feasibility toward robustness. Mostofi and Minaei [58] compared cantilever-transducer and load-cell-support arrangements on experimental and commercial potato-harvesting systems and demonstrated that measurement performance depended on the effective weighing length and the number of instrumented idlers. This result is important because a belt scale does not simply measure the total crop throughput; it measures the crop mass occupying a particular belt segment at a particular time. The geometry of that segment therefore affects both signal magnitude and temporal response. Figure 4 illustrates the main elements of a conveyor-based weight measurement system.

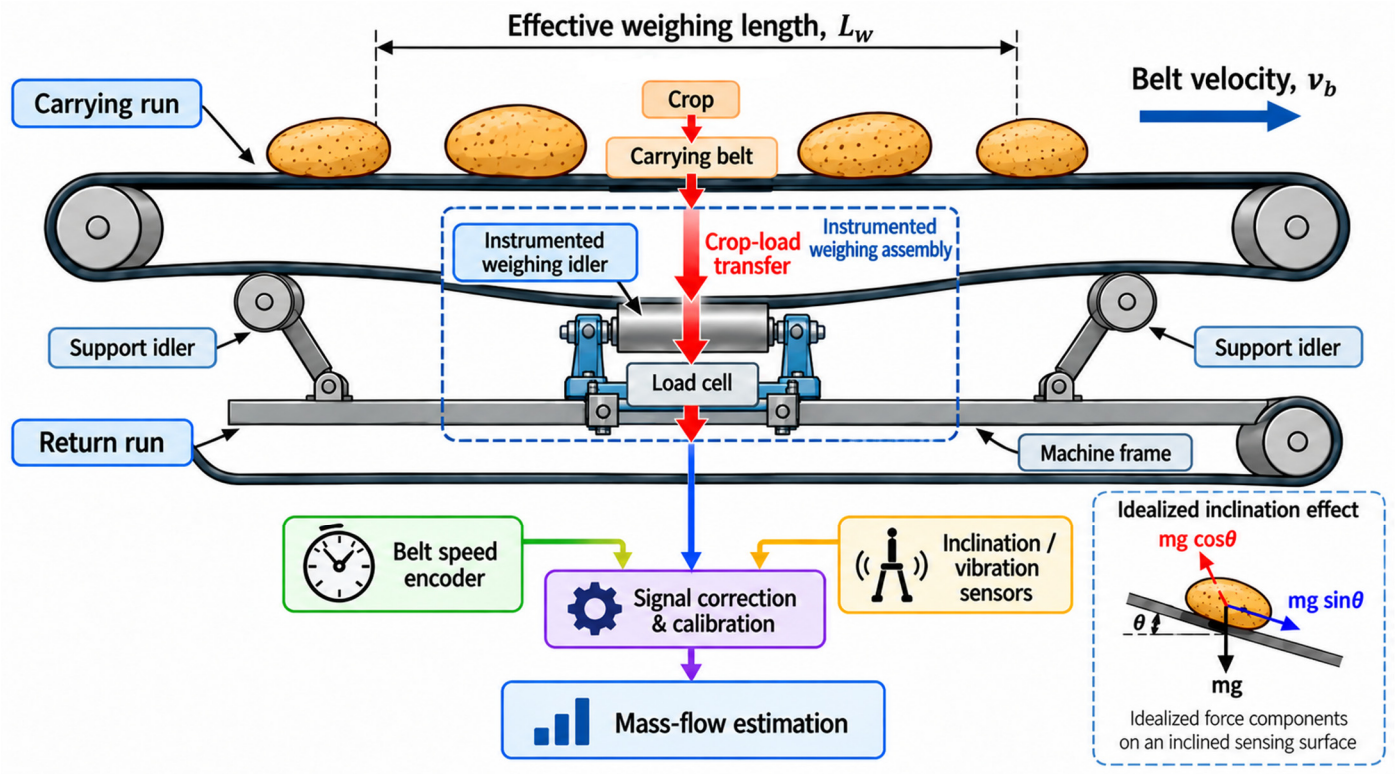


Figure 4. Conceptual conveyor-belt weighing arrangement showing the crop-carrying run, support idlers, instrumented weighing idler, load-cell support, return run, belt velocity, and effective weighing length. Conceptual illustration developed by the authors based on the literature synthesized in this review; not reproduced from a single cited study.

In Figure 4, the instrumented weighing idler supports the crop-carrying run of the conveyor rather than the return run. Crop load acting over the effective weighing length is transferred through the carrying belt and weighing idler to the load cell and subsequently to the fixed machine structure. The return run is mechanically separated from the weighing element to avoid ambiguity in the load-transfer path. As shown in Figure 4, the load cell is only one component of the measurement system. Belt speed is required because a given instantaneous load can correspond to different mass flow rates depending on conveyor velocity. Changes in hydraulic flow, engine loading, operator settings, or belt slip can therefore alter yield estimates if a nominal conveyor speed is assumed rather than measured. Inclination is another recurrent source of error. The force acting normal to a weighing section changes as conveyor or machine angle changes. This effect has particular relevance to highland and sloping fields. Korean potato sensor experiments identified slope as a significant source of measurement variability [21], while the radish impact study of Kiraga et al. [26] found that slope produced substantial errors in load-cell-derived mass measurements.

Inclination compensation should not be interpreted as a universal cosine correction. A simple F = mgcos θ relationship applies only to an idealized load acting along a known sensor axis. In an installed conveyor weighing system, pitch and roll can also modify belt tension, frame deformation, load sharing among multiple load cells, side loading, crop distribution, and dynamic acceleration. IMU-based compensation must therefore be derived for the specific weighing geometry and validated experimentally over representative pitch and roll conditions rather than applied as a generic angular correction.

Commercial potato monitoring has also highlighted an equally important issue: the weighing system measures everything transported over the sensing section. Davenport et al. [63] reported that potato yield monitors could overestimate actual tuber yield and

attributed part of the discrepancy to rocks, adhering soil, calibration differences, and machine-to-machine variation. Their three-year commercial-field study further showed that usable yield maps often required post-processing even after pre-harvest calibration. This issue is particularly important for root crops because soil contamination is spatially variable. Wet portions of a field may produce more adhering soil than dry portions, potentially creating apparent high-yield zones unrelated to biological productivity. Whelan and Mulcahy [64] similarly demonstrated the practical use of on-harvester potato yield monitoring within site-specific crop-management studies, while broader horticultural reviews have identified soil and foreign material as major limitations of conveyor weighing in root crops.

Crop-flow dynamics also influence spatial resolution. A longer weighing section contains more crop and averages the signal over a longer interval, reducing sensitivity to individual impacts and vibration. A shorter section responds more rapidly but produces a noisier signal, particularly for large discrete crops. This difference is important when transferring potato-oriented designs to Korean radish harvesters, where individual roots may produce distinct load pulses [26,27]. Spatial assignment requires additional consideration because the crop measured at the weighing section was excavated at an earlier position. Conveyor transport therefore introduces a time lag between crop acquisition and sensing. Errors become particularly visible during row entry, row exit, stops, and headland turns. Davenport et al. [63] observed anomalously high values near field boundaries associated with crop remaining in the harvesting system during transitions, demonstrating that mass accuracy alone is insufficient for reliable mapping.

The effective spatial resolution of a conveyor-based yield monitor is determined by more than GNSS accuracy or transport-delay correction. A useful first-order representation of the effective spatial averaging length is represented by Equation (4).

$$\Delta x_{eff} \approx v_g \left(\frac{L_w}{v_b} + T_a + T_f + T_m \right) \quad (4)$$

where Δx_{eff} is the approximate effective spatial averaging length (m), v_g is harvester ground speed m s^{-1}, L_w is the effective weighing-section length (m), v_b is conveyor speed m s^{-1}, T_a is the acquisition or integration interval (s), T_f is the effective temporal contribution of the filtering window (s), and T_m represents crop-mixing or residence-time dispersion within the harvester (s). This relationship is conceptual rather than a universal calibration equation, but it illustrates the inherent trade-off between signal stability and spatial detail. Longer weighing sections and stronger temporal averaging generally improve signal stability while integrating crop originating from a larger field distance. Therefore, high mass-measurement accuracy and high spatial resolution cannot always be maximized simultaneously.

Field-testing of load-cell-based sugarcane monitors provides comparable evidence from high-throughput conveyor systems. Magalhães and Cerri [65] demonstrated that useful yield information was concentrated at much lower frequencies than machine vibration, enabling low-pass filtering of dynamic load-cell signals. Molin and Menegatti [66] likewise showed that harvester-mounted load sensing could generate consistent spatial yield patterns even when field measurement accuracy remained influenced by system configuration. The literature consistently identifies conveyor weighing as one of the most mature continuous mass sensing methods for potatoes and comparable crops. The main limitation is not the load-cell principle itself, but the interaction of the sensor with belt mechanics, non-crop material, machine motion, and crop transport delay. Table 4 summarizes these error sources and the associated compensation strategies.

Table 4. Major error sources and compensation approaches in conveyor-based crop weight measurement.

Error Source	Mechanism	Practical Compensation Strategy
Machine vibration	Engine, digging blade and shaker web induce dynamic loads unrelated to crop mass	Mechanical isolation; spectral analysis; low-pass filtering; robust averaging during stable operation
Belt tension and tare drift	Tension changes or residue accumulation shift zero baseline	Daily zeroing; empty-belt baseline recording; automatic tare tracking
Inclination and slope	Change in gravitational component measured by load cell	Geometry-specific IMU/tilt compensation; experimental validation over representative pitch and roll angles
Variable belt speed	Hydraulic speed changes alter crop residence time and mass flow calculation	Encoder measurement; slip checks; mass-flow calculation using measured belt speed
Crop clumping	Discrete roots or tubers produce pulses and local overloads	Weighing section length optimization; event detection; median or moving-window smoothing
Soil/stones/trash	Non-crop material contributes to measured mass	Sensor placement after major soil separation; contamination-specific calibration or independently validated crop/non-crop estimation; report gross and cleaned mass separately where available

5.3. In-Bin, Hopper, and Cumulative Weighing Methods

Cumulative weighing represents a fundamentally different strategy from conveyor mass-flow measurement. Rather than determining the instantaneous mass transported through a short sensing section, cumulative systems measure the increasing mass of crop accumulated in a bin, hopper, trailer, basket, or other collection container. The change in accumulated mass over time can subsequently be related to field position or harvested area. Godwin et al. [67] provided one of the most relevant demonstrations of this concept for non-grain crops. They instrumented a high-sided trailer with load cells and used differential GPS to measure the accumulation rate of forage, potato, and sugar beet mass. Signal processing was applied to compensate for tractor-engine vibration and trailer pitch, roll, and yaw. The approach generated spatial yield maps for crops with very different material-flow properties, demonstrating that cumulative weighing can serve as an alternative to permanently instrumenting the harvester itself.

The major advantage of this architecture is that many short-duration crop-flow fluctuations are naturally integrated as the container fills. This reduces sensitivity to individual root or tuber impacts and makes industrial weighing technology directly applicable. However, the improvement in mass stability is accompanied by lower spatial resolution because each mass increment represents crop accumulated over a larger field segment. Figure 5 shows the basic configuration of an in-bin or hopper weighing concept.

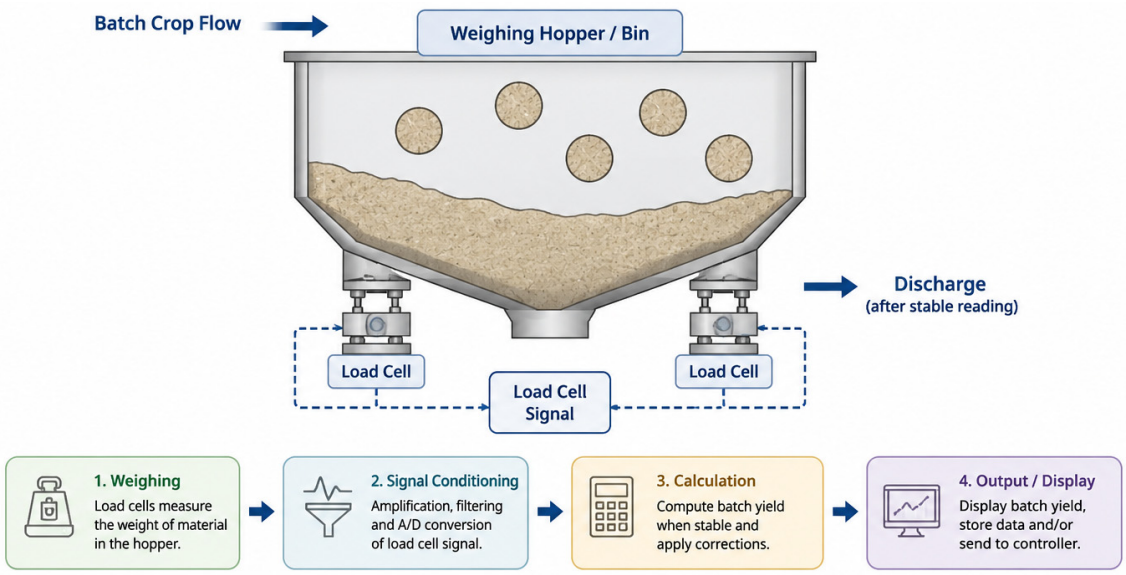


Figure 5. In-bin or hopper weighing concept for cumulative or batch-based measurement of harvested root and tuber crop mass (conceptual illustration developed by the authors based on the literature synthesized in this review; not reproduced from a single cited study).

The principle shown in Figure 5 can be implemented in several ways. A continuously filling hopper can be monitored as a cumulative mass signal, while a discrete weigh-bucket system divides crop mass-flow into repeated batches. Abidine et al. [68] and Cerri et al. [69] developed electronic weigh-bucket systems in which harvested produce was collected and weighed using multiple load cells before discharge. Kabir et al. [18] reported a strong relationship between weigh-bucket output and reference mass, demonstrating that batch conversion of continuous crop mass-flow can provide accurate measurements when the weighing interval is mechanically stable. Cumulative load-cell measurement has also been extensively evaluated in peanut harvesting. Vellidis et al. [57] used load cells to monitor the collection basket of a peanut combine and reported approximately 1% field-scale error after system development and field testing. The contrast between this cumulative performance and the greater uncertainty of short-interval instantaneous measurements illustrates a general feature of weight-based monitoring: aggregation suppresses dynamic noise but also reduces spatial detail.

For root and tuber crops, hopper weighing can therefore be interpreted as a spatial-resolution–measurement-stability trade-off. Conveyor weighing is advantageous when within-row variability is required, whereas cumulative weighing becomes attractive when total yield, batch accounting, or harvest logistics are primary outputs. This distinction has direct relevance to the degree of mechanization discussed in Section 3. Potato and radish harvesters with continuous collection conveyors provide natural locations for continuous weighing. Sweet potato harvesting, however, can involve mechanical digging followed by manual or semi-manual collection. In such situations, load-cell-equipped crates, carts, or collection bins can provide measured harvest mass without requiring a continuous crop stream through the harvester. Colaço et al. [52] similarly demonstrated that georeferenced weighing can support yield mapping for manually harvested crops.

Dynamic effects are not completely eliminated in hopper systems. Uneven loading can redistribute forces among multiple load cells, while machine slope, suspension movement, vibration, and side contact between the container and supporting frame can alter measured weight. Godwin et al. [67] showed that pitch, roll, yaw, and engine vibration required filtering even in a trailer-based cumulative system. Thus, hopper weighing reduces some high-frequency crop-impact problems but remains a dynamic vehicle-weighing problem

during on-the-go operation. A further issue is the spatial interpretation of the batch. Produce accumulated during a defined interval may originate from a long section of row, and mixing within the container prevents retrospective assignment to finer locations. Consequently, hopper-derived yield information represents the spatial support of the entire filling interval rather than the position at which the final weight value was recorded. Table 5 compares these characteristics with continuous conveyor weighing.

Table 5. Comparison of continuous conveyor weighing and cumulative hopper/bin weighing for root and tuber crop yield monitoring.

Criterion	Conveyor Weighing	Hopper/Bin Weighing
Measurement type	Continuous or semi-continuous mass flow	Batch or cumulative mass
Spatial resolution	Moderate to high depending on weighing length, belt/ground speed, crop mixing, acquisition interval, filtering, and lag correction	Moderate to low depending on batch size
Mechanical requirement	Stable belt section, load-cell idler, speed encoder	Weighing frame or instrumented bin with stable support
Best fit crops/machines	Potato, radish or carrot harvesters with conveyors	Sweet potatoes, carrots or semi-mechanized systems with collection bins
Main technical risk	Vibration, belt tension, inclination, crop clumping	Uneven loading, slope, stable reading, batch georeferencing
Farmer value	Yield maps, flow monitoring, machine diagnosis	Truck/container management, batch accounting, total harvested mass

5.4. Impact-Plate Sensor Methods

Impact-based measurement estimates crop mass from the dynamic force generated when harvested material strikes an instrumented plate. Unlike conveyor or hopper weighing, which primarily use the gravitational component of crop mass, impact sensing relies on momentum transfer. Consequently, the measured response depends not only on crop mass but also on impact velocity, trajectory, angle of incidence, contact duration, rebound, and crop mechanical properties. Impact sensing has been widely used in grain monitoring, but its application to horticultural crops has required additional consideration of individual object behavior. Upadhyaya et al. [55] developed impact-type electronic weighing systems for processing tomatoes using load-cell-supported plates positioned at the discharge of the harvester conveyor. Conveyor-speed measurements were recorded together with impact force, demonstrating that velocity information is integral to interpreting dynamic impact signals. Figure 6 illustrates the corresponding principle for root and tuber crop mass-flow using impact plate.

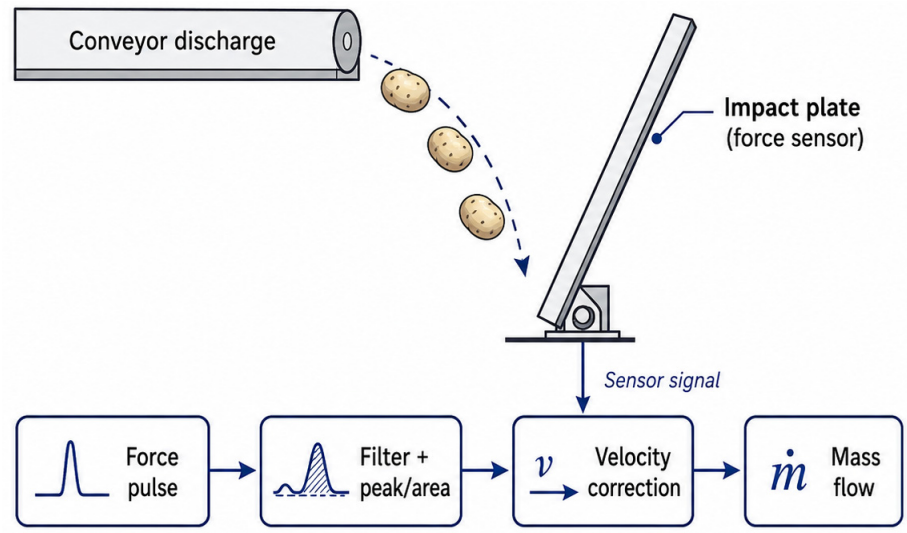


Figure 6. Impact-plate measurement concept for estimating harvested crop mass from momentum-related force signals at a conveyor transfer point (conceptual illustration developed by the authors based on the literature synthesized in this review; not reproduced from a single cited study).

For root vegetables, Kiraga et al. [26] provide particularly relevant experimental evidence. Single- and double-load-cell impact plates were evaluated for radish mass measurement under varying conveyor speed, plate angle, falling height, slope, and vibration. Impact-plate angle significantly influenced mass estimation, while conveyor speed affected several sensor configurations. Vibration and slope increased measurement errors, confirming that both crop-impact mechanics and machine dynamics contribute to the measured signal. The irregular geometry of root crops further complicates impact response. An elongated radish can contact the plate with its root tip, shoulder, or side surface, producing different force–time histories for the same mass. Potatoes can rebound, while sweet potatoes have irregular shapes and mechanically sensitive skins. These effects limit the direct transferability of calibration among crop types.

Impact-plate sensing also creates a more direct relationship between yield measurement and product quality than quasi-static weighing. A harder plate improves force transmission but can increase bruising or skin damage; a compliant covering reduces crop damage but changes contact stiffness, contact time, and pulse amplitude. This trade-off is particularly important for sweet potatoes and fresh-market root crops, for which external appearance affects economic value. Signal processing differs correspondingly from conveyor weighing. Peak force can be sensitive to sampling frequency and contact stiffness, whereas integrated force or impulse incorporates the full impact event but remains dependent on velocity and rebound [26,55]. At low crop-flow rates, individual impacts can be separated. At high throughput, multiple roots or tubers may strike the plate simultaneously, creating overlapping force pulses and weakening the relationship between individual object mass and signal amplitude [39,53]. Foreign material provides an additional challenge because stones and soil clods can generate force pulses comparable to or greater than crop impacts. Impact sensing is therefore more interpretable after substantial soil separation. However, downstream placement also means that harvested material lost earlier in the machine is not represented. Accordingly, impact-sensor studies should report sampling frequency, approximate impact-event duration, sensor/structural bandwidth, and filter settings because these parameters directly affect peak-force and impulse estimates.

Compared with continuous weighing, impact sensing offers a compact structure and can be mounted at an existing crop-transfer point without supporting the conveyor itself. The literature nevertheless indicates that calibration is more crop- and machine-specific

because the sensor responds to mass × impact dynamics, rather than to mass alone. For Korean radishes, the recent experimental evidence indicates technical feasibility but also demonstrates that slope, vibration, crop trajectory, and plate geometry remain central determinants of measurement uncertainty.

5.5. Other Contact and Mechanical Measurement Methods

Several additional contact or mechanically derived signals have been considered for agricultural yield monitoring, although the relationship between sensor response and harvested mass is generally less direct than for calibrated weighing. These include mechanical volume sensing, paddle or rotary displacement, hydraulic pressure, torque or power measurement, pressure-distribution sensing, and instrumented transport platforms [18,51]. Mechanical-volume approaches estimate crop mass-flow from the occupied volume or layer depth of harvested material. Their principal limitation for root crops is variation in bulk density. Two crop streams containing the same total potato mass can occupy different volumes depending on tuber size distribution, orientation, void fraction, soil content, and moisture. Volume-based mechanical sensing therefore requires an empirical conversion from volume to mass and is generally less deterministic than direct weighing.

Paddle and rotary-wheel systems similarly infer throughput from displacement or rotational response caused by moving crop. Although mechanically simple, their interaction with large irregular roots can be inconsistent. Bridging, jamming, orientation effects, and crop damage become increasingly important as crop dimensions approach the dimensions of the sensing mechanism. Hydraulic pressure and drive torque offer the advantage of using signals already available from machine systems. Increased crop throughput can raise elevator or conveyor torque, while accumulation in a hydraulically supported hopper can increase cylinder pressure. However, soil resistance, bearing friction, belt tension, hydraulic-oil temperature, machine slope, and component wear can generate similar changes. These signals are consequently better interpreted as contextual indicators of machine load rather than direct measurements of harvested crop mass.

Instrumented trailers and carts differ because they retain a direct gravitational relationship with crop mass. Godwin et al. [67] demonstrated that a load-cell-equipped trailer could generate yield information for potatoes, sugar beets, and forage, while georeferenced manually harvested approaches have also been reported by Colaço et al. [52]. These systems are therefore particularly relevant where crop collection remains separate from the harvester. Pressure mats or distributed force arrays theoretically provide information on both total load and load distribution across a conveyor. However, agricultural deployment is constrained by mechanical durability, mud, stones, moisture, and cleaning requirements. Their role remains considerably less established than conventional load-cell weighing. Table 6 summarizes the principal characteristics of these additional mechanical approaches.

The literature therefore suggests a clear hierarchy of measurement directness. Load-cell weighing provides a direct mass-related reference; impact measurement introduces dependence on crop velocity and collision mechanics; volumetric and paddle approaches introduce density and geometry dependence; and torque or pressure-based proxies are additionally confounded by machine operating conditions. This hierarchy is useful when considering their roles within integrated systems.

Table 6. Other contact and mechanically derived sensing approaches relevant to root and tuber crop yield monitoring.

Measurement Type	Principle	Potential Role	Key Limitation
Mechanical volume gate	Crop layer height or volume displacement	Relative flow indicator or auxiliary mass estimate	Bulk density varies with crop size, soil and void space
Rotary wheel/paddle	Crop mass-flow rotates a wheel or paddle	Simple flow-rate indicator in controlled chute	Jamming, crop damage and calibration drift
Hydraulic pressure	Pressure related to hopper load or machine power	Overload detection and auxiliary yield proxy	Confounded by friction, temperature and soil resistance
Instrumented cart/trailer	Load cells under manually or mechanically filled container	Batch yield logging in semi-mechanized operations	Lower spatial resolution and worker-dependent loading
Torque/power sensing	Motor or shaft load changes with crop mass-flow	Machine diagnosis and blockage detection	Indirect; affected by mechanical and soil conditions
Pressure mat/load distribution	Array detects pressure pattern under crop mass-flow	Research tool for distribution and clod detection	Durability and cost under field conditions

5.6. Integrated Multi-Sensor Modules

The progression from single-sensor yield measurement toward integrated monitoring systems reflects recognition that many errors cannot be resolved from the primary mass sensor alone. A load cell can measure force accurately without determining whether a signal change resulted from additional crop, a machine slope change, increased vibration, soil accumulation, or conveyor-speed variation. Multi-sensor systems address this ambiguity by combining direct mass measurement with contextual measurements [49].

This concept has existed since early non-grain yield monitors. Pelletier and Upadhyaya [20] combined load cells, conveyor-related measurements, a vibration-resistant angle sensor, signal processing, and DGPS in a processing tomato yield monitor and obtained an (R^2) of 0.997 between reference and predicted crop mass. Sugarcane systems have similarly integrated load sensing with elevator speed and inclination measurements [65]. These studies show that several technologies now described as sensor fusion originated from the practical requirement to correct direct mass measurements for machine operating conditions.

A root crop hybrid system can therefore be represented by several complementary sensing functions: a load cell for gravimetric mass measurement or an impact plate for contact dynamic mass estimation; an encoder for conveyor velocity; GNSS for spatial position; an IMU for inclination and machine motion; vibration sensing for dynamic-load characterization; and machine vision for crop/non-crop discrimination [49]. Each sensor addresses a specific uncertainty rather than independently estimating yield. The importance of this architecture is demonstrated by recent Korean yield-monitoring research. Kim et al. [70] combined a load cell grain tank sensor, impact plate flow sensing, GNSS positioning, filtering, time lag correction, and spatial yield mapping. Although the system was developed for rice rather than root vegetables, its field validation illustrates the broader benefit of

combining independent mass and flow measurements with spatial correction; total yield errors ranged from −4.3% to +1.7%, with a reported MAPE of approximately 1.5%.

For root crops, multi-sensor integration provides a potential pathway for interpreting gross transported mass, but machine-vision classification alone cannot quantitatively partition the total mass measured by a load cell. Vision systems can identify or characterize potatoes, radishes, stones, soil clods, foliage, and damaged produce within the observed material stream [23,27,53,71], whereas the load cell measures their combined mass. This distinction is particularly important under wet soil conditions, where adhering soil and other foreign material can increase the measured gross mass, as reported in commercial potato yield-monitoring studies [63]. Conversion of visual classifications into crop and non-crop mass fractions therefore requires an additional validated quantitative relationship, such as individual-object mass estimation, image-derived volume combined with calibrated density, class-specific mass calibration, or physical separation followed by reference weighing [53,71]. Similarly, identification of damaged produce does not directly provide marketable yield unless the mass contribution of the rejected fraction is also estimated. Hybrid weighing–vision systems should therefore be regarded as a promising approach for estimating cleaned or marketable yield, rather than as an already demonstrated method for directly partitioning total measured mass. Time synchronization is central to this integration. Load-cell, encoder, IMU, camera, and GNSS measurements are normally recorded at different frequencies. The crop also moves through the machine between excavation, cleaning, sensing, and discharge. Consequently, sensor fusion requires not only matching timestamps but also accounting for the physical transport delay of crop material. Figure 7 presents the existing multi-layer architecture in terms of sensing, signal processing, data management, decision support, and implementation. The architecture illustrates an important distinction between measurement sensors and context sensors. Load cells provide the principal yield-related measurement, whereas belt speed, inclination, vibration, position, and machine-state sensors increase the interpretability of that measurement. Optional vision systems add information on crop identity, foreign-material content, size, and quality.

Signal filtering should be applied according to the physical information contained in each processing branch. For gravimetric weighing, the DC and low-frequency components contain the supported crop-load information and must therefore be preserved; tare/baseline correction followed by appropriately selected low-pass or model-based filtering is more suitable for this branch. Band-pass or high-pass processing may be useful in a separate branch for characterizing machine vibration or extracting dynamic impact events, but such signals should not replace the gravimetric load baseline. Where vibration-derived features are used for compensation, they should be synchronized and recombined with the mass-measurement branch after processing. The phase or group delay introduced by causal filters must also be considered in spatial synchronization.

Data processing in these systems ranges from deterministic correction to statistical fusion. Deterministic approaches apply known physical relationships—for example, correcting belt loading using measured conveyor speed or correcting gravitational force using inclination. Statistical or machine-learning models can combine multiple signals where the physical relationship is less explicit. However, the literature on commercial potato monitoring indicates that calibration transfer among harvesters remains difficult even for comparatively simple systems [63]. Model complexity therefore does not eliminate the need for independent mass validation across machine and field conditions. Table 7 summarizes the functional roles of the different system layers.

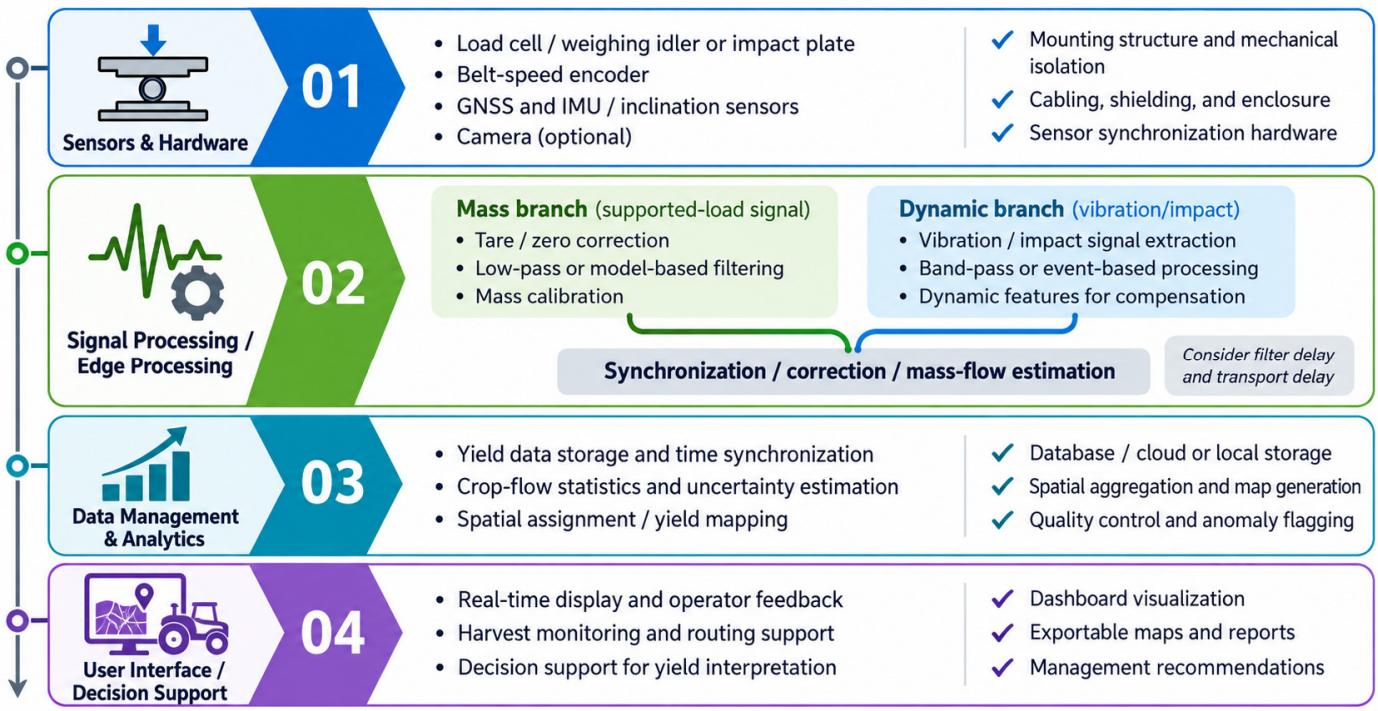


Figure 7. Functional architecture of an integrated contact- and weight-based yield-monitoring system for root and tuber crop harvesters, linking sensing, signal processing, data management, decision support, and implementation layers. Conceptual illustration developed by the authors based on the literature synthesized in this review; not reproduced from a single cited study.

Table 7. Functional architecture and outputs of an integrated multi-sensor yield-monitoring system for root and tuber crop harvesters.

Layer	Hardware/Software Components	Main Function	Example Output
Sensor layer	Load cells, encoder, GNSS, IMU, vibration sensor, optional camera	Capture mass, speed, location and operating context	Raw force, belt speed, position, slope, vibration level
Edge processing	Microcontroller or industrial PC; calibration and filtering algorithms	Convert signals into mass flow and quality control indicators	Instantaneous kg/s, cumulative kg, data-quality flag
Data management	Local storage, field ID, crop ID, calibration metadata	Preserve traceable harvest records	CSV/JSON records, plot summaries, field maps
User interface	Cab display or mobile app	Support operation and diagnostics	Total harvested mass, bin fill, calibration alerts, map preview
Decision support	Farm management platform or extension service dashboard	Use yield data for planning and next season management	Yield zones, truck scheduling, variable rate recommendations

Taken together, published research indicates that the contact- and weight-based technologies reviewed in this section differ primarily in measurement directness, temporal

resolution, mechanical integration, and sensitivity to operating conditions. Conveyor load-cell systems provide the strongest basis for continuous mapping where a stable crop conveyor is available, particularly for potatoes and potentially radishes. Cumulative hopper, bin, or trailer weighing sacrifices spatial resolution but provides more stable mass estimates and is compatible with intermittent or semi-mechanized collection. Impact plates provide compact and rapid measurement but introduce additional dependence on crop trajectory, collision mechanics, and crop damage. Mechanical-volume, pressure, and torque approaches provide useful auxiliary information but are more indirect measures of yield. Hybrid architectures combine these strengths by retaining direct mass measurement as the principal reference while using complementary sensors to account for belt speed, vibration, inclination, foreign material, and spatial position. This synthesis supports the broader interpretation that, for Korean root and tuber crops, the key technological distinction is not simply between individual sensor types but between harvesting systems that provide a controlled and measurable crop-flow pathway and those in which crop collection remains intermittent or mechanically variable.

6. Applications and Studies in Korea

Yield-monitoring research in Korea has developed along two partly parallel pathways. The first originated from grain harvesting and focused on impact-flow sensing, grain-tank weighing, moisture measurement, GNSS integration, time-lag correction, user-terminal software, and spatial yield mapping. The second emerged more recently for upland and root crops, particularly potatoes and radishes, where researchers have investigated load-cell-based mass measurement, impact sensing, image-based crop counting, mass estimation, and compensation for vibration and slope. Although the grain-monitoring pathway has progressed to integrated field validation, root- and tuber-crop research remains concentrated at the sensor, laboratory-test-bench, prototype, and limited field-validation stages.

This difference is important when assessing the current technological readiness of contact- and weight-based yield monitoring in Korea. The Korean literature demonstrates that the fundamental sensing principles are technically feasible, but development maturity differs substantially by crop. Potatoes have received the greatest attention among root crops, progressing from load-cell and CCD sensor feasibility tests to machine-vision-based field estimation and deep-learning-based mass prediction [21–23,36,71]. Radish research has focused primarily on impact-based load-cell sensing under simulated harvesting vibration and slope. By contrast, published Korean studies demonstrating harvester-integrated, spatially referenced direct yield measurement for sweet potatoes and carrots remain scarce. Korean grain research therefore provides an important domestic benchmark for the system integration steps that root-crop monitoring has yet to complete.

6.1. Development of Yield-Monitoring Research in Korea

Early Korean precision-agriculture research established that substantial spatial yield variation can occur even within relatively small agricultural fields, supporting the value of site-specific yield information. However, commercial yield monitors developed for large grain combines in North America and Europe cannot be transferred directly to Korean agricultural machinery [45]. Korean combines and upland harvesters are generally smaller, field lengths are shorter, turning frequency is higher, and crop-flow pathways differ markedly from those of large conventional combines [22,23,45]. These characteristics have driven Korean researchers toward sensors and software specifically adapted to domestic harvesting machinery.

For root crops, one of the earliest direct attempts was reported by Kim et al. [21], who evaluated mass- and volume-based sensing modules for small-sized Korean potato harvesters. A load cell was used for mass-flow measurement, while a CCD camera provided a volume-related measurement. The load cell approach produced an (R^2) of 0.95 and an RMSE of 11 g, while the volume-based sensor produced an (R^2) of 0.91 and an RMSE of 12 g. More importantly, the experiments demonstrated that vibration, slope, and load-cell arrangement significantly affected measurement performance. The study therefore established both the feasibility of direct potato mass sensing and one of the central limitations that continues to characterize Korean root-crop yield monitoring: the sensor must operate on a small machine whose dynamic forces can be comparable to the useful crop signal.

Subsequent Korean research diversified into two technological directions. One retained direct mass or impact measurement using load cells, while the other increasingly adopted machine vision to identify individual potatoes, distinguish them from foreign material, and convert geometric information into crop mass. This development reflects the specific characteristics of root-crop harvesting. Unlike clean grain flow, potatoes and radishes can be mixed with soil, stones, foliage, and other materials. Consequently, direct weighing provides an accurate gross-mass signal but cannot independently determine whether all measured material is marketable crop, whereas vision-based systems provide crop identity and size information but estimate rather than directly measure mass.

The progression of Korean research can therefore be interpreted as a gradual movement from single-sensor feasibility to dynamic error characterization, crop recognition and mass estimation, spatial integration, and field-validated yield mapping. This progression is much more advanced for rice than for root crops, but recent potato and radish studies indicate that the technological gap is narrowing.

6.2. Potato Yield-Monitoring Research

Potatoes have been the principal root crop used for yield-monitoring research in Korea. This is partly attributable to the mechanical structure of potato harvesting: after excavation, tubers normally pass through a separation or conveying stage that provides a suitable location for sensing. Korean research has consequently examined both contact-based load cell sensing and non-contact image-based methods.

Following the initial load-cell and CCD study of Kim et al. [21], Jang et al. [22] investigated mass- and volume-based sensors on a small potato-harvester test system. For the mass-based approach, potatoes discharged from the conveyor struck a spring-supported plate connected to a load cell. The impact response was calibrated against potato mass. Under selected conditions, particularly a 30 cm dropping height, the mass-based approach produced a linear calibration with an R^2 of approximately 0.98. In contrast, the volume-based calibration in that experiment was substantially weaker. The comparison reinforced the advantage of a physically measured force signal when the crop trajectory is sufficiently controlled. These results are significant because they show that early Korean potato research did not merely compare sensor accuracies; it revealed a fundamental distinction between direct deterministic measurement and empirical crop-feature estimation. The load cell responds directly to crop-induced force but is sensitive to vibration and impact conditions, whereas the imaging sensor avoids mechanical contact but requires a model linking visual geometry to crop mass.

Machine vision research progressed in parallel. Lee et al. [72] developed a vision-based potato detection and counting system that segmented potatoes on the soil surface and converted two-dimensional image information into estimated mass. Under moving conditions, the best reported mass-estimation error was approximately 7.79%, while repeated

measurements using newly prepared samples produced errors of approximately 10–13%. Although less accurate than controlled direct weighing, the study demonstrated that crop mass could be derived from image-based counting and geometry without physical contact. Lee and Shin [36] subsequently extended machine-vision yield monitoring into an actual potato field. Their system incorporated a digital camera, gimbal, wheel-triggered image acquisition, RTK-GPS, and image processing to estimate the mass of potatoes exposed on the soil surface during harvest. The reported percentage yield-estimation error was approximately 15.33%. The numerical accuracy was lower than that obtained in controlled sensor tests, but the study represented an important transition from isolated sensor evaluation to spatially referenced field measurement. It also demonstrated that field yield monitoring introduces additional uncertainties associated with illumination, soil background, object visibility, spatial sampling, and machine motion.

The next stage of Korean potato research focused on separating potatoes from foreign material and preventing repeated counting of the same object. Jang et al. [23] developed a YOLOv5–DeepSORT system for potato detection and tracking. The study used 9906 original images, which were substantially expanded through augmentation, and the dataset was randomly divided into training and validation subsets at an 8:2 ratio. Precision, recall, mAP, and F1-score values of 0.9997, 0.9994, 0.9872, and 0.9996, respectively, were reported after 300 training epochs. These values demonstrate strong within-domain object-detection performance, but they should not be interpreted as independent field-level yield accuracy because an independent field-scale test set was not reported and the augmented images originated from the same general acquisition domain. The study should therefore be considered evidence of algorithm feasibility rather than complete yield-monitor validation. Jang et al. [71] subsequently extended potato detection and tracking to mass estimation. The system was evaluated under laboratory conditions using 200 potatoes for individual mass estimation and three repeated continuous-flow tests of 400 potatoes each. The reported detection rate of 95.2% and total-mass error of approximately 9% therefore represent prototype-level laboratory performance rather than independent field-scale validation. The original study also identified the need for improved calibration/validation separation, computational optimization, vibration correction, and subsequent field testing. This development represents an important step from count-based monitoring toward mass-based spatial yield estimation, although mass remained inferred from image-derived geometry rather than measured directly. These results demonstrate excellent object-recognition performance, but they also illustrate an important distinction in yield-monitor evaluation: high detection accuracy is not equivalent to high yield-measurement accuracy. Counting potatoes can characterize crop mass-flow, yet yield is normally expressed as mass per unit area. Variation in individual tuber size means that accurate counting alone cannot produce sufficiently accurate mass yield without either direct weighing or a validated mass-estimation model.

Taken together, Korean potato studies reveal a clear technological progression. Load cells have provided the most direct mass reference and relatively strong calibration performance, whereas machine vision has increasingly contributed to crop identification, foreign-material exclusion, counting, and individual mass estimation. These technologies are therefore complementary. A hybrid system in which a load cell measures total crop-stream mass while machine vision estimates the proportion attributable to potatoes could address one of the main weaknesses of direct weighing—contamination by soil and stones—while retaining a physically measured total-mass reference.

6.3. Radish Yield Monitoring Research

Radish yield monitoring presents a different measurement problem from potatoes because individual Korean radishes are relatively large, elongated, and transported as discrete crop units. Crop mass-flow therefore produces isolated or clustered events rather than a quasi-continuous bulk flow. This characteristic makes impact sensing particularly relevant. Kiraga et al. [26] evaluated single- and double-load-cell impact plates for individual radish mass measurement under simulated harvesting conditions. Conveyor speed, falling height, impact-plate angle, slope, vibration, and sensor layout were varied systematically. Under conditions without slope and vibration, standard errors were below 4 g. The impact-plate angle significantly affected mass measurement, while vibration and slope increased relative errors. Signal processing using finite impulse response and moving-average filtering reduced the combined vibration/slope relative error from approximately 9.13% to 5.42%.

The significance of this study extends beyond the reported error values. It demonstrated that the principal uncertainty in direct radish weighing arises from the interaction between crop impact dynamics and harvester motion. A load cell itself can provide stable calibration, yet its output during harvesting includes crop collision, structural vibration, gravitational effects associated with slope, and transient machine motion. This finding is directly relevant to Korean upland fields, where compact harvesting machinery frequently operates on uneven or inclined surfaces. The radish work also illustrates why sensor layout cannot be considered independently from crop mechanics. A large elongated root can strike an impact plate at different orientations, generating different force–time responses for equal mass. Impact-plate angle and crop trajectory therefore become part of the calibration relationship. In contrast to grain impact sensors, where thousands of small kernels form an approximately continuous flow, radish sensing requires interpretation of individual transient events.

More recent Korean-associated research has investigated radish mass estimation using vision under simulated harvester dynamics. Kiraga et al. [39] investigated the effects of field-induced vibration and slope on vision-based radish volume estimation using a laboratory harvesting test bench. RGB images were acquired under slopes of 3–9° and vibration levels of 0.43–0.98 m s^{-2} to simulate dynamic harvesting conditions. The multiple linear regression (MLR) model outperformed the ellipsoidal approximation method, with maximum R^2 values of 0.94, 0.96, and 0.92 at slopes of 3°, 6°, and 9°, respectively. Average radish width was identified as an effective geometric feature for volume prediction. Kabir et al. [53] used RGB imaging and a genetic-algorithm-optimized extreme learning machine (GA-ELM) to estimate radish mass under combinations of vibration and slope. The R^2 values ranged from approximately 0.94 to 0.98 under selected operating conditions. Although this approach is non-contact and therefore outside the primary technology scope of the present review, it is relevant as a complementary sensor because it demonstrates that crop geometry can provide an independent mass estimate under the same dynamic disturbances that affect load-cell signals. The two approaches suggest a particularly suitable hybrid pathway for Korean radish harvesting. Impact sensing can provide a direct force-related mass measurement, while imaging can describe radish size, orientation, and potentially crop/non-crop status. Combining these signals could improve robustness where the impact response changes because of crop orientation or machine dynamics.

Nevertheless, the Korean radish literature remains primarily at the controlled test-bench and prototype stage. In the literature surveyed for this review, a peer-reviewed study demonstrating field-scale, harvester-integrated radish mass-flow measurement synchronized with GNSS and validated as a complete spatial yield map was not identified. Thus, the principal research transition for radishes is from dynamic sensor feasibility to complete field-integrated yield monitoring. As summarized in Table 8a, Korean studies have

evolved from basic load-cell and vision-based feasibility tests to dynamic compensation, deep-learning-based crop identification, mass estimation, GNSS integration, and field-scale yield mapping. Table 8b compares the validation basis, spatial outputs, and limitations of representative Korean yield-sensing studies.

Table 8a,b should be interpreted together. Table 8a summarizes the sensing approaches, experimental platforms, reported quantitative performance, and principal contributions of representative Korean studies, whereas Table 8b critically examines their validation basis, spatial-output capability, and major limitations. The comparison shows that the available studies represent substantially different levels of technological evaluation, ranging from laboratory calibration and dynamic test-bench experiments to harvester-based prototypes and limited field-scale assessment. Accordingly, high R^2, precision, recall, or mAP values obtained during sensor calibration or object detection should not be interpreted as equivalent to accurate field-scale yield measurement. In particular, several potato and radish studies demonstrated strong sensor- or model-level performance but lacked independent multi-field validation or complete GNSS-integrated mass-yield mapping. These differences highlight the need to evaluate reported performance together with the measurement output, experimental scale, reference method, spatial capability, and validation independence.

Table 8. (**a**) Representative Korean studies with quantitative comparison and validation characteristics on real-time yield sensing and monitoring relevant to root and tuber crops. (**b**) Critical comparison of validation basis, spatial outputs, and limitations of representative Korean yield-sensing studies relevant to root and tuber crops.

(a)

Study	Crop	Measurement Approach	Experimental/Platform Level	Quantitative Performance	Main Contribution to Korean yield Monitoring
Kim et al. [21]	Potato	Load cell + CCD camera	Small-harvester laboratory test bench	Mass: R^2 = 0.95, RMSE = 11 g; volume: R^2 = 0.91, RMSE = 12 g	Established feasibility of load-cell and optical potato sensing and quantified vibration/slope effects
Lee et al. [72]	Potato	Vision-based detection, counting, and mass estimation	Stationary and simulated moving conditions	Moving mass error ≈ 7.79% under the best condition; repeated tests ≈ 10–13%	Demonstrated image-based count-to-mass conversion
Jang et al. [22]	Potato	Impact load cell + CCD camera	Harvester-based laboratory system	Mass-based calibration up to R^2 ≈ 0.98 under selected conditions	Strengthened impact-based direct mass sensing for potatoes
Lee and Shin [36]	Potato	Machine vision + RTK-GPS	Potato field	Yield-estimation error ≈ 15.33%	Demonstrated field-scale georeferenced potato yield estimation
Jang et al. [23]	Potato	YOLOv5 + DeepSORT	Harvester conveyor	Precision = 0.9997; recall = 0.9994; mAP = 0.9872; F1 = 0.9996	Introduced deep-learning detection, tracking, and crop/foreign-material discrimination
Jang et al. [71]	Potato	Deep learning + geometry-based mass estimation + RTK-GPS	Harvester sorting/conveying system	Detection rate = 95.2%; weight-estimation error ≈ 9%	Advanced potato monitoring from counting toward mass estimation

Table 8. *Cont.*

Kiraga et al. [26]	Radish	Single/double load-cell impact plates	Dynamic test bench with slope and vibration	Filtered combined-condition relative error = 5.42%	Quantified effects of vibration, slope, sensor layout, and signal processing
Kabir et al. [53]	Radish	RGB + GA-ELM mass estimation	Dynamic slope/vibration test bench	$R^2 \approx 0.94$–0.98 under selected conditions	Demonstrated complementary non-contact mass estimation under harvester dynamics

(b)

Study	Sensing Principle/Output	Calibration/Validation Basis	Spatial Output/Resolution	Main Limitation
Kim et al. [21]	Gravimetric load-cell mass + CCD volume estimation	Estimated mass/volume compared with reference potato mass	No field yield map; NR	Vibration, inclination, and load-cell arrangement influenced response; laboratory validation
Lee et al. [72]	Vision-based count/geometry-to-mass estimation	Image-derived mass compared with measured mass	No georeferenced field map; NR	Indirect mass estimation; performance declined under movement
Jang et al. [22]	Contact dynamic/impact mass estimation + CCD sensing	Impact response calibrated against reference mass	No field yield map; NR	Sensitive to drop height, trajectory, velocity, vibration, and collision mechanics
Lee and Shin [36]	Machine vision + RTK-GPS	Estimated yield compared with field reference yield	Georeferenced field yield; numerical resolution NR	Illumination, soil background, visibility, sampling, and machine motion
Jang et al. [23]	YOLOv5 + DeepSORT detection/tracking/counting	Model evaluated against annotated visual reference	Object-level tracking; no direct mass-yield map	Detection accuracy is not equivalent to mass-yield accuracy
Jang et al. [71]	Deep learning + geometry-derived mass + RTK-GPS	Estimated tuber mass compared with reference mass	RTK-GPS-integrated monitoring; spatial resolution NR	Mass inferred from geometry; crop visibility, model transfer, and field validation remain limitations
Kiraga et al. [26]	Impact load-cell dynamic mass estimation	Estimated radish mass compared with reference mass	No GNSS-integrated yield map	Strong sensitivity to slope, vibration, impact angle, conveyor speed, orientation, and sensor arrangement
Kabir et al. [53]	RGB + GA-ELM indirect mass estimation	Predicted mass compared with reference mass	No field yield map; NR	Indirect/model-based mass estimation; image visibility and calibration dependence

Note: Reported performance values originate from different experimental scales and validation conditions and should not be interpreted as directly comparable measures of technological superiority. Laboratory calibration, dynamic test-bench evaluation, prototype-harvester testing, and field validation represent different levels of measurement uncertainty. NR = not reported or not sufficiently specified in the reviewed information. Reported metrics are not directly comparable across studies because they represent different performance levels, including sensor calibration, individual-object mass estimation, object detection, dynamic weighing, and field-scale yield determination. Laboratory or test-bench performance should therefore not be interpreted as equivalent to independent field validation.

6.4. Korean Grain Yield Monitoring as a Transferable Engineering Benchmark

Although the focus of this review is root and tuber crops, Korean grain-monitoring studies provide highly relevant engineering evidence because they demonstrate the transition from an individual yield sensor to a complete field-ready monitoring system. Lee et al. [73] developed an impact-plate flow sensor specifically for Korean head-feed rice

combines. The sensing unit combined an impact plate and load cell positioned where grain entered the tank. Impact-plate dimensions and installation geometry were evaluated, and signal filtering was incorporated. The developed prediction model produced an R^2 of 0.99, while the reported grain-flow measurement error was approximately 3.4%. This study demonstrates that impact sensing can achieve high accuracy when material trajectory, impact geometry, and machine installation are tightly controlled. The relevance to radishes is particularly strong. Both systems use load-cell responses generated by moving crop material, but radishes introduce much greater variation in object size, orientation, collision behavior, and impact frequency. Therefore, the Korean rice results represent an achievable engineering benchmark rather than a directly transferable calibration.

Sensor accuracy alone is also insufficient for yield mapping. Lee et al. [74] developed user-terminal software for Korean grain yield monitoring systems, incorporating calibration, position filtering, transport-delay correction, sensor-data logging, and spatial yield-map generation. Field tests produced yield and moisture-content errors of 4.24% and 2.51%, respectively. The delay time function improved the spatial coherence of the resulting yield maps. The same spatial problem occurs between excavation and sensing of root crops. Potatoes or radishes entering a harvester at one position can require several seconds to reach the load cell, impact plate, or hopper. Therefore, even a highly accurate mass measurement can produce an inaccurate yield map if it is associated with the GNSS position at sensing time rather than the position where the crop entered the machine. Kim et al. [70] evaluated an integrated combine yield-monitoring system incorporating a load-cell grain-tank weight sensor, impact-plate flow sensor, GNSS, filtering, time-lag correction, and a 1 m grid-mapping algorithm across seven rice paddies in Dangjin, Korea. Total yield errors ranged from approximately −4.3% to +1.7%, with a MAPE of about 1.5% and an (R^2) of 0.98 between monitored and measured yield.

These studies establish a useful domestic technological benchmark for Korean root-crop monitoring, and it should not be evaluated only by whether a sensor can predict individual crop mass with a high R^2. A mature yield-monitoring system also requires operation-state detection, lag correction, GNSS synchronization, field calibration, cumulative-mass verification, spatial filtering, and independent field validation. By this broader definition, Korean rice monitoring has reached an integrated field validation stage, whereas potato and radish monitoring remains at an earlier developmental stage.

6.5. Status of Sweet Potato and Carrot Applications

Compared with potatoes and radishes, direct yield monitoring studies for sweet potatoes and carrots remain limited in Korea. Research on these crops has focused more heavily on harvesting mechanisms, labor reduction, crop handling, and machine development than on spatial yield sensing. This difference can be explained partly by harvesting architecture. Potato harvesters commonly provide a continuous conveying pathway, whereas sweet potato harvesting in Korea may involve mechanized digging followed by manual or semi-manual collection. Under these conditions, a conventional conveyor yield monitor cannot capture all harvested produce because crop mass-flow does not pass through a single controlled sensing location. Hopper, instrumented-cart, crate-weighing, or batch-based approaches are consequently more compatible with current sweet potato production systems.

Sweet potatoes also have high mechanical sensitivity. Skin abrasion, cuts, breakage, and bruising directly influence market value and storability. Impact-based yield sensing is therefore less attractive unless impact energy is kept sufficiently low [75]. Direct hopper or cart weighing, in contrast, can provide crop mass without deliberately introducing additional crop impacts [42,75]. Carrots present a related but distinct challenge. Mechanical

harvesting can create a controlled crop mass-flow path, but foliage, adhering soil, root orientation, and elongated crop geometry complicate mass sensing [47,48]. A conveyor-based weighing system positioned after top and soil removal could theoretically provide direct yield measurement, yet published Korean field validation remains sparse.

The recent Korea-focused review by Dey et al. [27] similarly identified RGB/RGB-D, LiDAR, ultrasonic, thermal, and other non-contact sensors as potentially relevant to root-crop monitoring while emphasizing the need for integration with harvesting platforms. For contact- and weight-based systems, this reinforces the role of direct weighing as a mass reference around which additional sensors can be integrated. Peer-reviewed Korean studies demonstrating harvester-mounted, GNSS-synchronized, field-validated direct mass yield mapping for sweet potatoes or carrots remain limited. This limitation reflects a technology-development gap in integrating weighing systems with georeferenced field operations rather than an inherent unsuitability of direct mass measurement for these crops. Further research is therefore needed to develop and validate robust harvester-based weighing and spatial yield-mapping systems under practical field conditions.

6.6. International Benchmarks from Comparable and Large-Scale Mechanization Contexts

International research provides useful context for assessing the maturity of Korean systems, particularly for potatoes. Rawlins et al. [19] demonstrated continuous conveyor-based potato weighing and spatial mapping, while Demmel et al. [61] and Davenport et al. [63] extended potato yield monitoring to commercial harvesting environments. These studies demonstrated that conveyor weighing can operate effectively at field scale but also identified errors arising from soil, stones, machine calibration, and crop transport through the harvester. Similarly, Godwin et al. [67] demonstrated cumulative load cell measurement for potatoes and other non-grain crops using an instrumented trailer. This approach is particularly relevant to Korean semi-mechanized systems because it separates yield measurement from the internal architecture of the harvester.

Beyond conventional large-scale potato yield-monitoring studies, Japan and European mountain agriculture provide useful comparisons for Korean machinery development. Japanese slope-land mechanization has emphasized compact machines, maneuverability, labor reduction, and adaptation to restricted terrain [9], while research in the Italian Piedmont region has similarly highlighted the limitations of conventional large machinery for small mountainous farms and the need for intermediate, scale-appropriate equipment [10]. These parallels support the Korean emphasis on compact sensing modules and machine-integrated weighing. However, direct transfer remains limited because the cited Japanese and European studies concern different crop systems and do not themselves validate root-crop yield monitoring. Their relevance is therefore primarily in machinery scale, terrain adaptation, and mechanization strategy.

The international comparison therefore highlights a difference in research maturity rather than sensing principle. The fundamental load-cell, conveyor, hopper, and impact concepts have already been demonstrated internationally at field scale. Korean research has increasingly validated the same physical principles but under smaller machinery, shorter fields, greater slope variability, and crop-specific harvesting configurations. The central Korean research question is therefore not whether direct mass measurement is possible, but how these principles can be adapted to the structural and operational characteristics of domestic root-crop harvesters.

6.7. Qualitative Assessment of Research Progress and Remaining Gaps in Korea

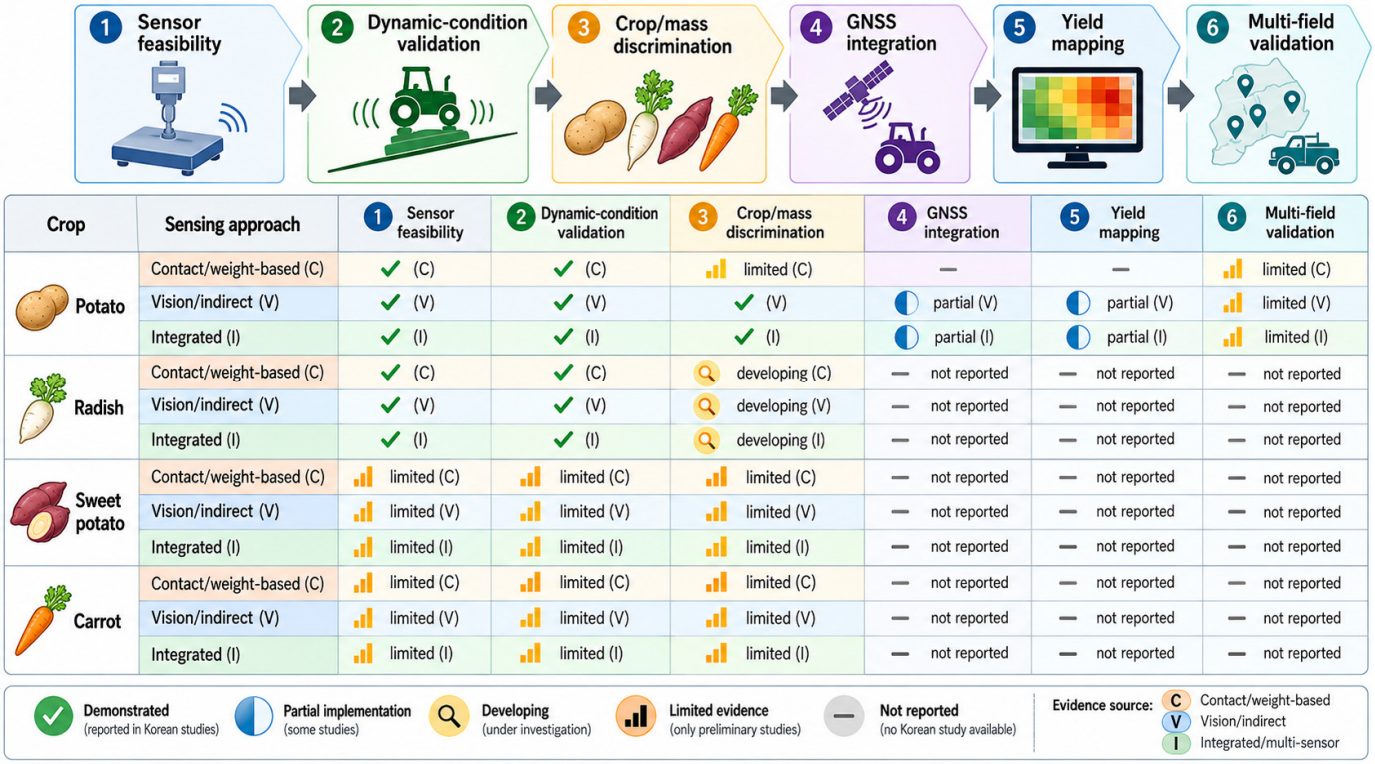
The reviewed Korean literature reveals three distinct levels of technological maturity. First, rice yield monitoring has progressed to integrated field validation, with calibrated

mass-flow sensing, grain-tank weighing, GNSS, time-lag correction, software, and spatial mapping operating as a complete system [70,73,74]. Second, potato monitoring has progressed beyond basic sensor feasibility but has not yet reached the same level of integrated commercial field validation. Korean studies have demonstrated load-cell mass sensing, impact measurement, machine-vision counting, RTK-GPS integration, deep-learning crop recognition, and image-based mass estimation [21–23,36,71]. However, these functions remain distributed across different experimental systems rather than consolidated into a standardized commercial monitoring architecture.

The evidence streams were evaluated separately to avoid attributing capabilities demonstrated by one sensing approach to another. In particular, Korean potato studies demonstrate load-cell gravimetric sensing and impact-based mass estimation [21,22], whereas much of the reported RTK-GPS integration and georeferenced field-yield estimation originates from machine-vision-based systems [36,71]. These results should not be interpreted as evidence that a Korean direct gravimetric potato monitor has already demonstrated complete GNSS-synchronized field yield mapping. Similarly, radish contact/impact studies demonstrate dynamic mass-estimation feasibility [26], while vision-based studies provide complementary mass-estimation evidence [39,53]; a complete GNSS-integrated direct radish yield-mapping system was not identified.

Third, radish monitoring remains primarily at the dynamic sensor-development stage, with strong evidence that impact-based load cells can estimate individual crop mass but that slope, vibration, impact geometry, and crop orientation substantially influence measurement accuracy [26]. Image-based mass estimation under simulated harvester dynamics provides a complementary pathway [39,53], but complete field-scale yield mapping remains to be demonstrated. Sweet potatoes and carrots are at an earlier stage still, with relatively little published Korean evidence for harvester-integrated real-time mass monitoring. Their future sensing architectures are likely to differ because sweet potatoes may favor cumulative weighing in semi-mechanized collection systems, whereas carrots could potentially support conveyor-integrated measurement following foliage and soil separation. Figure 8 summarizes the qualitative evidence coverage of Korean yield-monitoring research while distinguishing capabilities demonstrated by contact/weight-based systems from those demonstrated by complementary vision-based approaches.

Korean yield monitoring research has established a strong engineering foundation but remains uneven across crop groups. The grain monitoring literature demonstrates that high-quality yield maps require integration of sensing, calibration, filtering, machine-state information, time-lag correction, positioning, and field validation. Potato research has developed many of these components individually, and radish research has characterized several of the dynamic effects that limit direct weighing. The next stage of Korean root- and tuber-crop yield monitoring is therefore defined by the integration of these previously separate developments into complete harvesting systems capable of producing validated spatial yield information under commercial field conditions.



Crop	Sensing approach	1 Sensor feasibility	2 Dynamic-condition validation	3 Crop/mass discrimination	4 GNSS integration	5 Yield mapping	6 Multi-field validation
Potato	Contact/weight-based (C)	✓ (C)	✓ (C)	limited (C)	—	—	limited (C)
	Vision/indirect (V)	✓ (V)	✓ (V)	✓ (V)	partial (V)	partial (V)	limited (V)
	Integrated (I)	✓ (I)	✓ (I)	✓ (I)	partial (I)	partial (I)	limited (I)
Radish	Contact/weight-based (C)	✓ (C)	✓ (C)	developing (C)	— not reported	— not reported	— not reported
	Vision/indirect (V)	✓ (V)	✓ (V)	developing (V)	— not reported	— not reported	— not reported
	Integrated (I)	✓ (I)	✓ (I)	developing (I)	— not reported	— not reported	— not reported
Sweet potato	Contact/weight-based (C)	limited (C)	limited (C)	limited (C)	— not reported	— not reported	— not reported
	Vision/indirect (V)	limited (V)	limited (V)	limited (V)	— not reported	— not reported	— not reported
	Integrated (I)	limited (I)	limited (I)	limited (I)	— not reported	— not reported	— not reported
Carrot	Contact/weight-based (C)	limited (C)	limited (C)	limited (C)	— not reported	— not reported	— not reported
	Vision/indirect (V)	limited (V)	limited (V)	limited (V)	— not reported	— not reported	— not reported
	Integrated (I)	limited (I)	limited (I)	limited (I)	— not reported	— not reported	— not reported

Figure 8. Qualitative literature-based evidence coverage of Korean yield-monitoring research, distinguishing contact/weight-based (C), vision/indirect (V), and integrated multi-sensor (I) evidence where applicable. The evaluated capabilities comprise sensor feasibility, dynamic-condition validation, crop/mass discrimination, GNSS integration, yield mapping, and multi-field validation. Status categories are Demonstrated, Partial implementation, Developing, Limited evidence, and Not reported, as defined in Section 2.3. These categories represent a qualitative synthesis of the reviewed literature and do not constitute formal technology readiness levels (TRLs). Author-developed qualitative synthesis of the peer-reviewed literature reviewed in this article.

7. Challenges and Future Directions

Although contact- and weight-based yield sensing has demonstrated good calibration performance for potatoes, radishes, grains, and other crops, field implementation remains limited by machine dynamics, crop contamination, calibration transfer, and spatial assignment. These constraints are particularly important for Korean root- and tuber-crop harvesting because compact machines operate in short rows, on variable slopes, and under highly dynamic digging and conveying conditions.

Machine vibration is one of the dominant error sources in load-cell and impact-based yield measurement. Digging blades, shaker webs, conveyors, engines, crop impacts, and uneven terrain generate forces that can overlap with the crop-mass signal. Korean potato and radish studies have shown that vibration and slope can substantially increase measurement error, even when static calibration is highly linear [21,26]. Inclination introduces an additional error because changes in machine pitch or conveyor angle modify the gravitational component acting on the weighing structure. Filtering can reduce vibration-related noise, but excessive smoothing may suppress genuine short-term crop-flow variation and reduce spatial resolution. Reliable field measurement therefore requires coordinated mechanical isolation, inclination sensing, and dynamic signal processing rather than filtering alone.

Calibration relationships are affected by crop size, variety, crop-flow rate, belt speed, soil moisture, temperature, sensor aging, and machine configuration. Calibration obtained using clean crops under laboratory conditions may therefore not remain valid during com-

mercial harvesting. Davenport et al. [63] similarly reported machine- and field-dependent differences in potato yield-monitor performance. For root-crop monitoring, static calibration establishes basic sensor sensitivity, whereas dynamic calibration and independent field validation determine practical performance. Tare drift caused by soil accumulation, plant residues, belt-tension variation, or residual material can also create cumulative error. Consequently, reporting only (R^2) is insufficient; cumulative mass error, RMSE, MAE, bias, repeatability, and field-validation error provide more meaningful measures of system performance.

Direct weighing measures all material transmitted through the sensing point. For underground crops, this may include soil, stones, foliage, vines, clods, and other residues. The resulting signal can therefore represent gross transported mass rather than actual crop yield. This problem is strongly influenced by sensor location. Measurement immediately after digging captures most recovered material but includes greater contamination, whereas measurement after soil separation produces a cleaner signal but excludes crop lost upstream. Yield-monitoring studies should therefore distinguish among gross harvested mass, recovered yield, cleaned yield, and marketable yield.

Korean potato machine-vision studies provide a complementary pathway for resolving this limitation by distinguishing potatoes from soil, stones, and plant residues [23,71]. Combining crop classification with direct mass measurement is therefore particularly relevant for root crops. Mass-measurement accuracy does not necessarily ensure accurate yield mapping. Roots and tubers require time to move from the digging point through separation and conveying systems before reaching the yield sensor. The measured crop mass must therefore be shifted spatially to its original harvesting location.

This issue is especially important in Korean fields because short rows, frequent stops, and headland turns increase the proportion of transient data. Crop remaining on a conveyor after leaving a row can otherwise be assigned to an incorrect location. Yield map research has shown that time lag, field boundaries, machine transitions, and erroneous observations can substantially distort spatial patterns [76,77]. Korean grain monitoring systems have demonstrated the effectiveness of time-delay correction and machine-state filtering for improving spatial yield assignment [70,74].

Korean root-crop harvesters are generally compact, leaving limited space for isolated weighing structures, protective frames, electronics, and wiring. Sensors are also exposed to mud, water, stones, vibration, and repeated cleaning. These factors increase the importance of rugged mounting, overload protection, sealed electronics, accessible zeroing, and rapid calibration. The degree of mechanization also differs among crops. Potato and radish harvesters can provide relatively controlled crop-flow pathways, whereas sweet potato and some carrot operations remain partially mechanized. Consequently, a single monitoring architecture cannot be applied uniformly across crops. The principal technical challenges and their implications are shown in Table 9. Interoperability remains another limitation. Sensor data, GNSS, machine state, and operating parameters are often acquired using separate hardware. Standardized machine communication and data formats, following principles similar to ISO 11783/ISOBUS, can reduce integration complexity and facilitate future commercialization [78].

Future development in Korea should focus on converting successful sensor-level studies into crop-specific, field-validated monitoring systems. The major research need is not the introduction of additional sensing principles, but improved integration of direct mass measurement with machine dynamics, crop cleaning, positioning, and data quality. Different harvesting pathways require different measurement configurations. For potatoes, conveyor-based load-cell weighing after major soil separation represents the most suitable continuous approach. For radishes, event-based conveyor or impact sensing is appropriate

because individual roots generate discrete load events. For sweet potatoes, hopper, cart, or crate weighing is more compatible with semi-mechanized collection and lower-impact handling. For carrots, conveyor or hopper measurement after foliage and soil removal appears most applicable.

Table 9. Principal technical challenges and their implications for contact- and weight-based yield monitoring of Korean root and tuber crops.

Technical Challenge	Main Effect on Measurement	Relevant Mitigation
Vibration and shock	Produces false dynamic loads and unstable sensor signals	Mechanical isolation, vibration characterization, and validated signal filtering
Inclination	Alters the gravitational component measured by the load cell	Geometry-specific IMU/tilt compensation with experimental validation under representative pitch and roll conditions
Calibration drift	Causes condition-dependent measurement bias	Static and dynamic calibration with independent field validation
Soil and debris	Causes overestimation because non-crop materials contribute to measured mass	Sensor placement after soil separation and crop/non-crop discrimination
Tare variation	Produces progressive zero shift and cumulative mass error	Empty-system zeroing, baseline monitoring, and automatic tare correction
Crop transport delay	Assigns measured yield to an incorrect field position	Time-lag correction based on crop transport time and machine state
Short rows and headlands	Generates transient or false high/low yield values during starts, stops, and turns	Start/stop detection, headland filtering, and operation-state classification
Compact machinery	Limits available space for weighing structures, electronics, and isolation components	Compact modular sensing units and sensor-integrated machine design
Crop damage	Reduces marketable quality, particularly in impact-based systems	Low-impact sensing, optimized drop height/contact surface, and crop-damage evaluation

A Korea-specific evaluation framework would substantially improve comparability among studies. Evaluation should include static calibration, multiple crop-flow rates, belt or travel speeds, representative slopes, realistic vibration, soil contamination, independent reference weighing, and repeated field runs. Field studies should report cumulative mass error together with RMSE, MAE, bias, relative error, and spatial mapping accuracy. For impact-based systems, crop damage should also be evaluated because sensing performance and handling quality are directly linked.

A promising development pathway is the integration of load-cell measurement with machine vision. Direct weighing can provide total transported mass, while image analysis can identify crop, soil, stones, foliage, and potentially damaged produce. This combination could support estimation of crop, non-crop, cleaned, and potentially marketable mass fractions, provided that the relationship between visual classifications and their respective mass contributions is independently calibrated and validated. Such an approach is particularly relevant to Korean potato and radish harvesting, where soil contamination can substantially affect direct weight measurements. Korean machine-vision studies already provide a technical basis for crop/foreign-material discrimination [23,71].

Yield sensing is more reliable when considered during machine design rather than retrofitted after harvester development. Future Korean machines can incorporate stable weighing sections, protected sensor locations, overload stops, belt-speed sensing, GNSS, IMU data, and accessible calibration points. Standardized timestamps and interoperable data formats are also important for combining load-cell, GNSS, IMU, encoder, and vision data. Compatibility with broader smart-farming platforms would allow yield information to support not only mapping but also harvest logistics, field accounting, and long-term management. The next stage of Korean research should progress from laboratory and single-field tests to field-scale, multi-region, and multi-season validation. This is particularly important for potatoes and radishes, where existing studies have already demonstrated sensor feasibility but limited commercial-scale validation.

Deployment models should also reflect Korean farm structure and a development pathway for yield monitoring of Korean root and tuber crops is shown in Figure 9. Cooperative ownership, agricultural machinery rental centers, contractors, and shared harvesting services may provide greater equipment utilization than individual ownership by small farms. Korean smart-farm research has similarly shown that cost and compatibility with existing production systems influence technology adoption [79]. Thus, sensing architecture should follow the crop-flow pathway rather than using a common sensor configuration for all root crops.

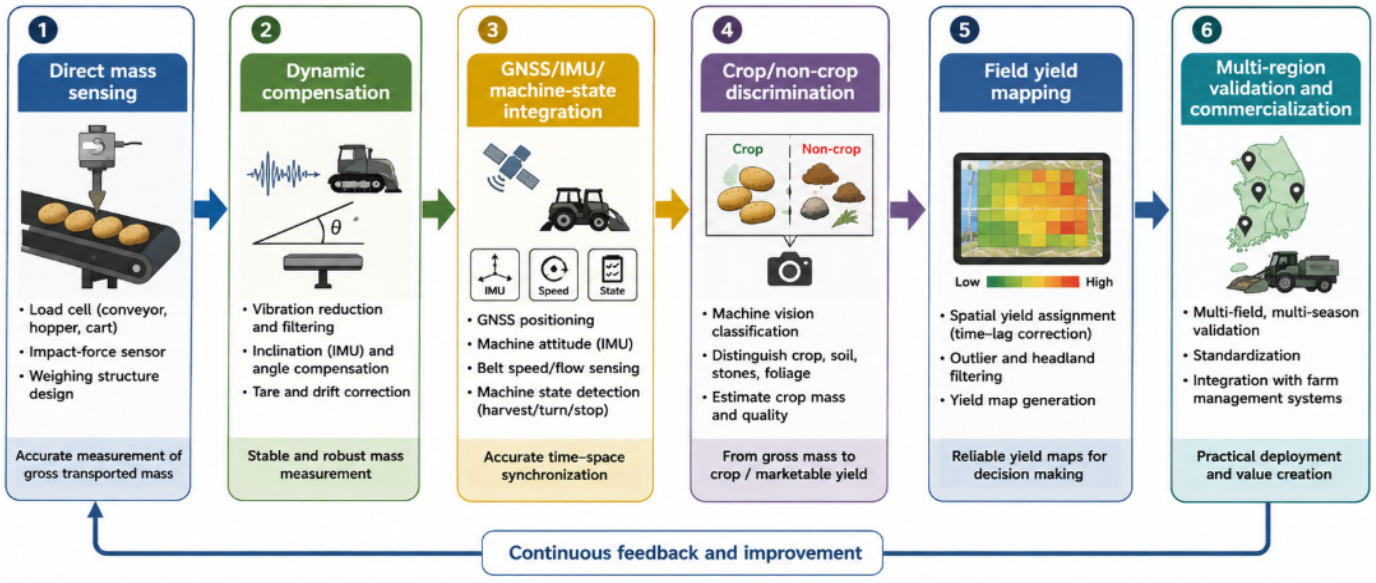


Figure 9. Author-proposed research sequence derived from the technical gaps identified in this review; the sequence is conceptual and does not represent a validated technology-development model.

Practical adoption depends on whether measurement accuracy can be maintained at commercially relevant crop throughput and at a cost compatible with the scale of Korean

farms. These aspects remain poorly documented in the Korean root-crop yield-monitoring literature. Most published studies report sensing or algorithmic accuracy but do not provide complete information on sensor bill-of-materials cost, retrofit cost, calibration labor, annual maintenance, service life, downtime, or economic payback. The absence of these data currently prevents a defensible comparison of cost-effectiveness among load-cell, impact, conveyor, hopper, and hybrid monitoring architectures.

Throughput evidence is similarly limited. Jang et al. [23] reported frame dropping during complete real-time processing of 1080p, 30-fps imagery, illustrating the difference between detector accuracy and system-level computational capacity. In the subsequent potato mass-estimation study [71], continuous-flow evaluation was conducted at approximately three potatoes s^{-1} using three repeated 400-potato tests, but the system remained a laboratory prototype rather than a validated commercial-throughput monitor. Thus, neither high detection accuracy nor low static weighing error should be interpreted as evidence of commercially adequate throughput.

No peer-reviewed Korean study identified in this review documented a commercially available contact/weight-based root-crop yield monitor with simultaneously reported installed cost, rated crop throughput, field capacity, calibration time, maintenance requirement, and payback period. These parameters should therefore become explicit reporting requirements in future field studies. For small and fragmented Korean farms, economic viability may also depend on annual machine utilization; contractor operation, machinery-rental centers, cooperatives, or shared harvesting services may achieve higher utilization than individual farm ownership. The principal commercialization-related evidence gaps identified in the reviewed Korean studies, together with recommended reporting parameters for future yield-monitoring research, are summarized in Table 10.

Table 10. Practical commercialization information that should be reported for Korean root-crop yield-monitoring systems.

Criterion	Current Evidence in Korean Root-Crop Studies	Recommended Future Reporting
Sensor/retrofit cost	Rarely reported	Hardware, installation, computing, and protection cost
Crop throughput	Mainly test-bench/prototype conditions	kg s^{-1}, plants/tubers s^{-1}, rated and maximum throughput
Computational performance	Limited reporting	FPS/latency, frame loss, processor specification
Calibration burden	Generally experimental	Time per calibration, frequency, reference-mass requirement
Maintenance	Rarely quantified	Cleaning, zeroing, sensor replacement, downtime
Commercial availability	Research prototypes predominate	Product status and compatible harvester models
Economic performance	Payback generally unavailable	Cost ha^{-1}, annual utilization, service life, payback period

Overall, the Korean research priority is to move from accurate individual sensors to validated harvesting systems. Potatoes currently provide the strongest opportunity for continuous conveyor weighing, radishes for event-based dynamic sensing, and sweet potatoes and carrots for batch or collection-based weighing. Integration of direct mass sensing with vibration compensation, GNSS, machine-state information, and crop recognition is likely to provide the most technically robust pathway toward practical root- and tuber-crop yield monitoring in Korea.

8. Conclusions

This review evaluated contact- and weight-based yield-monitoring technologies for major Korean root and tuber crops while distinguishing direct gravimetric weighing from contact dynamic/impact-based mass estimation and indirect vision-based approaches. Gravimetric conveyor, hopper, bin, and cart weighing provide the most physically interpretable relationship with harvested mass, whereas impact sensing requires calibration against crop velocity and collision conditions. Across all approaches, field performance depends strongly on machine dynamics, contamination, calibration transfer, and spatial synchronization rather than nominal sensor accuracy alone.

The Korean evidence remains uneven across crops and validation levels. Potatoes have the strongest root-crop evidence, including laboratory and prototype studies of load-cell and impact sensing and separate field or harvester studies using machine vision and RTK-GPS. However, these developments should not be interpreted as a fully validated GNSS-synchronized direct weighing system, and multi-field validation remains limited. Radish impact sensing has been evaluated under controlled vibration and slope conditions, demonstrating dynamic feasibility but also substantial sensitivity to operating conditions; complete field-scale GNSS yield mapping has not yet been demonstrated. For sweet potatoes and carrots, direct Korean yield-monitoring evidence remains sparse, and the proposed hopper-, cart-, batch-, or post-cleaning conveyor architectures are therefore engineering recommendations based partly on harvesting configuration and transferable international evidence rather than field-validated Korean systems.

The principal research need is consequently the transition from individual sensor feasibility to complete harvesting-system validation. Priority areas include dynamic calibration over representative throughput, vibration and slope; quantitative treatment of soil and foreign material; tare and calibration-transfer control; synchronization of mass sensing with conveyor speed, machine state, and GNSS; independent reference weighing; and multi-field, multi-region, and multi-season testing. Hybrid machine vision may assist crop/non-crop interpretation, but quantitative separation of gross mass into cleaned or marketable yield requires independent validation of the corresponding mass fractions.

Practical adoption also requires reporting of throughput, calibration time, maintenance requirements, installed cost, reliability, and economic payback. These parameters remain insufficiently documented for Korean root-crop yield monitors. Future development should therefore prioritize crop-specific systems whose technical and economic performance is demonstrated under commercial harvesting conditions rather than extrapolated solely from laboratory calibration or isolated sensing accuracy.

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