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Nevada Department of Transportation

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Comparison and Evaluation of Roadside Animal Sensing and Driver Warning Systems

April 2026

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16. Abstract

Animal-vehicle collisions involving large animals, particularly wild/feral horses and deer, pose a serious safety risk on Nevada roadways. The Nevada Department of Transportation (NDOT) sponsored a field evaluation of four roadside sensing technologies: radar, thermal infrared cameras, LiDAR, and optical cameras, deployed concurrently on an NDOT intelligent transportation system trailer at a wild/feral horse corridor in Storey County, Nevada. Three 14-day data collection cycles were conducted in October 2023, February 2024, and October 2024, capturing 187 confirmed horse presence events. Detection performance was evaluated against a thermal video ground-truth baseline using true positive, false positive, and false negative rates, stratified by distance and time of day. The report provides information and recommendations for sensor selection, deployment infrastructure, and operations to guide future NDOT roadside animal detection and driver warning system deployments.

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Comparison and Evaluation of Roadside Animal Sensing and Driver Warning Systems

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Prepared by:
Hao Xu | University of Nevada, Reno
Fraser Shilling | University of California, Davis
Jeff Gagnon | Arizona Game and Fish Department
Tim Hazlehurst | CrossTek Electrified Barriers, LLC

Field Evaluation of LiDAR, Radar, Thermal, and Optical Camera Sensing Technologies

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The project was carried out by a multidisciplinary team: Hao Xu, Ziru Wang, and Fei Guan of the Center of Advanced Transportation Education and Research, University of Nevada, Reno; Fraser Shilling and Vedant Srinivas of the Road Ecology Center, University of California, Davis; Tim Hazlehurst of CrossTek Electrified Barriers, LLC; and Jeff Gagnon, Brianna Russo, and Colin Beach of the Arizona Game and Fish Department, which also served in an independent evaluation role. The team also thanks Teledyne/FLIR for donating the Ranger R2 radar unit evaluated in this project.

EXECUTIVE SUMMARY

Animal-vehicle collisions (AVCs), particularly those involving large animals such as wild/feral horses and deer, continue to pose a serious safety risk on Nevada roadways. While fencing and wildlife crossings are highly effective, they are often infeasible due to cost, access requirements, right-of-way constraints, and site-specific land-use conditions. To address these gaps, the Nevada Department of Transportation (NDOT) sponsored this field evaluation of the most likely roadside sensing technologies for animal detection as a flexible mitigation alternative.

This project conducted a side-by-side, real-world evaluation of four roadside sensing technologies for automatic animal detection: radar, thermal passive infrared cameras, light detection and ranging (LiDAR), and optical cameras, using a standardized NDOT intelligent transportation system (ITS) trailer platform. All sensing systems operated concurrently under identical power, environmental, and communication conditions. The goal was to quantify detection accuracy and operational feasibility under Nevada conditions.

Three standardized 14-day continuous monitoring cycles were completed at a wild-horse-active corridor near Electric Avenue and Venice Drive in Storey County, in October 2023, February 2024, October 2024. Across the three cycles, 187 confirmed wild/feral horse presence events were recorded (73, 52, and 62 in the three cycles), representing more than 147 hours of animal presence near the roadway. Events were analyzed by distance from the sensor location and by daytime vs. nighttime conditions.

A rigorous ground-truth baseline was established through continuous thermal video review using independent reviewers. Automated detections from each sensing system were compared against this baseline to compute true positives (detection event recorded with animal presence confirmed), false negatives (animal presence confirmed without detection event recorded), and false positives (detection event recorded without confirmed presence of animals) within each respective sensor field of view.

The four sensing systems each brought distinct technical characteristics to the evaluation. The following summarizes each technology's profile:

Radar (Teledyne/FLIR R2): Detects moving objects via radio-wave reflection. Selected for its long range and all-weather, 24/7 capability. Strengths: longest detection range (~4,200 ft), insensitive to darkness and fog, tracks multiple targets simultaneously, filters vehicles from slower-moving animals. Limitations: cannot visually confirm targets, highest false positive rate among systems tested, requires tuning to suppress environmental noise. Approximate unit cost: $50,000–$65,000. Power demand: ~45 W for the radar unit; ~150 W for the combined thermal and radar system, including shared processing and communication components. Effective detection range: up to 4,200 ft.

Thermal Infrared Camera (FLIR Traffisense2): Detects heat signatures of warm-bodied animals. Selected for reliable nighttime and low-visibility detection. Strengths: effective in complete darkness, unaffected by headlight glare, configurable detection zones, dual use as detection sensor and ground-truth tool. Limitations: performance sensitive to configuration (size filters, field of view, timestamp alignment), reduced contrast in hot ambient conditions, higher data processing requirements. Approximate unit cost: $3,000 - $8,000. Power demand: ~14 W per camera (~28 W for the two cameras deployed) plus up to 65 W for associated interfaces and processing hardware. Effective detection range: 300 - 1,000 ft (recognition range ~300 - 500 ft).

LiDAR (Velodyne VLP-32C): Emits laser pulses to generate 3D point cloud data. Selected for precise spatial detection, object tracking, and trajectory analysis. Strengths: low false positive rates, 360-degree coverage, enables vehicle and animal trajectory analysis, consistent across lighting conditions. Limitations: effective range limited to ~300 ft effective detection radius under field conditions, complex integration and higher cost than optical systems, performance sensitive to algorithm tuning. Approximate unit cost: $8,000–$15,000. Power demand: <15 W per sensor plus <60 W for the edge computer (~75 W for a single sensor; ~100 W for two to three sensors). Effective detection range: ~300 ft radius.

Optical Camera (SCW Sharpshooter, 2 MP + NVIDIA Jetson edge compute): Uses AI-based computer vision on live video. Selected for low cost, daytime classification capability, and species identification. Strengths: lowest unit cost, lowest false positive rates, provides visual confirmation and species-level classification, low power draw. Limitations: strongly dependent on lighting, effectiveness drops sharply at night and in adverse weather; not designed for standalone 24-hour operation. Approximate unit cost: $800 - $1,200. Power demand: up to 31 W (21 W camera plus 10 W edge device). Effective detection range: ~300 - 500 ft (daytime).

Detailed field performance results for each system across all three data collection cycles are presented in Chapter 5.

Deployment and operational insights

Operating a multi-sensor system continuously in remote locations proved far more demanding than anticipated. Power requirements were underestimated, especially in winter. Despite solar, wind, and battery upgrades, daily generator operation was required during intensive data collection. All sensing systems required maintenance, recalibration, or replacement at least once during the project.

Wild/feral horse movement patterns were found to be highly dynamic. Construction, land-use changes, and water availability altered movement behaviors, sometimes eliminating activity at previously selected sites. This reinforces the need for flexible deployment strategies and careful site validation.

Implications for NDOT

Each of the four sensing systems evaluated in this study represents a specific product with its own integration of software, hardware, and system configuration. Although only one product from each sensing category was tested, the results demonstrate that accurate and reliable detection of wild/feral horses and other large animals in areas adjacent to the roadway is feasible. Alternative or newer versions of these sensing technologies, incorporating enhanced software and hardware, may further improve large animal detection performance.

Although the systems were evaluated independently, the performance results for each system support estimation of the potential performance of combined sensing approaches. No single sensing technology (and associated analytics) evaluated in this study was able to achieve 100% accuracy across all distances, lighting conditions, and seasons. The results strongly support a multi-sensor approach, where detection strength and false-alert control are balanced through complementary technologies. Roadside animal detection and driver warning systems should be viewed as targeted safety tools for high-risk locations where traditional mitigation is impractical or not desirable.

It should be noted that the field of view for the technologies evaluated in this study was located adjacent to a busy highway with heavy traffic during morning and evening periods. Detection of animals within the travel lanes was not evaluated and should be considered in future deployments.

Based on the evaluation results, the study offers actionable recommendations to guide NDOT on sensor selection, multi-sensor fusion strategies, deployment infrastructure, driver alert integration, and long-term operations and maintenance. Key themes include the advantages of multi-sensor configurations over single-sensor deployments, the preference for permanent utility-powered installations over trailer-based platforms for long-term use, and the critical importance of robust infrastructure and maintenance planning for reliable operation under Nevada's roadside conditions. Full recommendations are provided in Chapter 7.

Table 1 presents a comparative summary of costs and power consumption for the four sensor types evaluated in this study. Unit costs reflect sensor hardware and edge computing equipment; they do not include installation, civil works, power infrastructure, or ongoing maintenance, which can vary substantially by site and should be considered when projecting total deployment costs. Effective distances represent the approximate range within which each sensor reliably detects large animals under field conditions. Cost-per-foot values are calculated based on a single sensor's effective coverage radius. Given that the radar system demonstrated an effective range of approximately 4,200 feet, it offers low cost-per-foot coverage despite its substantially higher unit cost, making it particularly well suited for deployments where a single unit must monitor long highway segments.

Table 1. Comparison of Costs and Power Consumption of Sensing System Evaluated in This Project

Device Type	Cost (Sensor + Compute)	Effective Deployment (month)	Power Demand (Sensor + Compute, W)	Effective Distance (feet)	Cost/Distance ($/foot)
LiDAR	$12,000	48	75 (1 sensor + 1 edge computer)	300 (radius for 360-degree sensing)	$200
Thermal	$8,000	36	14 (1 camera) + up to 65 (interfaces and processing)	500	$160
Radar	$60,000	36	45 (radar unit); ~150 (combined thermal and radar system)	4200 (radius for 360-degree sensing)	$7
Optical	$929	48	31 (1 sensor + 1 edge computer)	300	$3

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LIST OF ABBREVIATIONS

Alternating Current (AC)
Animal Activation Detection System (AADS)
Animal Detection and Driver Warning System (ADDWS)
Animal-Vehicle Collision (AVC)
Arizona Game and Fish Department (AGFD)
Artificial Intelligence (AI)
Central Processing Unit (CPU)
Comma-Separated Values (CSV)
Direct Current (DC)
False Negative (FN)
False Positive (FP)
Federal Highway Administration (FHWA)
Field of View (FOV)
Graphics Processing Unit (GPU)
Infra Eco Network Europe (IENE)
Infrared (IR)
Intelligent Transportation System (ITS)
Light Detection and Ranging (LiDAR)
Nevada Department of Transportation (NDOT)
Pan-Tilt-Zoom (PTZ)
Passive Infrared (PIR)
Power over Ethernet (PoE)
Roadside Animal Detection System (RADS)
Tahoe-Reno Industrial Center (TRIC)
True Positive (TP)
University of California, Davis (UCD)
University of Nevada, Reno (UNR)
Variable Message Sign (VMS)
Western Transportation Institute (WTI)
Wildlife-Vehicle Collision (WVC)

1. INTRODUCTION

Large animals (deer, elk, wild/feral horses, livestock etc.) on highways present a significant safety hazard in Nevada, leading to frequent animal-vehicle collisions (AVCs) with serious human and ecological consequences. Each year in Nevada, vehicle collisions with wild or feral animals result in over 500 reported crashes, costing the public more than $19 million in associated damages and killing thousands of animals [1]. These incidents cause not only property damage but also human injuries and fatalities, while impacting animal populations. Traditional mitigation measures such as exclusionary fencing have proven highly effective at reducing AVCs (often reducing collisions by 80% or more) when combined with wildlife over and under crossings, but they are expensive and not always feasible due to high costs, right-of-way constraints, and site-specific limitations. Many Nevada roadways cannot readily accommodate extensive fencing or grade-separated crossings, especially where land use and access needs make such infrastructure impractical. This has motivated interest in alternative solutions to reduce AVCs. In this context, roadside animal detection systems (RADS) with active driver warning systems have emerged as a promising tool to dynamically alert motorists when large animals are on or near the roadway, potentially prompting drivers to slow down and avoid collisions. The Nevada Department of Transportation (NDOT) has identified reducing AVCs as a safety priority, prompting the exploration of technology-based mitigation strategies alongside traditional methods.

1.1.Problem Statement and Research Objectives

Despite rapid advances in sensor and detection technologies, transportation agencies currently lack an objective, up-to-date comparison of modern animal detection systems under real-world highway conditions. Numerous RADS technologies have been piloted to detect animals and trigger driver warning systems, including underground cable systems, break-the-beam systems, short-range motion detection, collared animal presence detection systems, thermal infrared cameras, radar systems, and LiDAR units. However, their relative performance, reliability, and practical requirements have not been consistently quantified under Nevada's unique roadway, environmental, and animal movement conditions.

To meet this need, NDOT sponsored this field study to evaluate several of the most promising roadside animal sensing systems side-by-side, under identical environmental and traffic conditions, and to assess their detection performance for large animals. The results provide NDOT and other agencies with evidence-based guidance on the effectiveness, advantages, and limitations of each sensing technology to support informed deployment decisions.

The primary goals of the study were to:

- Evaluate and compare multiple roadside sensing technologies for automatic animal detection, including LiDAR, optical camera, thermal, and radar. Each system was assessed using consistent criteria to ensure a technology-neutral comparison without bias toward any specific system or manufacturer. The evaluation measured detection completeness, classification accuracy, false alarm rates, and sensitivity to relevant animal movements.
- Assess practical deployment considerations, including equipment cost, power and communication requirements, installation and maintenance needs, and data management. The assessment considered both detection capability and the feasibility of deploying and

operating each technology in Nevada's highway environments, including remote locations.

- Develop implementation recommendations for NDOT based on evaluation results, including guidance on system selection, deployment strategies, and potential expansion of roadside animal detection and driver warning systems on Nevada highways.

1.2.Sensor Technologies Evaluated

Four sensor technologies representing a range of established large-animal detection approaches were evaluated in this project. All systems were installed on an NDOT ITS trailer and operated concurrently, enabling direct side-by-side comparison under identical environmental, power, and communication conditions. Full technical descriptions of each system, including hardware specifications, software, and configuration details, are provided in Chapter 2.

- **Passive Thermal Imaging Cameras:** Thermal cameras detect animals based on their heat signatures rather than reflected light, enabling reliable detection in complete darkness and low-visibility conditions. This makes them particularly well suited for nighttime monitoring along roadways where most large-animal collision risk occurs. Thermal cameras were selected for their proven performance in prior roadside animal detection deployments and their ability to serve as both a detection sensor and a ground-truth validation tool.
- **Radar Systems:** Radar uses radio-wave reflections to detect moving objects, offering long detection range and all-weather, day-and-night operation. Radar can track multiple targets simultaneously and filter higher-speed objects such as vehicles from slower-moving animals, making it well suited for roadside applications. A radar system was selected for its long-range capability and its potential to complement shorter-range sensing technologies in a multi-sensor configuration.
- **Light Detection and Ranging (LiDAR):** LiDAR sensors actively scan roadside areas using laser pulses to generate precise three-dimensional point cloud data. This capability supports detection and tracking of animals based on shape and movement, making it well suited for applications requiring accurate spatial awareness and object classification. LiDAR was selected for its ability to provide high-resolution, 360-degree coverage and to enable analysis of both animal and vehicle trajectories within the detection zone.
- **Optical Camera Systems:** Optical cameras use visible-light imaging combined with artificial-intelligence-based computer vision algorithms to detect and classify animals in real time. This approach leverages rapid advances in machine learning and offers a low-cost sensing option with the ability to provide species-level classification. Optical cameras were selected for their affordability, compatibility with existing ITS infrastructure, and capacity for automated detection without requiring specialized hardware.

1.3.Study Sites and Field Deployment

Field deployment was conducted at the intersection of Electric Avenue and Venice Drive in Storey County, Nevada, located within the Tahoe-Reno Industrial Center. This corridor was selected due to its documented wild/feral horse activity and its representation of the industrial

and semi-rural roadway conditions common across Nevada. Full details on site selection history, site characteristics, traffic conditions, and animal activity confirmation are provided in Section 2.1.

1.4.Project Timeline (2020–2025)

This project was conducted from late 2020 through 2025, spanning five years due to the compounding demands of field research in a remote, uncontrolled environment, as summarized in Table 2. Site relocation, power system failures, hardware delays, and the need to capture multiple seasons of data each required significant time to resolve before valid multi-sensor comparison could be achieved. The full account of project activities, challenges, and solutions by year is provided in Chapter 6.

Table 2 Project Timeline Summary

Phase	Period	Key Activities
Planning & Design	2020	System design, site selection, power system planning
Initial Deployment	2021	First site deployment, initial sensor integration
Sensor Expansion	2022	Full sensor suite installation, site relocation
Power Overhaul	2023	Power system redesign, first complete data collection cycle
Data Collection	2023–2024	Three 14-day multi-sensor evaluation cycles
Analysis & Reporting	2025–2026	Data analysis, findings, and final report

1.5.Project Team and Collaboration

This NDOT-sponsored research was conducted by a multidisciplinary team. UNR researchers led the project and coordinated system integration, deployment, operation, and maintenance. The UNR team also led the deployment of the roadside LiDAR sensing system and supported other teams' installation and maintenance of their sensing systems. Researchers from the Road Ecology Center at the University of California, Davis (UCD) contributed expertise in wildlife ecology, animal-vehicle conflict mitigation, and AI-supported optical camera sensing. The CrossTek team and partners supported hardware design, system integration, and the thermal and radar sensing systems. NDOT project champions, NDOT District II, the NDOT Traffic Operations Division, and the Research Office were actively involved in site selection, permitting, and deployment support. The Arizona Game and Fish Department (AGFD) participated throughout the project, contributing practical experience from a roadside animal sensing user perspective and serving in an independent evaluation role. This collaboration ensured that the study combined technical rigor with practical applicability. The results are intended to support informed decision-making to improve roadway safety and reduce animal-vehicle collisions in Nevada.

2. ROADSIDE ANIMAL SENSING SYSTEMS

2.1.Site - Electric Avenue & Venice Drive, Nevada

The final study site selected for field deployment was the intersection of Electric Avenue and Venice Drive in Storey County, Nevada, located immediately east of the Tahoe-Reno Industrial Center (TRIC), as shown in Figure 1 map. Electric Avenue is a two-way, two-lane industrial connector extending from USA Parkway (State Route 439) to the Tesla Gigafactory, providing the primary public access route to Tesla and other major industrial, logistics, and data-center facilities within TRIC. Venice Drive intersects Electric Avenue from the south at the study location. As a result, the corridor carries a mix of commuter and freight traffic associated with industrial shift changes and product movement.



Figure 1. Sensor evaluation site at Electric Avenue and Venice Drive, Storey County, Nevada

The surrounding environment is characterized by sparsely developed desert terrain with low sagebrush vegetation. While industrial development is concentrated near the Gigafactory to the east, much of the corridor traverses open rangeland. Portions of the roadway are fenced, but wild/feral horse access remains prevalent. The site lies within a semi-arid basin grassland ecosystem and overlaps with documented wild/feral horse habitat. Regional observations and agency reports indicate that large wild/feral horse populations occupy the broader TRIC area and the entire Virginia Range between I-80 to the north, US 50 to the South, I-580 to the west, and US 95 to the east.

Wild/feral horse activity at the site was confirmed through LiDAR monitoring conducted from June 21 to June 28, 2021, shortly after the sensing trailer was relocated to this location. During this one-week period, seven wild/feral horse crossing events were detected, including four events on June 22 and three events on June 26. And all flagged events were manually reviewed and confirmed as horses. These observations demonstrate that wild/feral horse activity at the site occurs with sufficient frequency to interact with roadway traffic. Figure 2 is a field photo showing wild/feral horses nearby Electric Avenue at the site; Figure 3 shows a photo of wild/feral horses crossing Venice Drive.



Figure 2. A site photo with wild/feral horses, the sensor trailer and traffic on Electric Avenue



Figure 3. Wild/feral horses crossing Venice Drive

Traffic volumes on Electric Avenue exhibit distinct weekday commuting patterns based on one-week traffic study data generated by the LiDAR sensor on the sensing trailer. Weekday traffic volumes ranged from approximately 11,800 to 12,800 vehicles daily traffic, while weekend volumes declined to approximately 7,600 to 8,000 vehicles daily traffic. Directional traffic volumes were nearly balanced. Peak traffic periods occurred during early morning (approximately 5:00-6:45 AM) and late afternoon to early evening hours (approximately 5:00-6:30 PM), corresponding with industrial shift changes. Heavy vehicles longer than 30 ft accounted for approximately 4 to 5 percent of total traffic, with higher truck volumes observed on weekdays than weekends. The intersection is unsignalized, with turning movements accommodated by marked lanes. Paved shoulders are present near the study location. It should be noted that the ambient lighting was high given the industrial lighting environment, particularly light coming from the Giga Factory.

The sensing trailer was deployed at the southwest corner of the intersection to collect high-resolution vehicle and wild/feral horse trajectory data. Due to the very narrow county rights-of-way along Electric Avenue and Venice Drive, the trailer could not be placed within the public roadway corridor, but was therefore installed on Tesla-owned property, and the project team obtained permission from Tesla to place and operate the system at this location. This deployment configuration provided a realistic and representative setting for evaluating roadside sensing technologies under active traffic, animal presence, and environmental conditions typical of industrial corridors in Nevada.

2.2.NDOT ITS Trailer Deployment Platform

All sensing, computing, and communication equipment evaluated in this project was deployed on a standardized NDOT ITS trailer, which served as a self-contained, mobile roadside platform. Components of the sensing systems and the trailer are demonstrated in Figure 4. The trailer enabled deployment at locations without permanent infrastructure and supported continuous operation under harsh environmental and roadside conditions. Core platform components included off-grid power generation and storage, onboard computing hardware, sensor mounting infrastructure, and wireless communications.

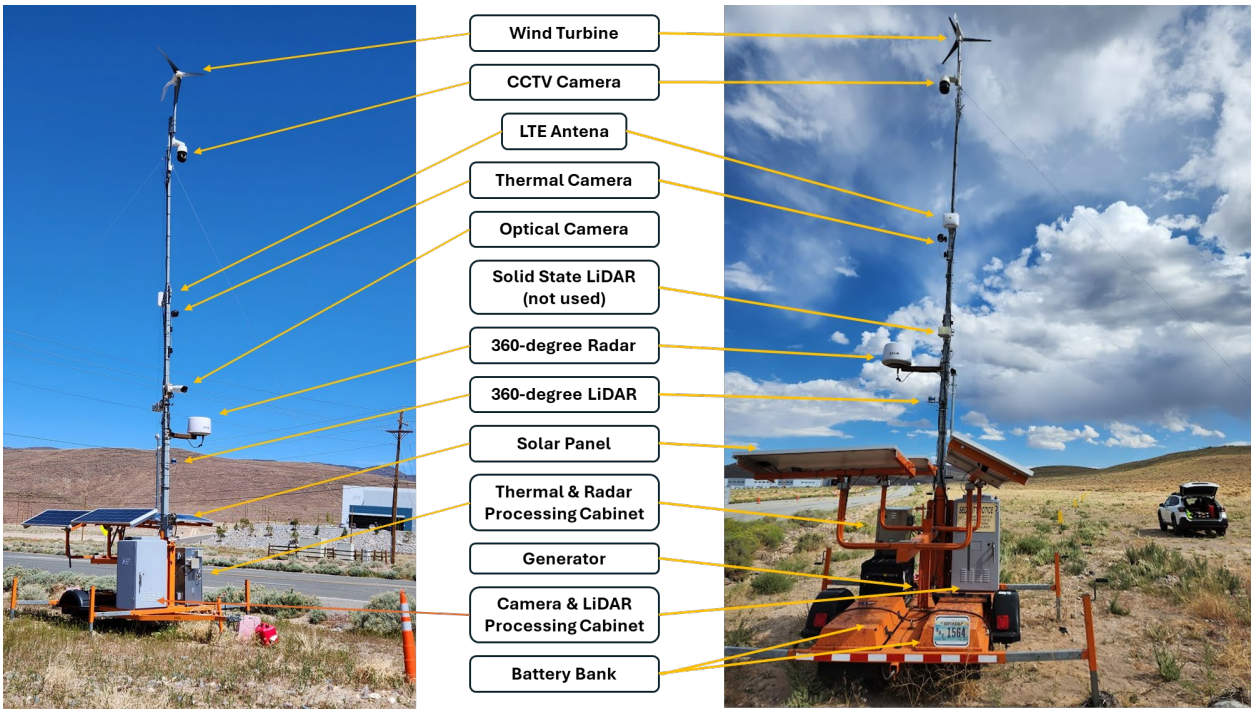


Figure 4. NDOT ITS trailer used as the evaluation platform for LiDAR, optical camera, radar, and thermal sensors. The left image shows the trailer oriented towards the northeast, and the right image shows the trailer oriented towards the south.

Primary power was supplied by solar panels supplemented with a wind turbine. A battery storage system with integrated power management electronics provided voltage stabilization for sensitive sensing and computing equipment. Due to the combined power demands of multiple sensing systems, edge computing, and communication hardware, a backup gasoline generator was integrated into the platform. During intensive two-week continuous data-collection periods, the generator was operated daily to maintain uninterrupted system operation, particularly during periods of limited solar and wind availability.

Onboard computing hardware supported local processing of sensor data and execution of real-time detection algorithms. Data were stored locally on solid-state drives for review and analysis. Cellular communication capabilities enabled remote system monitoring, configuration updates, and limited data access, reducing the need for frequent site visits. The use of a single, integrated ITS trailer platform ensured that all sensing technologies operated under identical power, communication, and environmental conditions, enabling direct, side-by-side performance

comparison across sensor types. At the same time, the mobile configuration provided flexibility for relocation between candidate study sites as field conditions evolved.

Installation planning and coordination began in late 2021. Deployment of the optical camera system with its companion AI-enabled edge-computing device, along with the LiDAR system, occurred during the second quarter of 2021. Although radar and thermal sensors were initially planned for concurrent installation, delivery of the ruggedized computing hardware and equipment cabinet was delayed due to industry-wide supply chain disruptions during the COVID-19 pandemic. Cabinet fabrication and system integration continued as components became available, with installation scheduled once assembly was complete. Additional delays to radar and thermal system installation resulted from coordination and scheduling constraints documented during this period.

Field observations during installation confirmed frequent wild/feral horse activity near the trailer deployment location. Concurrent construction activity was also observed in the vicinity, raising concerns that temporary disturbances could alter animal movement patterns and shift crossing locations outside the effective sensing range. These observations highlight the sensitivity of animal behavior to localized land-use changes and reinforce the importance of continued site monitoring during field deployments.

A major installation milestone was reached on August 4, 2022, with deployment of two thermal cameras, one radar unit, and a pan-tilt-zoom (PTZ) low-light optical camera mounted at the top of the trailer mast. The PTZ camera supported system validation and visual confirmation of detection events. Initial software installation and configuration were completed during the same site visit. However, post-installation testing identified a hardware fault in the radar unit, likely attributable to shipping damage. The unit was removed and returned to the manufacturer for evaluation, and a replacement radar unit was provided and installed on September 20, 2022, minimizing schedule impacts. During the same visit, a replacement LiDAR sensor was installed and integrated, including direct connection to the trailer battery cabinet to ensure stable power delivery.

These installation and replacement activities underscore the importance of incorporating contingency time, spare components, and vendor coordination into mobile field deployments. From an operational perspective, ITS trailer platforms require flexibility in scheduling and maintenance planning to sustain reliable data collection over extended evaluation periods.

The trailer-based animal sensing platform consisted of the following key components, each supporting continuous, unattended operation in remote roadside environments:

- **Wind turbine generator:** A mast-mounted micro wind turbine supplemented solar power by charging the battery bank during windy conditions. While beneficial as a supplemental source, wind generation was variable and could not be relied upon as a primary power supply.
- **Pan-tilt-zoom camera:** A mast-mounted PTZ camera provided 360-degree visual coverage and remote zoom capability. This camera supported system validation, visual confirmation of detections, and general site surveillance for operations and maintenance staff.

- **Communications antenna:** A cellular or radio antenna enabled remote system monitoring, data access, and alert transmission. Reliable communications were essential for minimizing field visits and supporting unattended operation.
- **Optical camera:** An outdoor, ruggedized security camera (SCW Sharpshooter) provided continuous coverage whenever trailer power was on. The device was remotely operated through cell technology.
- **Thermal camera:** Fixed thermal cameras provided continuous detection capability during nighttime and low-light conditions. Thermal sensing proved effective for identifying large animals based on heat signatures and complemented radar, optical and LiDAR systems.
- **360-Degree radar:** Mast mounted radar with 4200-ft range for detecting animals in all weather conditions with size equivalent to that of a crawling human and with range accuracy within +/- 0.3M and ability to track up to 500 objects simultaneously.
- **360-Degree LiDAR sensor:** A mast-mounted LiDAR sensor provided high-resolution three-dimensional detection and tracking of animals and vehicles. LiDAR performance was consistent across lighting conditions and was a key contributor to accurate, real-time detection.
- **Solar panel array:** Solar panels served as the primary power source for the trailer. Solar generation supported continuous off-grid operation but required sufficient battery capacity and backup power to ensure reliability during extended low-sun conditions.
- **Equipment cabinets:** A weather-resistant, lockable cabinet housed batteries, power controllers, computing hardware, and communications equipment. Centralizing these components improved system reliability and simplified maintenance access.
- **Telescoping mast:** The telescoping mast elevated sensors and antennas to improve detection range and coverage. The mast enabled rapid deployment and relocation while maintaining adequate sensor stability during operation.

From an NDOT operations perspective, the ITS trailer platform proved effective for system evaluation and pilot testing. It allowed controlled comparison of multiple sensing technologies under consistent conditions and supported deployment in locations without permanent infrastructure. However, the platform required significant coordination, power system oversight, and maintenance attention. Hardware delays, component failures, and changing site conditions affected deployment schedules. These experiences reinforce that mobile trailer platforms are best suited for short-term evaluation and research purposes until supplier experience over time addresses all contingencies for mobile animal detection systems. That said, unless connected to shore power, these systems will generally be solar/battery powered and as such will naturally require the additional maintenance needs typical of all battery powered systems. For long-term RADS deployment, permanent, hardened installations with utility power and fixed infrastructure are expected to reduce operational burden and better align with NDOT maintenance practices.

2.3.Power System

Power supply feasibility was evaluated as part of the system setup, including assessment of alternating current (AC) and direct current (DC) power distribution and voltage losses over cable runs exceeding 500 feet. Results showed that LiDAR-based sensing has relatively low power

demands. Each LiDAR unit required less than 15 W, and associated computing hardware required less than 60 W, resulting in an overall LiDAR system demand of approximately 100 W for two to three sensors.

The optical camera system required power for the camera and edge-computing device. The camera uses a maximum of 21 W and the edge device 10 W (max). The max utilization occurs when the devices are tasked (e.g., tilt for the camera, which was not used), so actual power use was lower. The overall demand was 31 W at maximum capacity and use.

Thermal and radar systems require additional power. Two thermal cameras operated at approximately 14 W each during normal conditions, while associated interfaces and processing hardware required up to 65 W. The radar unit required approximately 45 W. Including miscellaneous system and processing components (DC/AC inverter, computer, cell modem, Power over Ethernet (PoE) devices, controls), the combined thermal and radar system required approximately 150 W to support continuous operation with some contingency capacity.

Coordination with NDOT District II confirmed that the trailer was equipped with eight 12 V batteries rated at 85 amp-hours. Several power expansion options were evaluated. Rather than adding additional battery cabinets, the project replaced the original lead-acid batteries with lithium batteries, significantly increasing usable capacity. A backup generator with automatic start capability was also implemented. However, automated switching did not function reliably under field conditions, and manual daily generator operation was required to maintain uninterrupted 24-hour system operation during data collection periods. The trailer also included a 160 W wind turbine to supplement battery charging, though wind generation was variable and not sufficient as a primary power source.

From an operations and maintenance perspective, these findings highlight that mobile, off-grid RADS deployments require substantial power system oversight. While feasible for short-term evaluation and pilot testing, trailer-based systems demand frequent monitoring, generator management, and maintenance attention. For long-term deployments, permanent installations with utility power are expected to significantly reduce operational burden, improve reliability, and better align with NDOT maintenance practices.

2.4.Radar Sensing System

The FLIR Ranger R2 radar unit was generously donated to the project by Teledyne/FLIR for demonstration and evaluation during the study period. The radar was installed at a height of 14 feet on the trailer mast. The R2 is a high-resolution, mid-range radar designed and used for military-grade perimeter security and surveillance applications, including airports and critical infrastructure. The maximum detection range is 4,593 ft; however, the radar is specifically optimized to detect a crawling human or similarly sized mammal at 1,640 ft. The unit scans 360 degrees every second and covers a total area of over 2.4 square miles. In this project application, radar evaluation was limited to the horizontal extent of the camera sensors' field of view and to the furthest distance at which high-confidence validation using those cameras was feasible. As a result, effectively 13% of the radar's range capability and less than 1% of its total potential detection area coverage could be validated for accuracy. The radar operates in the Ka band, detects moving objects within ±1 ft of their actual location, and can simultaneously track up to 500 moving objects. This radar is well suited for animal detection in and around roadways due to its ability to filter and distinguish higher-speed moving objects such as vehicles from slower-moving objects such as animals. The unit is designed to operate in harsh environmental

conditions ranging from -30°C to +65°C. The project also employed the FLIR Cameleon software platform, running on an industrially hardened Windows computer, to support sensor integration — in this case specifically with the thermal camera. The Cameleon platform can combine video streams from cameras and detection feeds from other sensors with radar detections, and can be programmed to apply additional layers of logic for real-time determination of when to activate driver warning signs and for how long. It should be noted that establishing appropriate detection zones and tuning radar settings for each new deployment location requires a planned validation period following installation.

2.5.Thermal Sensing System

The thermal camera-based roadside sensing system employed a Teledyne/FLIR Traffisense2 camera throughout the study period. This camera has edge video analytics built into the camera unit itself. The video analytics for animal detection were developed by FLIR and CrossTek in a partnership established approximately ten years ago and subsequently added to this camera's capabilities. The thermal camera was configured with a 36-degree lens for maximum detection distance and can delineate up to 24 separate detection zones within the field of view. This capability is useful for adding additional layers of logic, for example, driver warning signs may only be activated when wild/feral horses are present in zones that represent a potential animal-vehicle collision risk, as opposed to animals that may be loitering or grazing within the right-of-way. The camera outputs H.264, MPEG-4, and MJPEG video compression formats and can be configured and controlled through a web interface. The input power range is 12 - 60 VDC and nominal power consumption is less than 14 W. The camera uses PoE for output state events, configuration, and monitoring, including streaming video, at a frame rate of 30 fps. The camera detects long-wave infrared radiation in the 7-14 μm range. The camera setup included a digital interface adapter for generating 10- to 20-second buffered pre-event, event, and post-event recordings stored to a database. The system also captured time-lapse snapshots from the thermal camera video stream at five-second intervals for use in validating detection event results across all sensors.

2.6.LiDAR Sensing System

The LiDAR-based roadside sensing system used a Velodyne VLP-32C 32-channel spinning LiDAR sensor as the primary unit for performance evaluation. Multiple LiDAR configurations were assessed during the project, including 16-channel and 32-channel spinning units as well as an image-grade solid-state sensor; the 16-channel unit demonstrated insufficient effective detection range for roadside animal sensing applications, and adequate software support for the solid-state unit could not be obtained during the project period. The VLP-32C was selected based on its balance of performance, cost, and compatibility with the roadside sensing software developed by the UNR team. The sensor operates at a wavelength of 905 nm and provides 360-degree horizontal coverage through a dense multi-beam scanning pattern, with a vertical field of view spanning approximately 40 degrees, enabling simultaneous coverage of the roadway surface and adjacent roadside areas. It operates at configurable rotation rates between 5 and 20 Hz, allowing a balance between spatial resolution and temporal update rate, and returns distance measurements with centimeter-level accuracy to support precise object localization and trajectory tracking. Although the sensor has a theoretical maximum detection range of approximately 600 ft, the UNR-developed roadside sensing software’s effective detection range for vehicles, pedestrians, and large animals is within approximately 300 ft radius under field conditions, with performance beyond this distance constrained by increasing sparsity of point

returns at longer ranges. Higher-resolution 64-channel and 128-channel LiDAR sensors can provide denser point clouds and longer effective detection distances but were not evaluated in this project due to their significantly higher cost. LiDAR data were processed using an industrial-grade edge-computing platform equipped with an Intel i7 processor and 32 GB of system memory; no dedicated graphics processing unit (GPU) was required, as the UNR detection software runs on the central processing unit (CPU). An industrial computer was selected to ensure stable performance under Nevada's wide temperature ranges and challenging roadside conditions, including exposure to dust, vibration, and mechanical shock. When deployed at the roadside, the system continuously monitored a defined roadway segment, with detection events processed in real time.

2.7.Optical Sensing System

The camera-based roadside sensing system is a low-cost solution that uses optical imaging and edge computing to detect and classify animals near roadways in real time. The system consisted of a single long-range optical bullet camera — an SCW Sharpshooter (2 MP) deployed in 2021 and used consistently throughout the four-year project and all three testing periods — paired with an NVIDIA Jetson-based embedded computing module serving as the edge processor. The edge device included an NVIDIA Maxwell GPU with 128 CUDA cores capable of 472 GFLOPs, 4 GB of 64-bit LPDDR4 RAM, and 16 GB of eMMC storage, running Linux. This low-power platform provided sufficient GPU capability to run real-time computer vision algorithms on-site without the need for continuous data transmission to a central server. The device executed a YOLO v5 (You Only Look Once, version 5) deep learning object detection model to analyze live video streams and identify animals or vehicles approaching the roadway, with detection events logged as images or video clips on onboard storage. When deployed at the roadside, the system continuously monitored the landscape and roadway for animal movement, processing detection events on the edge device in real time, typically in under one second. Detection and classification results could be used to trigger driver warning signs when animals were approaching or near the roadway. The system also supported remote connectivity, allowing engineers to monitor performance, retrieve data, and deploy software or model updates without requiring on-site access, an important capability for maintaining and tuning systems in remote roadside environments.

3. Ground-Truth Data and Evaluation Procedures

Manually reviewed thermal images and video were used as the ground-truth baseline for wild/feral horse detection in this project. Thermal video was selected because it can reliably record animal presence under all lighting conditions, which is particularly important at this Nevada study site where vegetation consists primarily of low sagebrush and no trees or bushes taller than wild/feral horses are present. It is important to clarify that ground-truth data were generated through manual review of the raw thermal video recordings, rather than from the automated detection outputs of the thermal sensing system. The automatic detection results produced by the thermal sensing system were not used as ground truth and were instead treated as an evaluated sensing modality, consistent with the other systems assessed in this study.

A predefined detection zone was required for evaluation because the sensing systems under study have different fields of view and sensing characteristics. The LiDAR and radar systems provide 360-degree scanning, whereas the thermal and optical cameras used in this project are directional. To enable consistent performance comparison and ensure that ground-truth data could be generated reliably, the detection zone was defined as the area that could be observed by all sensing systems, towards to the south of the trailer, as shown in Figure 5. The defined detection zone did not impose a strict maximum detection distance. This approach allowed the effective sensing ranges of different technologies to be observed and compared as part of the evaluation. For example, radar systems demonstrated the ability to detect objects at substantially longer distances than other sensing technologies, particularly given the open terrain at the study site.

The detection zone was delineated by the Electric Avenue boundary and distance reference markers, as illustrated in Figure 5. Yellow reflective arrows were mounted at labeled distances from the trailer to support distance estimation during manual review and ensure consistent event logging across reviewers.



Figure 5. Defined detection zone for evaluating the different sensing systems in the same region

Thermal video was selected as the ground-truth reference because it reliably records animal presence under all lighting conditions, including complete darkness, and is unaffected by headlight glare or ambient light sources. At this study site, where vegetation consists primarily of low sagebrush with no tall obstructions, thermal imagery provided unobstructed visibility across the full detection zone. This rationale applies throughout the chapter and is not restated in subsequent sections.

3.1.Dual-Reviewer Approach for Objective Validation

To ensure objectivity, completeness, and reliability of the ground-truth dataset, a dual independent reviewer approach was used to analyze the 24-hour thermal time-lapse video footage. This approach was designed to validate that manually extracted animal presence from thermal recordings is accurate and suitable for use as ground-truth data.

Two trained reviewers independently examined the same thermal video clips and logged all observed animal detections. Reviewers worked separately to avoid influencing one another's observations. After the independent review process, the two detection logs were compared and reconciled. Any discrepancies were jointly reviewed using the original thermal footage to reach a consensus. This process reduced the likelihood of missed detections and minimized individual interpretation bias. In practice, reviewer agreement was high, indicating that the dual-review process produced a consistent and reliable ground-truth dataset.

To further validate the suitability of thermal video as the ground-truth baseline, a subset of thermal and optical (PTZ) video data was independently reviewed by two trained observers. Three dates, **February 9, February 12, and February 17, 2024**, were selected for review without prior knowledge of traffic conditions, animal activity, or environmental context. This blind selection was intended to avoid bias in the validation process.

Each observer independently reviewed the same video segments and documented wild/feral horse and human activity events, including event timing, object type, approximate distance from the camera, and source imagery (thermal or PTZ optical). The results from both observers were then compared to assess inter-reviewer agreement, identify discrepancies, and evaluate the suitability of thermal video as the baseline reference for system validation.

Overall, the two observers demonstrated strong agreement in identifying wild/feral horse events across both thermal and optical imagery. Minor differences were observed in recorded event start and end times, primarily due to subjective interpretation of when an object entered or exited the camera field of view. Table 3 and Table 4 listed the manual event log results from the two observers. These differences were small and did not affect event matching across observers or subsequent evaluation outcomes.

One notable discrepancy occurred on February 12, 2024, when Observer 2 documented a large-animal detection in thermal imagery that Observer 1 did not record. Conversely, Observer 1 documented a human presence event that Observer 2 did not classify as such. These differences reflect expected variability in human interpretation rather than systematic bias.

Importantly, both observers were able to identify animals using thermal imagery in nearly all documented wild/feral horse events. There was only one instance in which an animal detected in thermal imagery was not clearly visible in the corresponding PTZ optical footage. This outcome supports the use of thermal video as a conservative and reliable reference, particularly under low-light and nighttime conditions.

Although the validation dataset was limited in size, the results indicate that thermal imagery provides sufficient visibility for human observers to consistently identify wild/feral horse presence. These findings support the use of manually reviewed thermal video as the ground-truth baseline for evaluating automated animal detection systems in this project.

Table 3. Observer 1 Event Log for Dual-Reviewer Approach Validation

Date	Time Start	Time End	Duration	Object	Distance Range (ft)	Record Source
2/9/2024	13:12:40	13:47:05	0:34:25	Human	0–500	PTZ Camera
2/9/2024	13:12:40	13:47:05	0:34:25	Human	0–500	Thermal
2/9/2024	14:40:40	14:41:40	0:01:00	Horse	100–300	PTZ Camera
2/9/2024	14:40:40	14:41:40	0:01:00	Horse	100–300	Thermal
2/9/2024	18:32:35	18:33:40	0:01:05	Coyote	100–200	PTZ Camera
2/9/2024	18:32:35	18:33:40	0:01:05	Coyote	100–200	Thermal
2/17/2024	13:09:35	13:09:50	0:00:15	Horse	0–100	PTZ Camera
2/17/2024	13:09:35	13:09:50	0:00:15	Horse	0–100	Thermal

Table 4. Observer 2 Event Log for Dual-Reviewer Approach Validation

Date	Time Start	Time End	Duration	Object	Distance Range (ft)	Record Source
2/9/2024	14:40:41	14:41:41	0:01:00	Horse	150–200	PTZ Camera
2/9/2024	14:40:15	14:41:15	0:01:00	Horse	150–200	Thermal
2/9/2024	18:32:41	18:34:36	0:01:55	Coyote	300–500	PTZ Camera
2/9/2024	18:32:15	18:34:10	0:01:55	Coyote	300–500	Thermal
2/12/2024	23:03:21	23:03:36	0:00:15	Large Animal	300–500	Thermal
2/17/2024	13:09:09	13:09:29	0:00:20	Horse	50–100	PTZ Camera
2/17/2024	13:09:40	13:09:55	0:00:15	Horse	50–100	Thermal

3.2.Event Logging of Animal Detections

Each confirmed animal detection observed in the thermal video was documented using a structured event log. For each event, reviewers recorded a standardized set of attributes to support later comparison with automated sensing systems. Logged information included:

- **Time of Detection:** The time when the animal first appeared and, if applicable, when it exited the camera's field of view. Timestamps were recorded with sufficient precision to enable alignment with other sensor data.
- **Animal Type:** The species or general animal category, when discernible. If precise identification was not possible, a broader classification such as "unknown mammal" was used.
- **Observer Confidence:** A qualitative confidence level indicating the reviewer's certainty that the detected heat signature represented an animal. Confidence levels help flag ambiguous cases for further review.
- **Duration and Behavior (if observable):** Information on how long the animal remained visible and whether it was stationary, moving, or crossing the roadway.
- **Approximate Distance or Zone:** A coarse estimate of the animal's proximity to the roadway or camera, categorized into broad distance ranges based on known scene geometry.

All detections were logged in a consistent format and merged into a single validated event log after reconciliation between reviewers. This log represents the final ground-truth record of animal activity captured by the thermal camera.

The validated thermal video event log served as the ground-truth reference for evaluating the performance of all animal sensing systems tested in this project. Each automated sensing system independently generated its own detection records, including event timestamps and, where available, object classification outputs. These system-generated detections were systematically compared against the thermal video baseline.

Manual review of thermal videos was conducted 24 hours per day over each 14-day data-collection period. During the review process, trained reviewers examined the thermal footage and manually logged each instance in which a large animal appeared within a predefined detection zone. In this project, only wild/feral horses were observed as large animals. For each event, reviewers recorded the event timestamp and the approximate distance of the animal from the trailer. These manually extracted thermal event logs were used as the ground-truth dataset for evaluating the performance of all four sensing systems. For each ground-truth event, the evaluation assessed whether a sensing system successfully detected the animal or failed to register the event. System detections that did not correspond to any thermal event log entry were treated as potential false positives. This comparison framework enabled consistent identification of true positives, false negatives, and false positives across sensing technologies.

By using a single, independently reviewed thermal video baseline, system performance was evaluated against a consistent and transparent reference for animal activity. This approach avoided circular validation and ensured that differences in performance reflected sensing and processing capabilities rather than inconsistencies in ground-truth definition.

3.3.Evaluation Framework

Detection Events: In this project, a detection event was defined as a discrete instance of an animal's presence within the monitored area. An event began when an animal entered the defined detection zone (the coverage area of the sensors) and ended when the animal exited that zone. In other words, one animal intrusion into the sensor coverage area, from entry to exit,

constituted a single detection event of interest. This definition ensured that prolonged presence or multiple triggers by the same animal were treated as one continuous event for analysis. Each sensing system monitored the same detection zone so that an animal passing through would ideally be captured by all systems concurrently, allowing direct performance comparisons.

Detection Zones and Distance Bands: The detection zone refers to the physical area within which a sensor can detect an animal. To improve comparison, the sensors were positioned so that their detection zones overlapped over a common area (e.g., a segment of a field or roadside) of interest. Within this zone, the evaluation introduced distance bands, sub-divisions of the detection area by range, to stratify detection performance as a function of distance. As shown in Figure 5, the zone was segmented into bands radiating outward from the sensor location or the center of the monitored area using large yellow signs that were placed on the landscape for reference at 0-50 ft, 50-100 ft, 100-150 ft, 150-200 ft, 200-300 ft, 300-500 ft, and at 500 ft. Using a combination of visible light cameras and thermal, distance lines were added to the thermal images that could be seen by the reviewer in the time-lapse images used for the baseline evaluation. This framework allowed the team to analyze how detection success varies with distance: for instance, performance in the 0-50 ft range (near-field) could be compared to performance at 50-100 ft (mid-field), and so on. Such stratification is important because detection reliability often declines as distance increases. By assigning each animal encounter to a distance band, the evaluators could determine, for each technology, the ranges at which detection was most and least reliable. No specific distance thresholds are reported here, but the banding approach ensured a structured assessment of range effects on sensor performance.

3.4.Data Collection Procedure

Concurrent Operation: All four sensing systems were deployed and run concurrently over a defined evaluation period (two weeks of continuous monitoring during each round of data collection) to capture a robust sample of baseline detection events. During this period, the thermal, radar, LiDAR, and optical camera systems were all active in parallel, watching the same environment. This simultaneous operation ensured that each animal event in the area would be witnessed by all systems under the same conditions (weather, lighting, animal behavior), allowing for a fair comparison of their responses. The multi-system deployment was set up in a representative field location frequented by animals, so that “natural” animal entries into the detection zone could serve as test events. Running the systems for an extended period (e.g., 14 days) provided a sufficient number of animal encounters and a variety of conditions (day/night cycles, different weather) to establish baseline performance for each sensor. Similar multi-day reliability tests are common in such evaluations. For example, one study conducted four seasonal trials of 10 days each to assess an animal detection system’s performance. In our project, the two-week timeframe was chosen to balance practical constraints with the need for statistically meaningful observation hours.

Observation and Ground-Truth Baseline: Throughout the data collection phase, each system independently logged its detection events (with timestamps and/or event IDs). To provide a ground-truth baseline for evaluating these detections, the project employed manual observations of animal presence against which sensor triggers were compared. Ground-truth confirmation was obtained through continuous thermal video review, as described in the chapter introduction. Each sensor's detection logs were matched against the manually extracted thermal event timeline to identify true positives, false negatives, and false positives. Each sensor’s logs were later matched with the manually extracted event timeline to identify potentially true animal events. By using an

independent observation method, the team established a timeline of what were assumed to be all animal presence events (the ground truth). These events were the basis for all performance calculations: the occurrences when an animal was verified in the zone (with known entry and exit times) were treated as the "real" events to detect, and each system's success or failure was judged against this putative baseline. Any sensor activation that did not correspond to a verified animal presence was noted, and any animal presence that went undetected by a system was also documented, as described next.

3.5.Key Performance Metrics

To evaluate and compare system performance, the project focused on several key detection metrics, defined as follows:

- **False Positives (FP):** Instances where a system signaled a detection in the absence of any actual animal in the detection zone. In other words, the sensor "cried wolf" – it triggered an event when nothing (or no target animal) was truly there. Such false alarms can arise from sensor noise or misinterpreting other stimuli (e.g., moving vegetation or non-target animals) as animals. During analysis, every logged detection was cross-checked with ground truth; if no animal was present at that time, the detection was recorded as a false positive. (For example, one test documented false alerts when no large animal was in the zone, often due to wind-blown objects triggering a sensor.) A low false positive rate is desirable to avoid needless alerts and alarm fatigue.
- **False Negatives (FN):** Instances where a system failed to detect an animal that was present in the detection zone. In these cases, an animal passed through or stayed in the monitored area but the sensor did not generate a detection event. Using the event logs and ground-truth timeline, if an animal's presence was confirmed but a given system did not register it, that omission was counted as a false negative. (For example, if a deer walked through the zone and only some of the sensors detected it, any system that did not trigger would record a false negative for that event.) Minimizing false negatives is critical, as they represent missed detections of actual animals, which is a serious problem for safety and monitoring effectiveness.
- **Detection Success Rate:** For each system, a success rate or detection rate was calculated to summarize overall effectiveness. This metric was defined as the percentage of confirmed animal events that the system successfully detected. In formula terms, success rate = (Number of true events detected by the system / Total number of true events in the baseline) × 100%. It essentially represents the probability that a given animal intrusion is caught by the sensor. A higher success rate (approaching 100%) means the sensor captured nearly all animals, whereas a lower rate indicates many misses. This measure is directly related to the false negative rate (since every missed event lowers success). For example, if a sensor missed 10% of actual events, its success rate would be 90%. Industry evaluations often set performance benchmarks using such percentages, e.g., one transportation study considered a system acceptable if it missed no more than about 9% of animals (i.e., 91% detection success). In our project, the success rate for each technology was computed overall and within each distance band (as discussed below) to identify at what ranges the sensor was most effective.

(Note: "True positives" or "correct detections" – cases where an animal is present and the system correctly detects it – are essentially the complement of false negatives and contribute to

the success rate. In this chapter, we emphasize false positives, false negatives, and success rate as the primary metrics, while true positives are counted implicitly as successful detections.)

3.6.Analysis Procedure

Distance-Stratified Success Analysis: After data collection, the detection events were analyzed by distance band to assess how each sensor's performance varied with range. All confirmed animal events were grouped into the predefined distance categories (e.g., events occurring 0–50 ft from the sensors, 50–100 ft, etc.). For each band, the **detection success rate** of each system was calculated (using the method above). This produced a profile of performance vs. distance – for instance, the team could compare the percentage of animals detected in the 0–50 ft range to the percentage detected in 50–100 ft for each technology. The analysis looked for drop-offs in success at greater distances, as well as any range at which a sensor might cease to detect reliably. By examining these strata, the evaluators could identify the effective range limits of each system. (As expected, most technologies showed stronger performance at closer range and some degradation as distance increased, but the specific trends are beyond the scope of this chapter.) This stratified approach ensured that each system's advertised range capabilities were empirically verified and that direct comparisons could be made (e.g., if radar outperformed thermal beyond 100 ft, or vice versa). The distance-band analysis was a cornerstone of the evaluation, allowing recommendations on optimal deployment ranges for each sensor type.

Event Timeline Review for Errors: A comprehensive event timeline was constructed combining the ground-truth animal events and each system's detection log. This chronological timeline of events enabled the identification of false positives and false negatives by direct temporal comparison. Specifically, for every time interval where an animal was known to be in the detection zone (from entry to exit), the logs of each system were checked: if a system failed to register that interval as an event, a missed detection (false negative) was recorded for that system at that time. Conversely, for every sensor-reported detection time, the timeline was checked to see if an animal was present; if not, that instance was labeled a false alarm (false positive). By aligning all detections on a unified timeline, the evaluators could easily see which system triggers corresponded to real animal movements and which did not. This process was often aided by software: the timestamped data from each sensor and the observation logs were merged in a spreadsheet or database, and an automated script flagged mismatches (e.g., sensor trigger with no confirmed animal, or confirmed animal with no sensor trigger). Visual verification was also used – e.g., playing back the thermal video and noting timestamps of animal entries, then cross-referencing those with sensor trigger times. Using this methodical timeline approach, every detection event was accounted for as either a true detection or one of the error types. The timeline review also highlighted any consistent timing patterns (such as whether certain sensors had delays or only picked up animals after they were within a certain distance). By the end of this step, the team had a categorized list of detections for each system: true positives (correct detections), false positives, and false negatives, each tied to specific events.

Temporal Aggregation Bins for False Positive Analysis: Because the sensing systems log detections at different rates and a single cause can trigger repeated records within a short period, raw counts of spurious detections are not directly comparable across systems. False positive results in Chapter 5 are therefore reported using temporal aggregation bins of 1 hour, 30 minutes, and 10 minutes. For each bin size, the 14-day evaluation period was divided into consecutive intervals of that length, and an interval was counted as a false positive interval for a system when

the system logged one or more detections while the ground-truth record showed no horse present in the detection zone. The false positive percentage is the share of such intervals among all intervals in the period. Bin size changes what a false alert means in practice. A 1-hour bin approximates how often a driver warning sign held active for an hour after a trigger would be lit with no horse present; scattered spurious detections are penalized heavily, so this bin gives the most conservative view of each system. A 10-minute bin resolves individual clusters of spurious detections more precisely and yields lower percentages, but a single cause, such as wind-moved vegetation or a passing vehicle, can be counted more than once when its detections fall in adjacent bins. Bins also absorb small timestamp offsets between the sensing systems and the baseline, such as the thermal system lag documented for Cycle 3. Reporting all three bin sizes shows how sensitive each system's false alert behavior is to the aggregation window and allows the reader to select the window that matches an intended alert hold time.

Post-Processing and Sensor Calibration: Based on the initial analysis of events and errors, the team performed post-processing steps to refine the data and improve interpretation. One aspect was filtering and consolidating detection logs: for example, if a single animal caused multiple rapid-fire triggers on one sensor (due to stepping in and out of range), those could be merged into one event to align with how other sensors saw one continuous event. The data was also scanned for any systematic anomalies – such as a sensor that triggered repeatedly at a certain time of day with no animals (perhaps due to sunrise heating causing thermal noise) – and such periods were noted or excluded in calculating performance metrics so as not to skew results. Additionally, insights from the error analysis were used to suggest calibration adjustments to the sensors. If a particular system had many false positives, the team examined the likely causes. For instance, suppose the radar unit showed frequent false alerts when aimed toward a stand of trees; investigators would suspect wind-blown branches causing radar returns. In such a case, a recommendation might be to narrow the radar's field of view or adjust its sensitivity threshold. In fact, during this project, when one sensor (a passive infrared module) was found to be frequently triggered by moving foliage behind it, the evaluators decided to disable or reposition that rear-facing sensor in future deployments. Similarly, if false positives occurred mostly beyond a certain distance, the system's range setting could be truncated to ignore detections in that problematic far zone. On the software side, calibration might involve tuning the detection algorithms – for example, increasing the required confidence level or signal threshold to declare a detection, thereby filtering out spurious signals. No such changes were applied to the data retroactively (to keep the evaluation baseline fair), but they were noted as potential improvements. In summary, the analysis phase not only quantified each system's performance but also pinpointed the root causes of errors, which informed a set of calibration or configuration changes to test in subsequent trials. These could include adjusting sensor orientation, shielding sensors from environmental noise, updating firmware, or applying smoothing algorithms to the detection time series. The result was a clearer picture of how each technology performed and what could be optimized.

3.7.Accuracy Expectations and Limitations

The use of human-validated thermal video provides a high-confidence baseline for assessing sensing system performance, relative to thermal sensors. However, both system performance and the ground-truth process itself have practical limitations that must be recognized, including the lack of an absolute reference point.

Automated sensing systems are expected to detect most, but not all, animal events recorded in the thermal baseline. Detection performance can vary depending on sensor type, environmental conditions, animal size, and distance from the roadway. False positives may also occur due to environmental noise or non-animal objects, which the thermal baseline helps identify. The dual-reviewer process resulted in a highly reliable ground-truth dataset, with only rare cases of disagreement that were resolved through consensus. This level of agreement indicates that missed detections in automated systems are unlikely to be caused by errors in the baseline data.

At longer distances, animals occupy fewer pixels in thermal imagery, making identification less certain, and distance estimates from single-camera footage remain approximate. These constraints were managed through confidence scoring and conservative treatment of ambiguous detections.

These limitations were managed through careful study design, confidence scoring, and focus on the roadway corridor and adjacent areas most relevant to collision risk. Ambiguous detections were documented accordingly and treated conservatively in performance analyses.

The thermal video validation methodology was assumed to have a robust and unbiased foundation for evaluating animal sensing systems. The dual-reviewer process produces a reliable and objective ground-truth record. Structured event logging captures key contextual information needed for detailed performance comparison. Although both sensing systems and thermal validation have inherent limitations, these constraints are acknowledged and managed within the evaluation framework. Overall, some of the investigators felt that the thermal-based ground truth enabled consistent, transparent assessment of sensor accuracy and supports data-driven conclusions regarding sensor comparisons.

4. WILD/FERAL HORSE PRESENCE EVENTS DURING THE THREE CYCLES OF DATA COLLECTION

Building on the ground-truth baseline described in Chapter 3, this chapter presents wild/feral horse presence events recorded across three 14-day monitoring cycles: Cycle 1 (October 2023, fall), Cycle 2 (February 2024, winter), and Cycle 3 (October 2024, fall). Events are stratified by distance category — close (within 300 ft), mid-range (300–500 ft), and far (beyond 500 ft) — and by time of day (daytime and nighttime). Cumulative loiter time is reported alongside event counts to capture both the frequency and duration of horse presence near the roadway. Close-range events are those in which horses came within 300 ft of the trailer at some point during the event; mid-range events came within 500 ft but not within 300 ft; far events remained beyond 500 ft.

4.1. Cycle 1 – October 2023 (Baseline Horse Events)

Cycle 1 was conducted in mid-October 2023. A total of 73 horse events were recorded during the 14-day monitoring period. Most events involved horses remaining far distances from the roadway. Far-distance events accounted for approximately two-thirds of all detections, while close-range events represented about one-quarter.

The cumulative horse presence time during Cycle 1 was approximately 49 hours. Nighttime activity dominated both event counts and total loiter time. Approximately 60 percent of events occurred at night, accounting for roughly 61 percent of total horse presence time. Daytime activity was less frequent and shorter in duration.

4.2. Cycle 2 – February 2024 (Winter Horse Events)

Cycle 2 was conducted in early February 2024 and represents winter conditions. A total of 52 horse events were recorded during this cycle, fewer than in Cycle 1. However, the total cumulative loiter time reached nearly 59 hours, the highest among the three cycles.

The average duration per event in Cycle 2 was notably longer than in the fall cycles, indicating that horses tended to remain in the monitored area for extended periods during winter. Mid-range events were rare during this cycle (2 of 52), and the proportion of far-distance events was slightly higher than in Cycle 1.

The daytime and nighttime split was more balanced in Cycle 2 than in Cycle 1, though nighttime still accounted for the majority of cumulative loiter time.

All sensors were active during the cycle, except for the optical camera. There was a period from February 6–14, 2024, where the optical system was off. It is unclear what caused this off-time, as the system logs did not have details on this. Because the system did not record detailed logs during this period, this means that the failure occurred in a way that made logging unavailable (i.e., power loss, or loose contact). For the remainder of the four years, when power was available, system logs were created. There was no explanation for the power loss to the optical system.

4.3. Cycle 3 – October 2024 (Second Fall Dataset)

Cycle 3 was conducted in mid-October 2024, approximately one year after Cycle 1. A total of 62 horse events were recorded, more than in Cycle 2 but fewer than in Cycle 1. However, total loiter time decreased to approximately 40 hours, the lowest among the three cycles.

Cycle 3 exhibited a distinct distance pattern. Close-range events increased to the highest level observed across all cycles, while mid-range events became very rare. This resulted in a polarized distribution between close and far events, with very few mid-range detections.

Daytime close-range events increased substantially relative to prior cycles, while nighttime activity continued to account for the majority of total loiter time.

4.4.Trends Across Cycles

Table 5 through Table 9 summarize horse detection event counts and total loiter times for Cycle 1, Cycle 2, and Cycle 3, respectively. Each table is organized by distance category and time of day, including combined 24-hour totals as well as daytime-only and nighttime-only results.

Table 5 summarizes overall wild/feral horse activity observed during the three monitoring cycles. Cycle 1 recorded the highest total number of events (73), followed by Cycle 3 (62) and Cycle 2 (52). Notably, Cycle 2 exhibited the highest cumulative loiter time, indicating that horses remained in the monitored area longer during winter conditions. In contrast, Cycle 3 recorded the lowest total loiter time, suggesting shorter-duration events despite a higher number of events than in Cycle 2. These results indicate that event frequency alone does not fully capture exposure risk and that duration of presence is an important complementary metric.

Table 5. Summary of Horse Events by Cycle

Cycle	Monitoring Period	Total Events	Close (<300 ft)	Mid-range (300–500 ft)	Far (>500 ft)	Total Loiter Time
Cycle 1	Oct 2023	73	18	5	50	49 h 12 min
Cycle 2	Feb 2024	52	11	2	39	58 h 54 min
Cycle 3	Oct 2024	62	21	2	39	39 h 39 min

Table 6 illustrates how the spatial distribution of horse events varied across cycles. In Cycle 1, the majority of events occurred at distances greater than 500 ft from the trailer, establishing a baseline condition in which horses generally remained well away from traffic. Cycle 2 had the highest proportion of far-distance events and very few mid-range events, so the winter cycle did not show horses moving closer to the roadway corridor. In Cycle 3, the distribution became more polarized, with most events occurring either very close to the roadway or remaining far away, and very few events occurring at intermediate distances. This pattern indicates a change in how horses interacted with the corridor during the later fall period.

Table 6. Percentage Distribution of Horse Events by Distance Category

Cycle	Close (<300 ft)	Mid-range (300–500 ft)	Far (>500 ft)
Cycle 1	25%	7%	68%
Cycle 2	21%	4%	75%
Cycle 3	34%	3%	63%

Table 7 compares horse activity between daytime and nighttime conditions. Across all cycles, nighttime accounted for the majority of cumulative loiter time, confirming that after-dark periods represent the highest overall exposure to horse presence near the roadway. Event counts, however, were more evenly distributed between day and night. This indicates that while horses may appear during both daylight and nighttime hours, they tend to remain in the area longer during nighttime periods. These findings reinforce the importance of ensuring that detection and warning systems perform reliably under nighttime and low-light conditions.

Table 7. Horse Presence Events by Time of Day

Cycle	Daytime Events	Nighttime Events	Daytime Loiter Time	Nighttime Loiter Time
Cycle 1	30	43	19 h 10 min	30 h 03 min
Cycle 2	25	27	21 h 32 min	37 h 22 min
Cycle 3	26	36	15 h 57 min	23 h 42 min

Table 8 focuses specifically on close-range events, defined as horses approaching within 300 ft of the roadway. In Cycle 1 and Cycle 2, close-range events were more common at night than during the day. However, Cycle 3 showed a clear shift, with a substantial increase in daytime close-range events and fewer such events occurring at night. This reversal suggests a change in horse behavior or site conditions during the later fall period, with horses more frequently approaching the roadway during daylight hours. From a safety perspective, this finding highlights the need for systems that can provide timely warnings during both daytime and nighttime conditions.

Table 8. Close-Range (<300 ft) Events by Time of Day

Cycle	Daytime Close Events	Nighttime Close Events
Cycle 1	5	13
Cycle 2	5	6
Cycle 3	15	6

Table 9 presents approximate average event durations derived from total loiter time and event counts. Cycle 2 stands out with the longest average duration per event, indicating that horses lingered near the roadway for extended periods during winter. Cycle 1 showed moderate event durations, while Cycle 3 had the shortest average durations, reflecting more transient horse presence. These differences have implications for system design and operation. Longer-duration events may require sustained tracking and prolonged warning activation, whereas shorter events emphasize the importance of rapid detection and response to minimize collision risk.

Table 9. Average Event Duration by Cycle (Approximate)

Cycle	Total Events	Total Loiter Time	Avg. Duration per Event
Cycle 1	73	49 h 12 min	~40 min
Cycle 2	52	58 h 54 min	~68 min

Cycle 3	62	39 h 39 min	~38 min

Comparison of the three cycles reveals several important trends in wild/feral horse activity near the roadway.

Event counts and distance distribution: Total event counts ranged from 52 in the winter cycle to 73 in fall 2023, and the distance distribution varied by season. Cycle 1 and Cycle 2 were dominated by far-distance events, with Cycle 2 showing the smallest share of close-range events. Cycle 3 remained dominated by far-distance events but showed a pronounced increase in close-range detections and very few mid-range events. These shifts suggest that seasonal conditions and site-specific factors influence how closely horses approach the roadway.

Loiter time and event duration: Cumulative loiter time was highest during the winter cycle, despite fewer total events. This indicates longer average event durations in winter, potentially reflecting slower movement or extended foraging behavior. In contrast, Cycle 3 featured shorter events overall, suggesting quicker crossings or reduced lingering near the roadway. From an engineering perspective, these differences imply varying system requirements. Longer winter events may require sustained tracking, while shorter fall events may demand faster detection and response.

Daytime and nighttime patterns: Across all cycles, nighttime accounted for the majority of total horse presence time, confirming that nighttime is a critical period for animal–vehicle conflict risk. However, Cycle 3 showed a clear increase in daytime close-range events, indicating a potential shift in horse behavior or site conditions over time. Detection and warning systems must therefore function reliably under both day and night conditions, with particular emphasis on nighttime performance and responsiveness to close daytime approaches.

Implications for system design and mitigation: The observed variability across seasons highlights the need for detection systems that accommodate changing animal behavior patterns. The prevalence of far-distance detections suggests that sensing zones should extend beyond the immediate roadway to provide early awareness. The increase in close-range daytime events in later observations may warrant additional attention to daytime warning strategies during periods of elevated activity.

4.5.Summary Wild/feral horse Activities

The three data collection cycles provide a comprehensive baseline of wild/feral horse activity near the roadway under varying seasonal conditions. Winter periods were characterized by longer loiter times and a higher share of far-distance events, while fall periods showed more polarized distance behavior and increased close-range daytime activity in later observations.

These findings provide essential context for evaluating the performance of roadside animal detection and warning systems. They also inform subsequent assessment of mitigation strategies by identifying when, where, and how horses interact with the roadway environment.

5. Performance Comparison of Animal Detection Systems Across Data Collection Cycles

This chapter presents detection performance results for all four sensing systems across the three data collection cycles. Performance metrics (true positives, false positives, false negatives) and the ground-truth baseline are defined in Chapter 3; wild/feral horse presence event summaries are provided in Chapter 4. Results are reported separately for daytime and nighttime conditions and stratified by distance category. The distance groups are cumulative: within 300 ft includes the events in which horses came within 300 ft of the trailer, within 500 ft includes all events within 500 ft (including those within 300 ft), and all distances includes every evaluated event. Table 10 summarizes the baseline horse event counts and distance breakdowns for each cycle and time-of-day period and serves as the reference for all performance discussions that follow. False positive results are reported using three temporal aggregation bins (1 hour, 30 minutes, and 10 minutes); the definition of the bins and the reasons for reporting all three are given in Section 3.6.

Table 10. Summary of Baseline Horse Events and Distance Breakdowns

	Period	Total Events (all distances)	Within 300 ft	Within 500 ft	Beyond 500 ft	Total Loiter Time
Cycle 1	Daytime	30	5	8	22	19 h 10 min
Cycle 1	Nighttime	43	13	15	28	30 h 03 min
Cycle 1	Combined	73	18	23	50	49 h 13 min
Cycle 2	Daytime	25	5	6	19	21 h 32 min
Cycle 2	Nighttime	27	6	7	20	37 h 22 min
Cycle 2	Combined	52	11	13	39	58 h 54 min
Cycle 3	Daytime	26	15	15	11	15 h 57 min
Cycle 3	Nighttime	36	6	8	28	23 h 42 min
Cycle 3	Combined	62	21	23	39	39 h 39 min

5.1. Cycle 1 – October 2023 (Baseline Period Oct 13–26, 2023)

Cycle 1 was conducted October 13-26, 2023. A known limitation affecting Cycle 1 involves the thermal sensing system. During this period, the thermal camera was configured with a size filter that allowed detections of animals at rodent size and larger. As a result, the thermal system

recorded a high number of detections that included non-target animals, which artificially inflated the reported true positive rate for thermal sensing. This configuration issue is documented and should be considered when interpreting thermal performance results for Cycle 1, particularly when comparing performance across sensing modalities and subsequent data collection cycles

5.1.1. Cycle 1 Daytime Performance

Daytime baseline events for Cycle 1 are summarized in Table 10. Figure 6 shows Cycle 1 daytime true positive percentages for the four sensing systems stratified by distance range. The low all-distance performance across most systems reflects the fact that a large portion of daytime horse activity occurred beyond effective detection ranges.

LiDAR detected 13.3% of the baseline daytime horse events when all distances are considered, 50% of the events under 500 ft, and 60% of the events under 300 ft. Performance improves at shorter range, but LiDAR remained the lowest of the four systems at every range in Cycle 1 daytime, consistent with its limited effective detection range.

Radar achieved the highest daytime true positive rates in Cycle 1, detecting 83.3% of baseline events at all distances and 100% of the events under 500 ft and under 300 ft. Radar was the only system that detected most of the far-range daytime events.

The thermal camera system detected 26.7% of baseline events at all distances, 87.5% of the events under 500 ft, and 100% of the events under 300 ft, indicating reliable daytime detection once horses were within 500 ft. These rates are subject to the size-filter limitation noted in Section 5.1.

The optical camera system detected 23.3% of baseline events at all distances, 75% of the events under 500 ft, and 100% of the events under 300 ft, following the same pattern as thermal with a somewhat lower rate at mid-range.

Overall, radar provided the strongest daytime detection in Cycle 1 at every range. Thermal and optical cameras detected every horse event within 300 ft and most events within 500 ft but missed most far-range events, and LiDAR trailed the other systems at every range. The large share of daytime events beyond 500 ft is the main reason the all-distance rates are low for the three shorter-range systems.

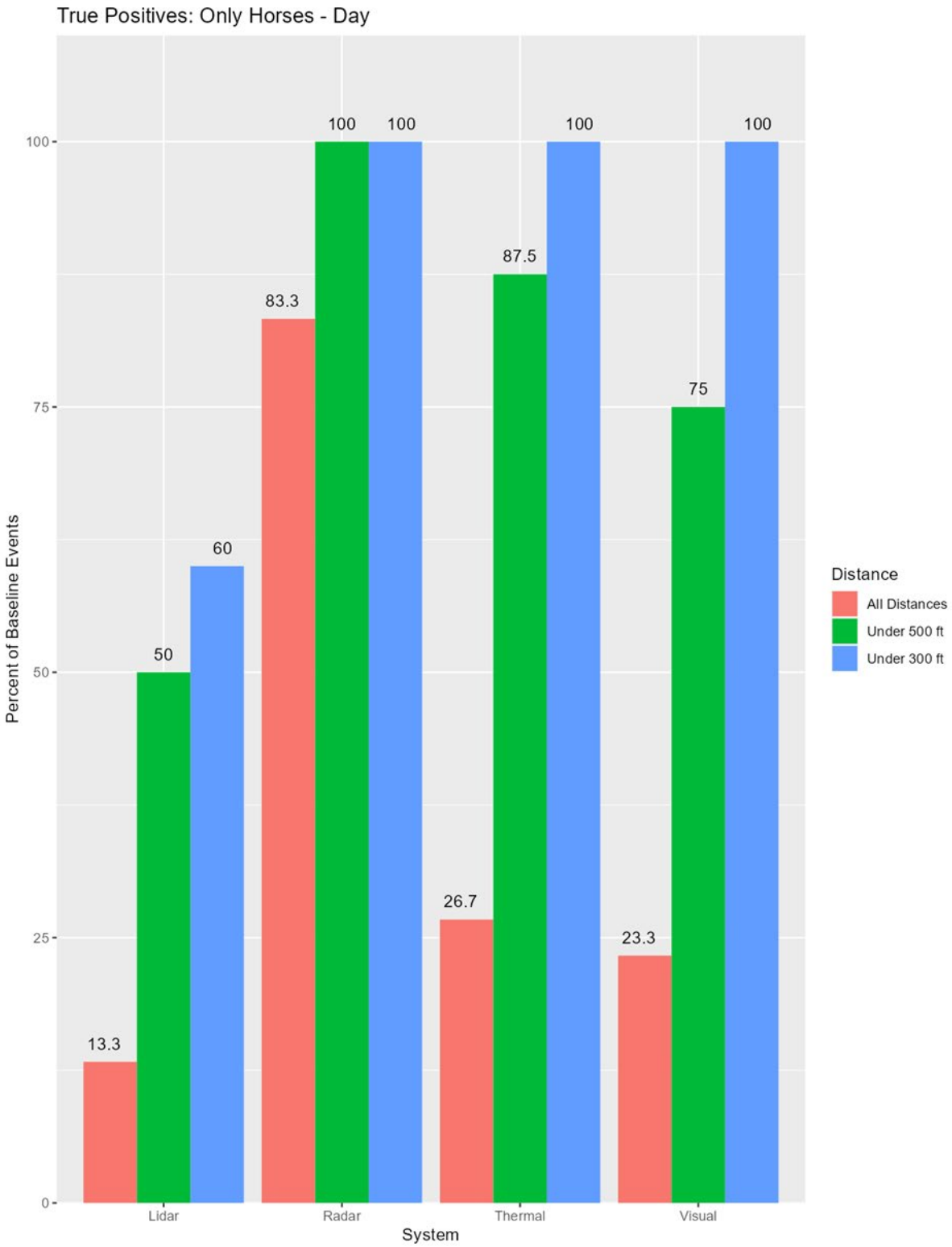


Figure 6. Cycle 1 daytime true positive percentage of four sensing systems at different distance ranges

Figure 7 shows Cycle 1 daytime false positive percentages across all distances for the four sensing systems, evaluated using three temporal aggregation bins (1 hour, 30 minutes, and 10 minutes) described in Section 3.6. The results indicate substantial differences in false alert behavior among sensing modalities, with strong sensitivity to temporal aggregation, particularly for radar.

Across all distances, LiDAR maintains consistently low false positive rates, at 1.5% (1-hour bin), 0.9% (30-minute bin), and 0.3% (10-minute bin). This indicates stable daytime performance with minimal spurious detections, even when distant background activity is included.

In contrast, radar exhibits the highest false positive rates among all systems. Radar false positives reach 36.6% at the 1-hour bin, decrease to 23.8% at 30 minutes, and further reduce to 12.7% at the 10-minute bin. These results indicate that radar is highly sensitive to non-target detections over longer distances and that aggressive temporal filtering is required to reduce false alerts.

The thermal camera system shows moderate false positive rates, with 4.8% (1 hour), 2.8% (30 minutes), and 1.4% (10 minutes). While higher than LiDAR, thermal false positives remain relatively low compared to radar, even when all-distance detections are included.

Similarly, the optical camera system exhibits moderate false positive behavior, with 5.7% (1 hour), 3.1% (30 minutes), and 1.5% (10 minutes). Optical false positives are slightly higher than thermal but remain substantially lower than radar across all temporal bins.

Overall, the Cycle 1 daytime results separate the systems clearly with respect to false alerts. LiDAR is the most conservative system at every aggregation bin, followed by the thermal and optical camera systems, which remain within about one percentage point of each other. Radar produces far more false alerts than the other three systems at all three bins, and its rate falls most steeply as the bin shortens, indicating that its spurious detections are scattered across many short intervals. In short, LiDAR offers the strongest daytime false alert control in Cycle 1 while radar requires the most filtering, which is the reverse of the true positive ranking above, in which radar detected the largest share of daytime events.

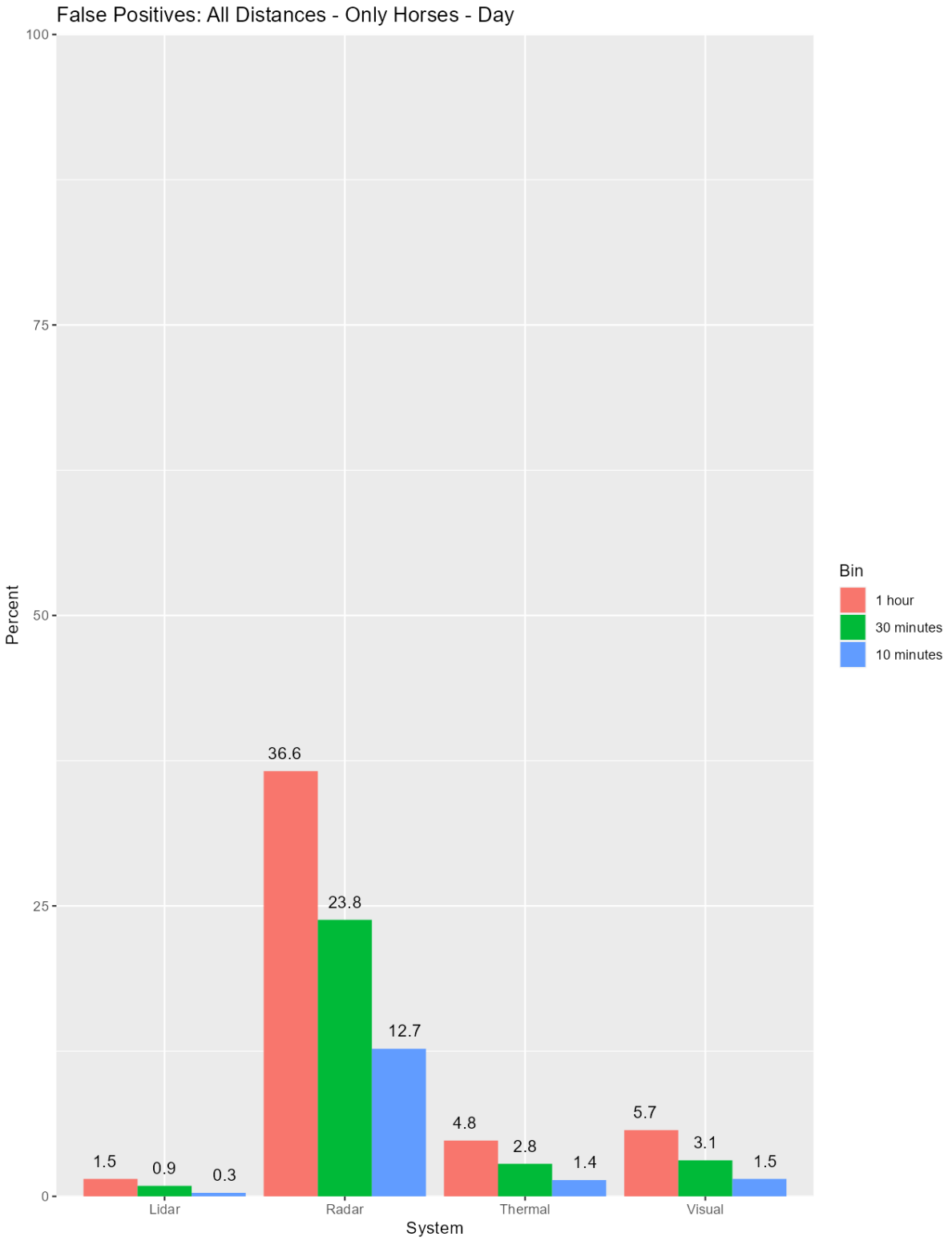


Figure 7. Cycle 1 daytime false positive percentage of four sensing systems across all distances by temporal aggregation bin

5.1.2. Cycle 1 Nighttime Performance

Nighttime baseline events for Cycle 1 are summarized in Table 10. Figure 8 presents the Cycle 1 nighttime true positive detection percentages for the four sensing systems across different distance ranges. Overall, nighttime detection performance is substantially stronger than daytime performance for all sensing modalities, particularly at shorter distances.

LiDAR detected 27.9% of the baseline nighttime horse events at all distances, 80% of the events under 500 ft, and 92.3% of the events under 300 ft, a clear improvement over its daytime results.

Radar detected 90.7% of nighttime events at all distances and 100% of the events under 500 ft and under 300 ft, the highest rates of the four systems.

The thermal camera system detected 46.5% of nighttime events at all distances and 100% of the events under 500 ft and under 300 ft.

The optical camera system detected 27.9% of nighttime events at all distances, 80% of the events under 500 ft, and 84.6% of the events under 300 ft, comparable to LiDAR at near range despite the low-light conditions.

Overall, radar and thermal provided the most consistent nighttime detection in Cycle 1, detecting every event within 500 ft, and radar also captured most of the far-range events. LiDAR and the optical camera detected 80% of the events within 500 ft and the great majority within 300 ft, but their all-distance rates were held down by the high proportion of nighttime activity beyond 500 ft.

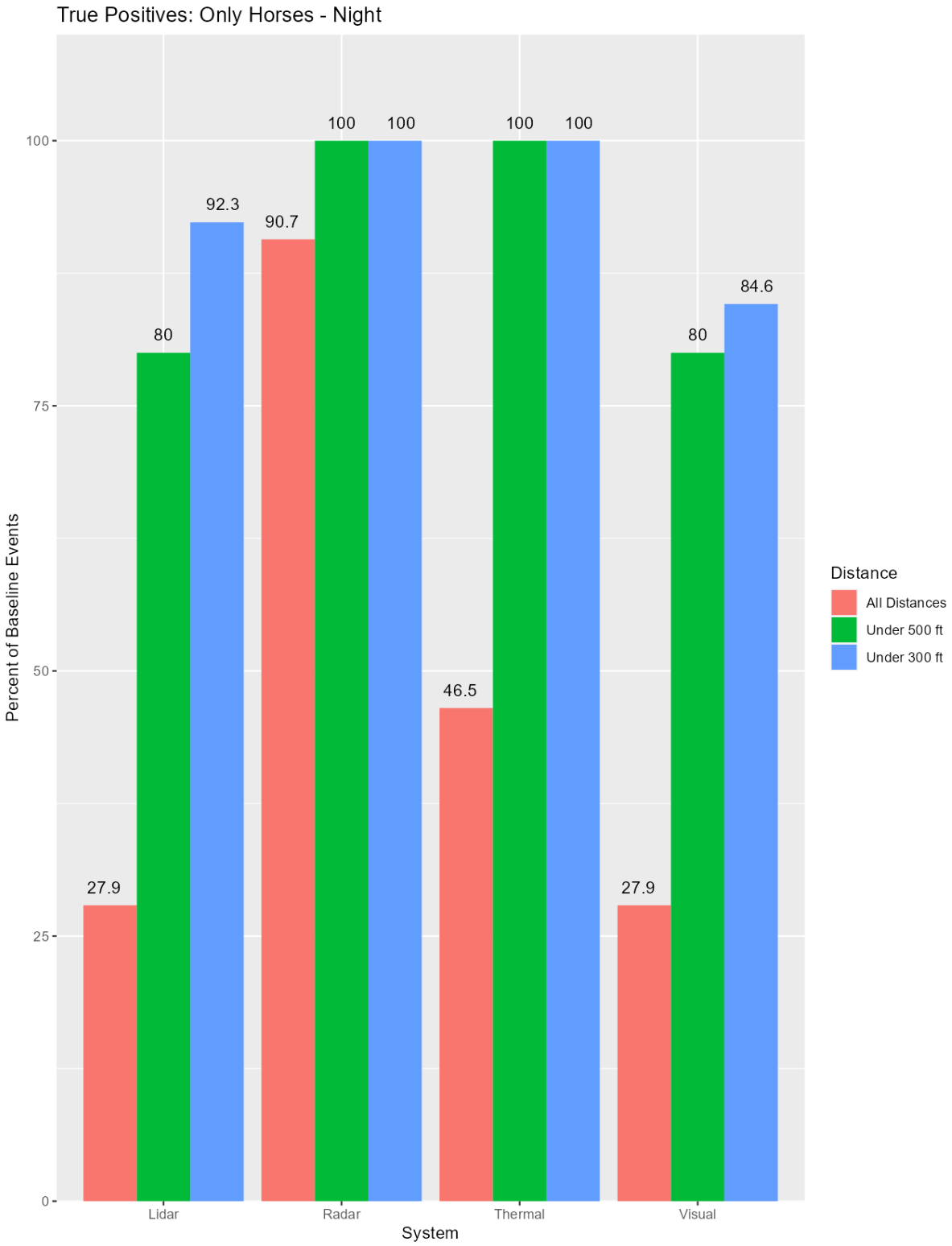


Figure 8. Cycle 1 nighttime true positive percentage of four sensing systems at different distance ranges

Figure 9 presents the Cycle 1 nighttime false positive percentages across all distances for the four sensing systems, summarized using three temporal aggregation bins (1 hour, 30 minutes, and 10 minutes). Compared with daytime conditions, nighttime operations generally result in higher false positive rates, particularly for radar and thermal sensing systems.

LiDAR maintains the lowest false positive rates at night, with values of 4.5% (1-hour bin), 2.7% (30-minute bin), and 1.3% (10-minute bin). Although higher than its daytime values, LiDAR remains the most conservative system with respect to false alerts during nighttime conditions.

Radar exhibits the highest false positive rates among all systems at night, with false positives of 35.4% (1 hour), 27.2% (30 minutes), and 18.5% (10 minutes). These elevated rates indicate strong sensitivity to non-target nighttime activity and environmental noise, even when shorter temporal aggregation is applied.

The thermal camera system shows substantially increased nighttime false positives compared with daytime, reaching 24.7% (1 hour), 15.5% (30 minutes), and 7.0% (10 minutes). This suggests that thermal sensing is more susceptible to non-target heat sources and background thermal variability during nighttime operations when all distances are included.

The optical camera system exhibits moderate nighttime false positive rates, with 4.8% (1 hour), 3.0% (30 minutes), and 1.6% (10 minutes), remaining lower than radar and thermal but slightly higher than LiDAR.

Overall, the results show a clear separation in nighttime false alert behavior among the detection systems. LiDAR stands out as the most conservative system, producing the fewest unnecessary alerts even when conditions are more challenging after dark. The optical camera system performs nearly as well, trailing LiDAR by less than half a percentage point at each bin. Thermal sensing becomes considerably less precise at night likely because of non-target heat sources and background thermal variability, and radar shows the greatest difficulty, generating many spurious detections likely in response to non-target movement and environmental noise. In short, LiDAR offers the strongest nighttime false alert control while radar produces the most false alerts, which is the reverse of the true positive ranking above, in which radar and thermal detected the largest share of nighttime events.

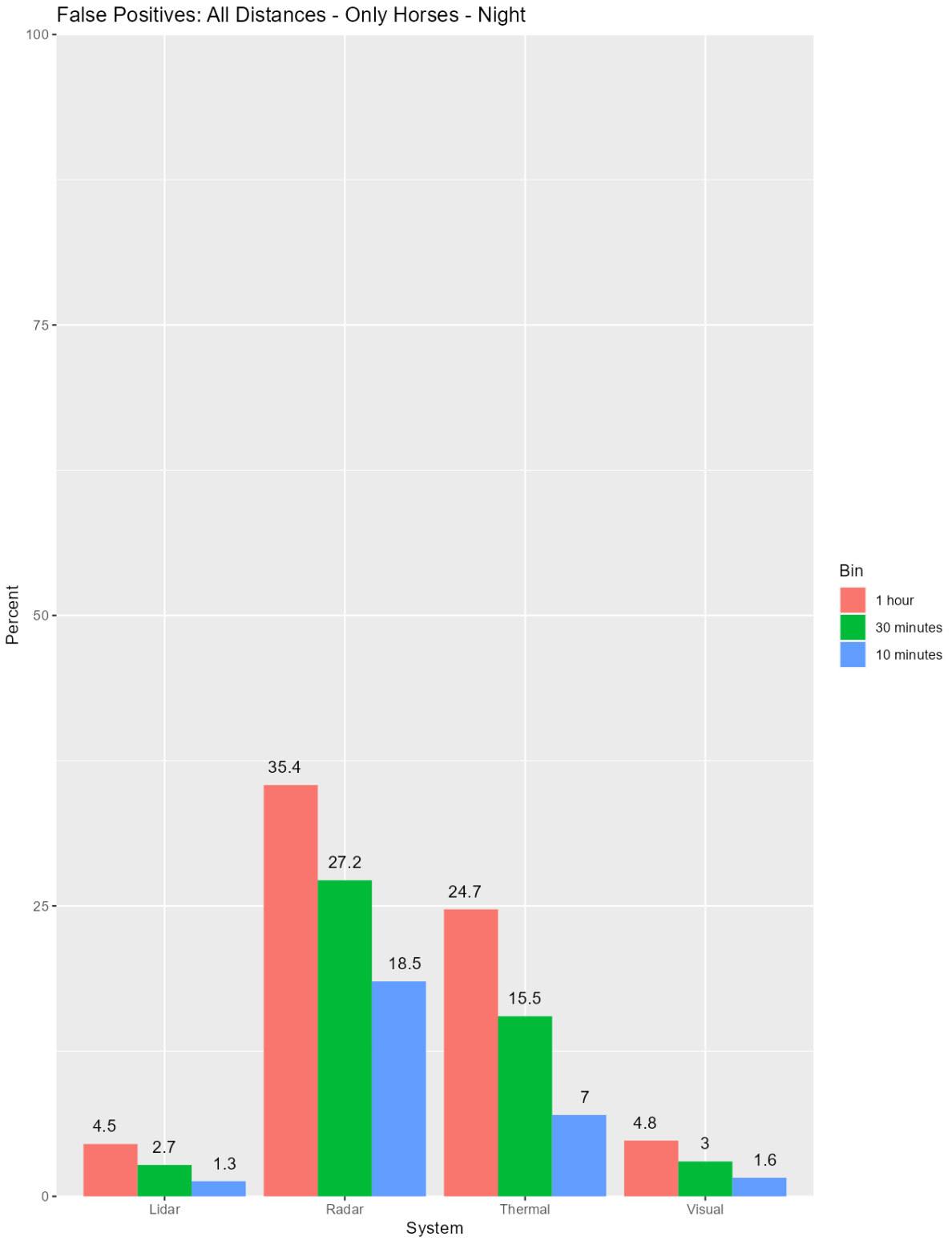


Figure 9. Cycle 1 nighttime false positive percentage of four sensing systems across all distances by temporal aggregation bin

5.2.Cycle 2 – February 2024 (Baseline Period Feb 1–14, 2024)

Cycle 2 was conducted February 1–14, 2024. Several data and system limitations affected Cycle 2 and are important for interpreting the performance results. During the 14-day analysis period, 108 hours, 9 minutes, and 7 seconds of baseline thermal video footage were missing or corrupt. Any system detections that occurred during these missing baseline time intervals were excluded from the performance comparison to ensure consistency with the ground-truth dataset. In addition, several sensor-specific issues were observed. The LiDAR system recorded detections for five horse events beyond 500 ft, which is outside the expected effective detection range (300 ft radius) of the system but in the maximum sensor detection range (600 ft radius). The thermal camera system continued to operate with a size filter that allowed detections of animals at rodent size and larger, which likely inflated reported true positive rates by including non-target detections. Finally, the optical camera system was not operational from February 6 to February 14, 2024, and data during this period were treated as no data rather than missed detections.

These limitations are documented and explicitly considered in the interpretation of Cycle 2 performance results, particularly when comparing system performance across sensing modalities and between data collection cycles.

5.2.1. Cycle 2 Daytime Performance

Daytime baseline events for Cycle 2 are summarized in Table 10. As noted in Section 5.2, data gaps and system-specific limitations should be considered when interpreting Cycle 2 results. Figure 10 presents Cycle 2 daytime true positive detection percentages for the four sensing systems across different distance ranges. As in Cycle 1, detection performance during daytime conditions is strongly influenced by distance to the sensors.

LiDAR detected 32% of the baseline daytime horse events at all distances, 83.3% of the events under 500 ft, and 100% of the events under 300 ft. The improvement over Cycle 1 reflects the algorithm parameter adjustments made to raise LiDAR true positive rates, with the tradeoff in false positives discussed below.

Radar detected 52% of daytime events at all distances and 100% of the events under 500 ft and under 300 ft, again the highest all-distance rate.

The thermal camera system detected 40% of daytime events at all distances and 100% of the events under 500 ft and under 300 ft. As in Cycle 1, the thermal size filter allowed detections of small animals, which may have inflated these rates.

The optical camera system detected 24% of daytime events at all distances, 66.7% of the events under 500 ft, and 80% of the events under 300 ft. The system was not operational from February 6 to 14, 2024, which limits the events available to it in this cycle.

Overall, Cycle 2 daytime results follow the Cycle 1 pattern: radar was strongest at all distances, and every system detected all or nearly all events within 300 ft. LiDAR moved from the weakest system in Cycle 1 to 83.3% under 500 ft and 100% under 300 ft after its parameter adjustments, while the optical camera had the lowest rate at each range, partly because of its outage during the second half of the cycle.

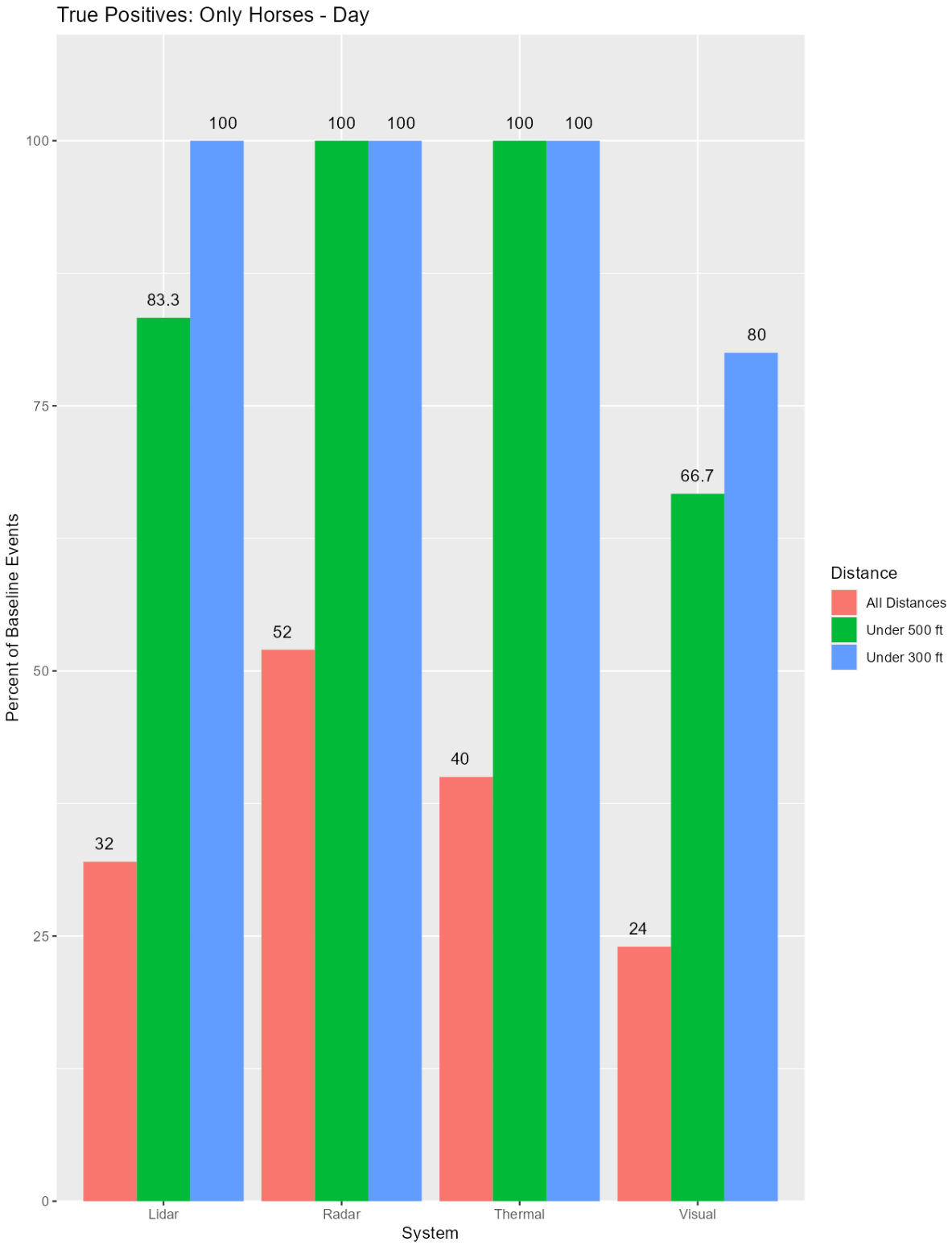


Figure 10. Cycle 2 daytime true positive percentage of four sensing systems at different distance ranges

Figure 11 presents the Cycle 2 daytime false positive detection percentages for the four sensing systems across different distance ranges.

LiDAR exhibits the highest daytime false positive rates in Cycle 2 when all distances are included, with 24.4% (1-hour bin), 16.7% (30-minute bin), and 5.8% (10-minute bin). This elevated false positive rate suggests increased sensitivity to non-target detections during daytime winter conditions when distant activity is considered. It was noted that the LiDAR sensing system's algorithm parameters were adjusted to enhance the true positive rates, and the increased false positive rates were a tradeoff.

The radar system shows moderate false positive rates, with values of 15.6% (1 hour), 10.0% (30 minutes), and 3.3% (10 minutes). While lower than LiDAR, radar still produces a notable number of false alerts at longer aggregation intervals.

The thermal camera system demonstrates lower false positive rates relative to LiDAR and radar, with 13.3% (1 hour), 7.0% (30 minutes), and 1.6% (10 minutes). This indicates improved daytime false alert control for thermal sensing during Cycle 2.

The optical camera system exhibits the lowest false positive rates among all sensing modalities, with 3.7% (1 hour), 2.2% (30 minutes), and 0.5% (10 minutes), indicating stable and conservative daytime performance when all distances are considered.

Overall, the Cycle 2 daytime false alert ranking differs from Cycle 1. The optical camera system is the most conservative at every bin, followed by thermal and then radar, while LiDAR produces the most false alerts at all three bins as a result of the algorithm parameter changes made to raise its true positive rates. At the 10-minute bin the four systems converge to within about five percentage points of one another. In short, the optical camera offers the strongest daytime false alert control in Cycle 2, and the LiDAR results illustrate the tradeoff between detection sensitivity and false alerts. Note that the optical camera was not operational from February 6 to 14, 2024, so its Cycle 2 results reflect roughly half of the cycle.

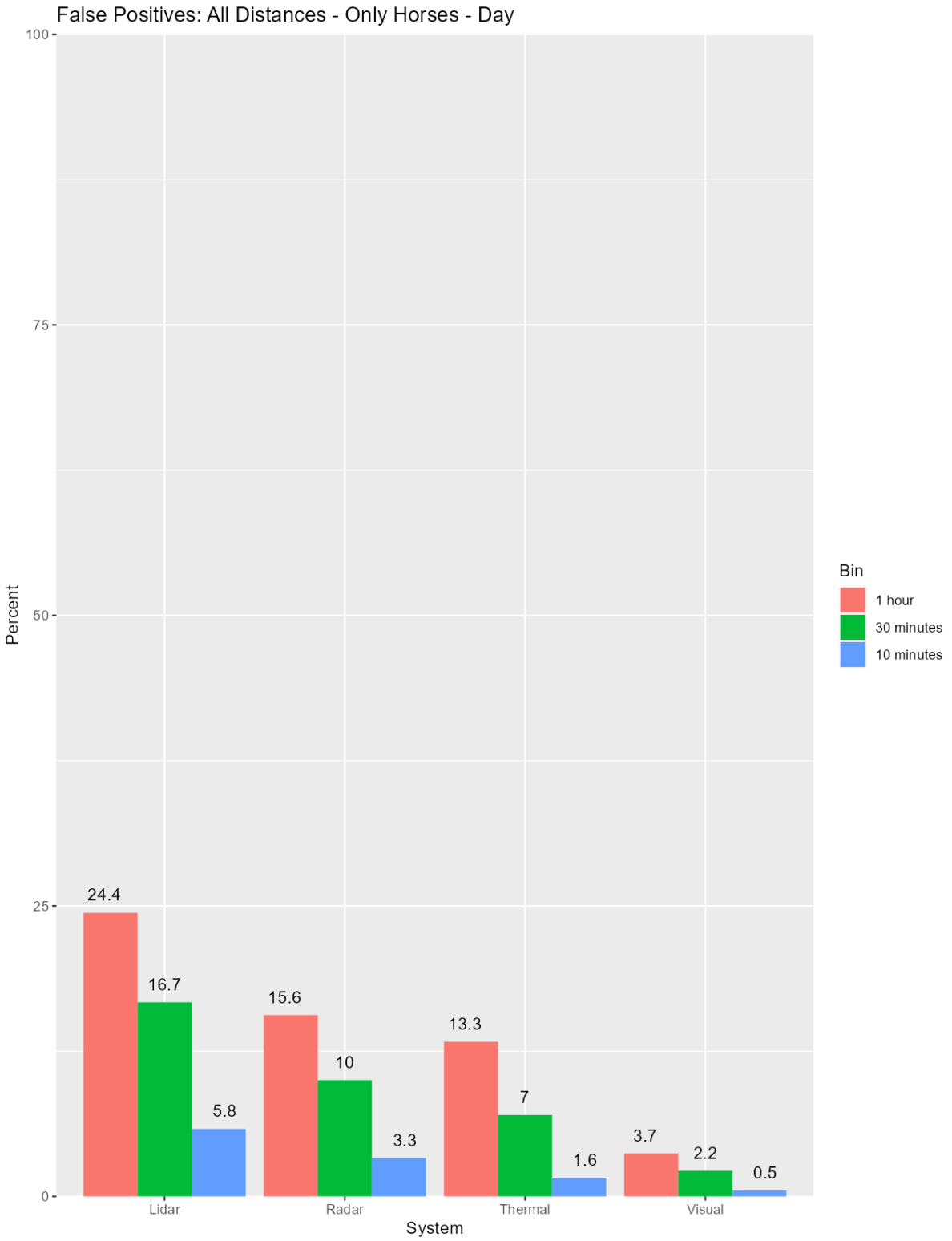


Figure 11. Cycle 2 daytime false positive percentage of four sensing systems across all distances by temporal aggregation bin

5.2.2. Cycle 2 Nighttime Performance

Nighttime baseline events for Cycle 2 are summarized in Table 10. Figure 12 presents the Cycle 2 nighttime true positive detection percentages for the four sensing systems across different distance ranges. Overall, nighttime detection performance in Cycle 2 is strong at shorter distances for all sensing modalities, while all-distance performance remains constrained by the prevalence of horse activity beyond effective detection ranges.

LiDAR detected 29.6% of the baseline nighttime horse events at all distances, 85.7% of the events under 500 ft, and 100% of the events under 300 ft.

Radar detected 51.9% of nighttime events at all distances, 85.7% of the events under 500 ft, and 83.3% of the events under 300 ft. Cycle 2 nighttime is the only period in which radar did not detect every event within 300 ft.

The thermal camera system detected 55.6% of nighttime events at all distances, the highest all-distance rate in this period, and 100% of the events under 500 ft and under 300 ft.

The optical camera system detected 29.6% of nighttime events at all distances and 100% of the events under 500 ft and under 300 ft, although the February 6 to 14 outage limits the events available to it.

Overall, the four systems were closely matched at near range in Cycle 2 nighttime: all of them detected at least 85.7% of the events within 500 ft and at least 83.3% within 300 ft. Thermal and radar led at all distances because they detected a larger share of the far-range events, while LiDAR and the optical camera were limited to about 30% at all distances by the many events beyond 500 ft.

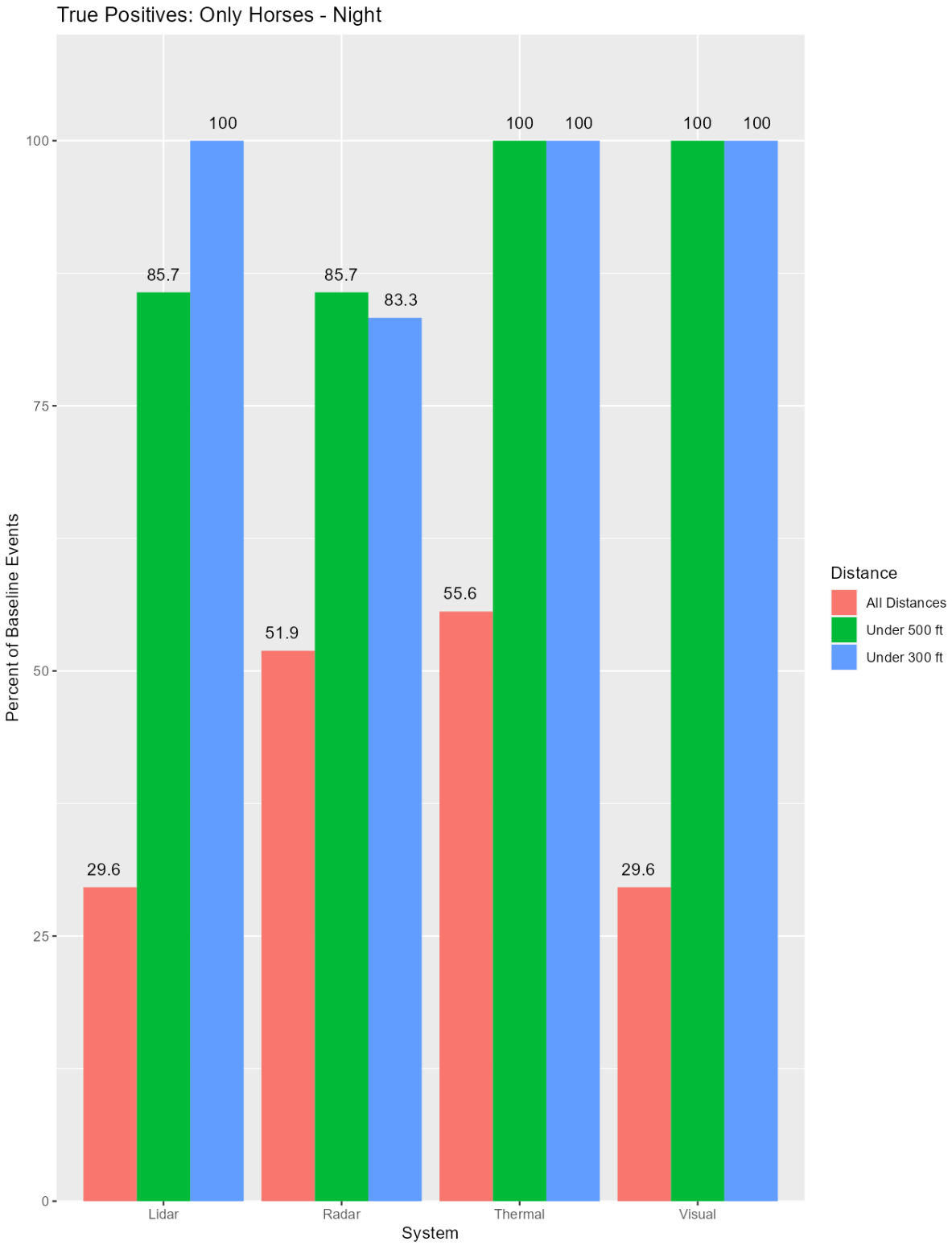


Figure 12. Cycle 2 nighttime true positive percentage of four sensing systems at different distance ranges

Figure 13 presents the Cycle 2 nighttime false positive percentages across all distances for the four sensing systems, evaluated using three temporal aggregation bins (1 hour, 30 minutes, and 10 minutes). Compared with daytime conditions, nighttime false positive behavior varies substantially by sensing modality and remains highly sensitive to temporal aggregation.

Thermal sensing exhibits the highest nighttime false positive rates in Cycle 2, with 38.5% at the 1-hour bin, 25.9% at 30 minutes, and 6.9% at 10 minutes. These elevated rates indicate increased sensitivity to non-target thermal sources and background heat signatures during nighttime conditions when detections at all distances are included.

The radar system also shows relatively high nighttime false positive rates, reaching 25.2% (1 hour), 15.9% (30 minutes), and 4.5% (10 minutes). Although lower than thermal, radar continues to generate a substantial number of false alerts at longer aggregation intervals during nighttime operations.

LiDAR demonstrates moderate nighttime false positive rates, with 9.6% (1 hour), 7.4% (30 minutes), and 3.3% (10 minutes). These values are higher than daytime LiDAR false positives in Cycle 2 but remain lower than those observed for radar and thermal sensing.

The optical camera system exhibits the lowest nighttime false positive rates among all sensing modalities, with 7.4% (1 hour), 4.4% (30 minutes), and 1.9% (10 minutes), indicating stable and conservative nighttime performance even when detections across all distances are considered.

Taken together, the findings show a clear ordering in nighttime false alert behavior: the optical camera system produced the fewest false alerts and remained lowest at all three aggregation bins. LiDAR also performs well, with rates slightly above the optical camera and higher than its Cycle 1 nighttime values. Radar struggles more with false triggers, particularly over longer aggregation periods, likely reflecting its sensitivity to non-target movement and environmental noise. Thermal sensing produces the most false alerts after dark in this cycle, likely because non-target heat sources and background thermal variability trigger detections. In essence, the optical camera system provides the strongest nighttime false alert control in Cycle 2 while thermal sensing produces the most false alerts.

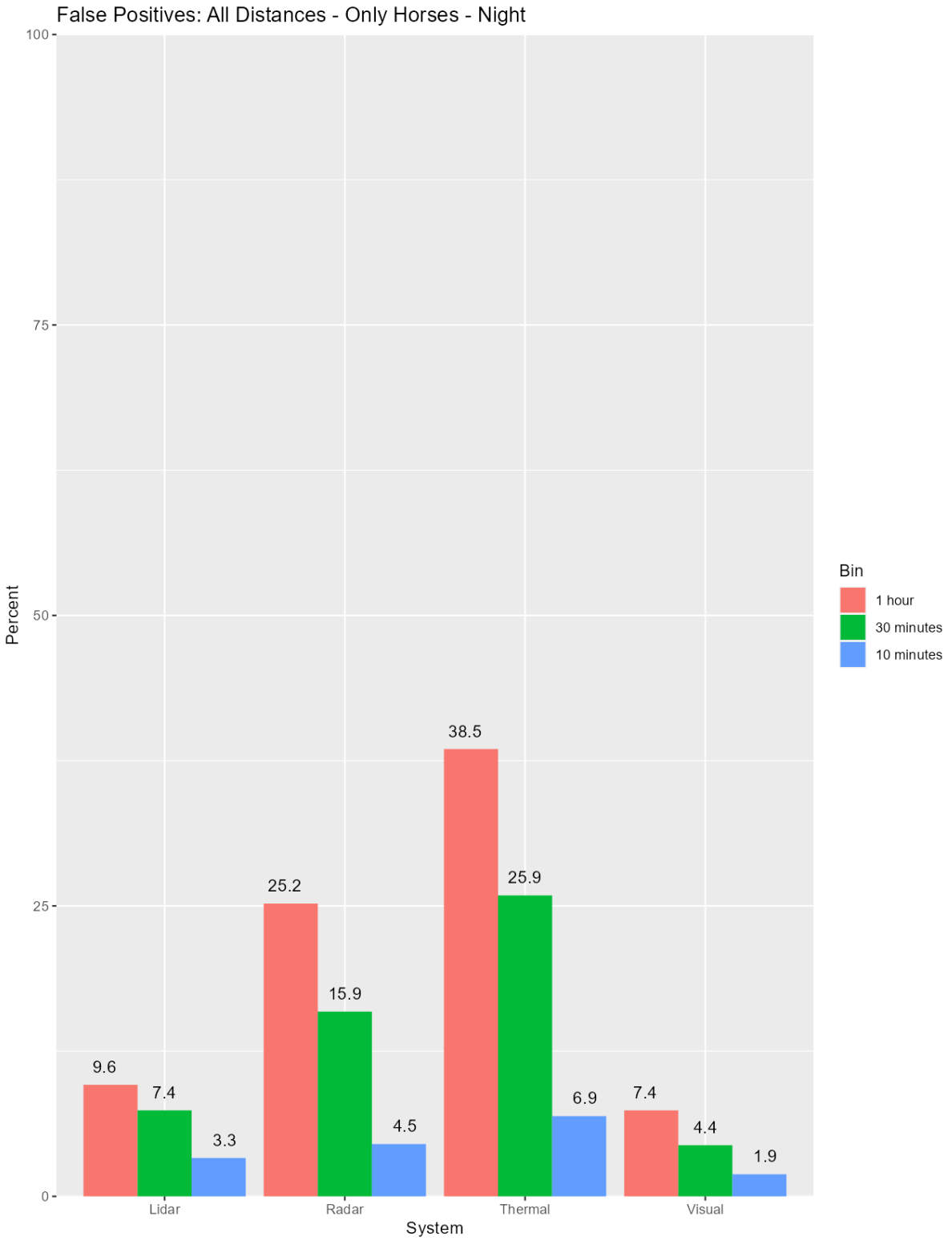


Figure 13. Cycle 2 nighttime false positive percentage of four sensing systems across all distances by temporal aggregation bin

5.3.Cycle 3 – October 2024 (Baseline Period Oct 17–30, 2024)

Cycle 3 was conducted October 17–30, 2024. Several system configuration changes and data timing issues affected Cycle 3 and are important for interpreting the performance results. The thermal time-lapse and thermal detection system field of view was adjusted by tilting the camera downward compared to previous cycles. This change reduced coverage at longer distances and lowered the likelihood of accurately observing and detecting horse activity beyond 500 ft, particularly for baseline identification and system performance evaluation at far ranges. Because the thermal time-lapse imagery used for ground-truth review and the thermal detection system share the same camera, the reduced far-range coverage applied to the human reviewers as well as to the automated thermal detections. Horse activity beyond 500 ft may therefore be under-represented in the Cycle 3 baseline itself, which affects the all-distance results for all four sensing systems, while coverage of the area within 500 ft was maintained.

In addition, the LiDAR system recorded detections for three horse events beyond 500 ft, which exceeds the expected effective detection range of the system, but in the range of maximum sensor range.

The thermal detection system also experienced a timestamp lag when recording detections to the .csv output file. Comparison of timestamps from the thermal time-lapse footage and the PTZ camera with those in the thermal detection .csv indicated a delay of approximately 10 seconds to 1 minute. This timing offset introduces uncertainty in event matching between baseline observations and system detections and is documented as a limitation in the interpretation of Cycle 3 thermal performance results.

These configuration changes and timing issues are explicitly considered in the analysis of Cycle 3 results, particularly when comparing detection performance across sensing modalities and relative to earlier data collection cycles.

5.3.1. Cycle 3 Daytime Performance

Daytime baseline events for Cycle 3 are summarized in Table 10. As noted in Section 5.3, thermal field-of-view adjustments and timing offsets should be considered when interpreting Cycle 3 results. Figure 14 presents the Cycle 3 daytime true positive detection percentages for the four sensing systems across different distance ranges. Compared with earlier cycles, daytime detection performance in Cycle 3 is generally strong at short and mid ranges, with greater variation observed when detections at all distances are included.

LiDAR detected 65.4% of the baseline daytime horse events at all distances and 100% of the events under 500 ft and under 300 ft, its strongest daytime result of the three cycles.

Radar detected 100% of daytime events at every range, including all far-range events, the only all-distance rate of 100% recorded in the study.

The thermal camera system detected 42.3% of daytime events at all distances and 66.7% of the events under 500 ft and under 300 ft. The lower rates are consistent with the downward tilt of the thermal camera in this cycle, which reduced coverage at the farther portions of the monitored area, and with the timestamp lag noted in Section 5.3.

The optical camera system detected 53.8% of daytime events at all distances and 93.3% of the events under 500 ft and under 300 ft, its highest daytime rates at all distances and under 500 ft of the three cycles.

Overall, Cycle 3 daytime detection was strong for radar, LiDAR, and the optical camera, which detected all or nearly all events within 500 ft, and radar detected every event at every range. Thermal was the exception, with lower rates at every range that reflect the field-of-view change specific to this cycle rather than a change in the sensor itself.

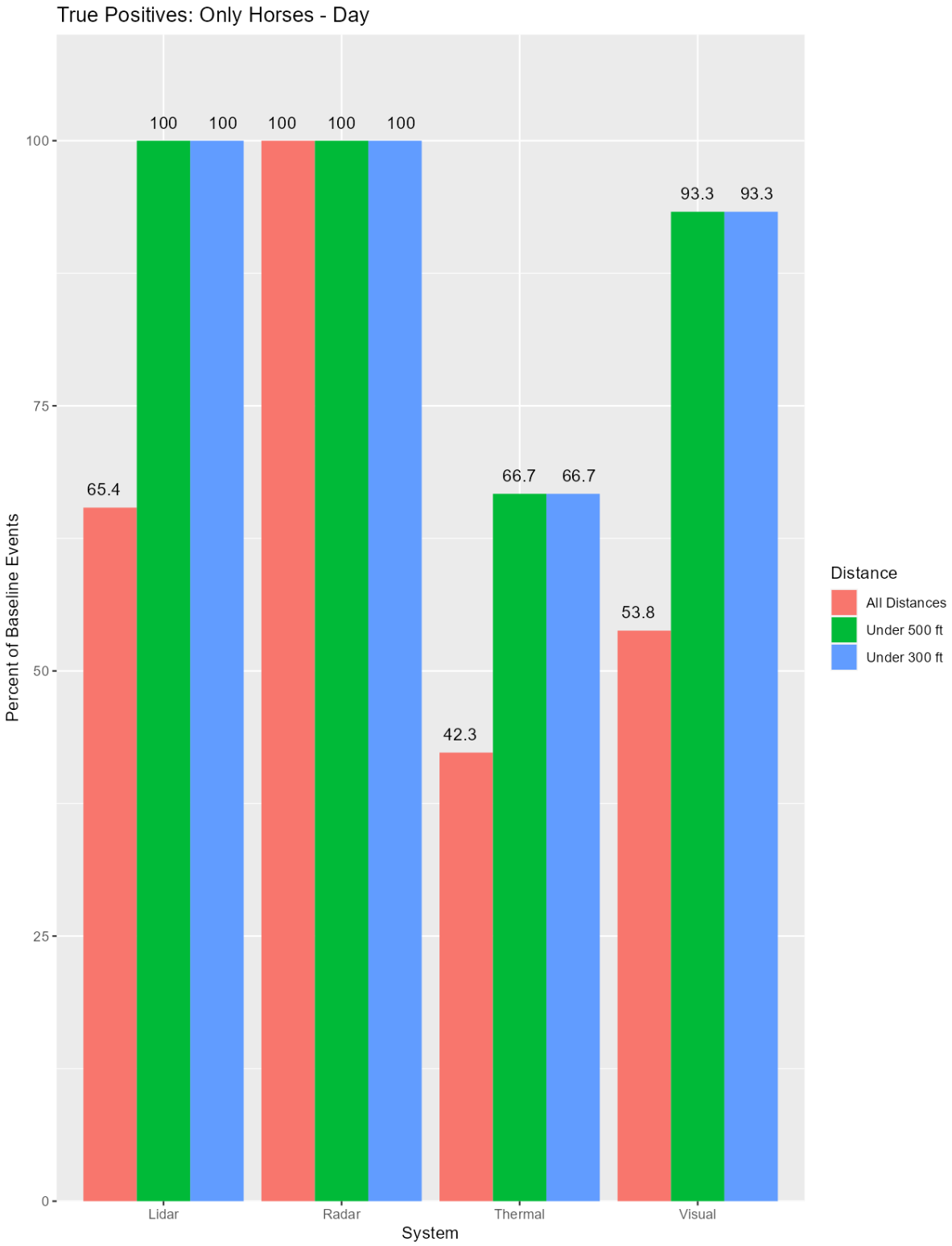


Figure 14. Cycle 3 daytime true positive percentage of four sensing systems at different distance ranges

Figure 15 presents Cycle 3 daytime false positive percentages across all distances for the four sensing systems, evaluated using three temporal aggregation bins (1 hour, 30 minutes, and 10 minutes). Compared with Cycle 2, daytime false positive rates in Cycle 3 are lower for LiDAR and thermal at the 1-hour and 30-minute bins but higher for radar and the optical camera.

Radar exhibits the highest daytime false positive rates in Cycle 3, with 30.4% (1-hour bin), 21.7% (30-minute bin), and 12.5% (10-minute bin). These results indicate continued sensitivity of radar to non-target detections during daytime operations, particularly when longer temporal aggregation windows are applied.

LiDAR shows moderate false positive rates, with 15.5% (1 hour), 9.7% (30 minutes), and 4.8% (10 minutes). While higher than thermal and optical systems, LiDAR false positives decrease substantially as the aggregation window shortens.

The thermal camera system demonstrates relatively low false positive rates, with 8.3% (1 hour), 4.8% (30 minutes), and 2.0% (10 minutes). This improved performance is consistent with the reduced field of view during Cycle 3, which limited detections from distant background sources.

The optical camera system exhibits the lowest daytime false positive rates among all sensing modalities, with 6.0% (1 hour), 3.6% (30 minutes), and 1.7% (10 minutes), indicating stable and conservative daytime performance.

Overall, the Cycle 3 daytime results again separate the systems clearly. The optical camera system is the most conservative at every bin, closely followed by thermal, whose lower rates are consistent with its reduced field of view in this cycle. LiDAR is intermediate, and radar produces the most false alerts at all three bins. In short, the optical camera offers the strongest daytime false alert control in Cycle 3 while radar requires the most filtering, even though radar detected every baseline daytime event in this cycle.

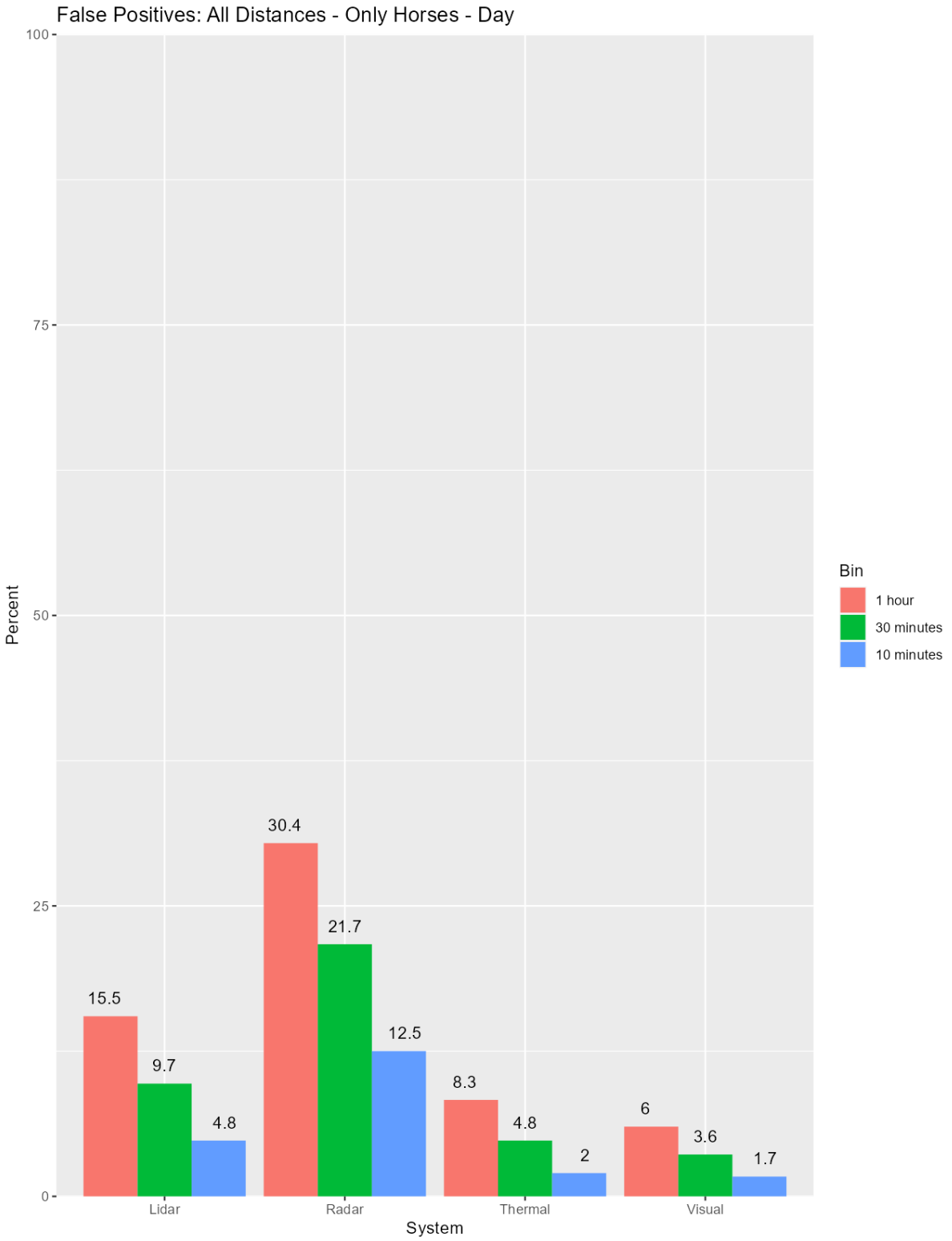


Figure 15. Cycle 3 daytime false positive percentage of four sensing systems across all distances by temporal aggregation bin

5.3.2. Cycle 3 Nighttime Performance

Nighttime baseline events for Cycle 3 are summarized in Table 10. As noted in Section 5.3, thermal field-of-view adjustments and timing offsets should be considered when interpreting Cycle 3 nighttime results. Figure 16 presents the Cycle 3 nighttime true positive detection percentages for the four sensing systems across different distance ranges. Compared with daytime conditions in Cycle 3, nighttime detection performance shows greater variability across sensing modalities, particularly when detections at all distances are considered.

LiDAR detected 19.4% of the baseline nighttime horse events at all distances, 75% of the events under 500 ft, and 100% of the events under 300 ft.

Radar detected 86.1% of nighttime events at all distances and 100% of the events under 500 ft and under 300 ft, again the highest rates of the four systems.

The thermal camera system detected 22.2% of nighttime events at all distances, 75% of the events under 500 ft, and 83.3% of the events under 300 ft; the reduced field of view and the timestamp lag noted in Section 5.3 affect these results.

The optical camera system detected 5.6% of nighttime events at all distances, 25% of the events under 500 ft, and 33.3% of the events under 300 ft, the lowest nighttime rates recorded in the study.

Overall, radar was the only system with strong nighttime detection at all distances in Cycle 3. LiDAR and thermal detected most events within 500 ft and all or most events within 300 ft but few of the far-range events, and the optical camera detected only a small share of events at any range, reflecting its dependence on lighting.

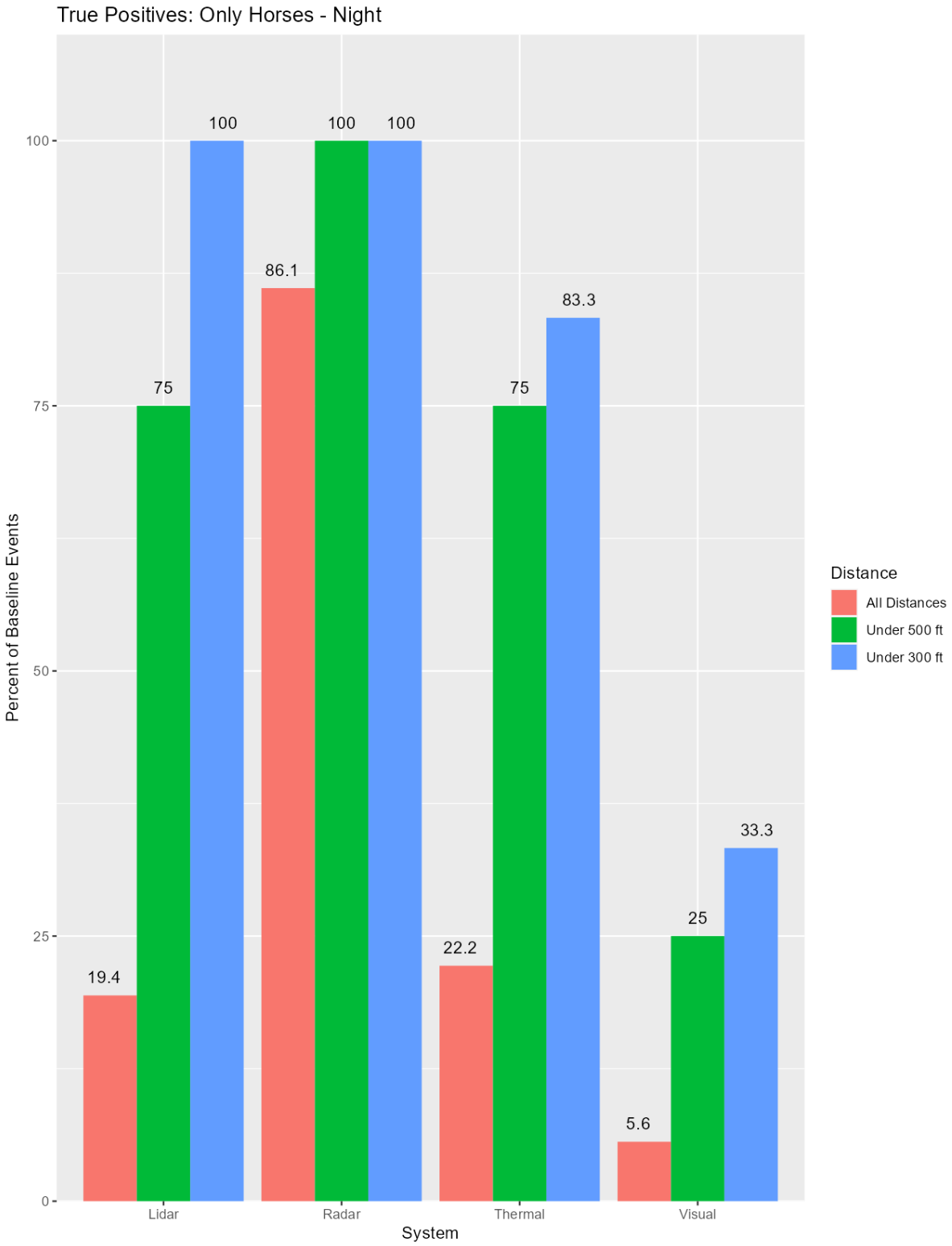


Figure 16. Cycle 3 nighttime true positive percentage of four sensing systems at different distance ranges

Figure 17 presents the Cycle 3 nighttime false positive percentages across all distances for the four sensing systems, evaluated using three temporal aggregation bins (1 hour, 30 minutes, and 10 minutes). Overall, false positive rates during Cycle 3 nighttime conditions are lower than those observed in earlier cycles, particularly for thermal and optical sensing systems.

Radar exhibits the highest nighttime false positive rates in Cycle 3, with 30.4% at the 1-hour bin, 23.7% at 30 minutes, and 15.5% at the 10-minute bin. These results indicate continued sensitivity of radar to non-target nighttime detections, even as shorter temporal aggregation reduces false alerts.

LiDAR demonstrates relatively low nighttime false positive rates, with 6.2% (1 hour), 3.7% (30 minutes), and 1.7% (10 minutes), indicating stable nighttime performance and effective false alert control compared with radar.

The thermal camera system shows low false positive rates, with 6.0% (1 hour), 3.3% (30 minutes), and 1.3% (10 minutes). This improvement relative to earlier cycles is consistent with the reduced thermal field of view and improved filtering during Cycle 3.

The optical camera system exhibits the lowest nighttime false positive rates among all sensing modalities, with 0.9% (1 hour), 0.4% (30 minutes), and 0.1% (10 minutes), indicating highly conservative nighttime performance with minimal spurious detections.

Overall, the Cycle 3 nighttime results again separate the systems clearly. The optical camera system generated almost no false alerts, below 1% at every bin, and the thermal and LiDAR systems were also low and nearly identical to each other, with thermal benefiting from its reduced field of view and improved filtering in this cycle. Radar remained well above the other three systems at all bins. In short, the optical camera and, to a slightly lesser degree, thermal and LiDAR offer strong nighttime false alert control in Cycle 3, while radar requires the most filtering. As in the earlier cycles, this is the reverse of the true positive ranking above, in which radar detected the largest share of nighttime events and the optical camera the smallest.

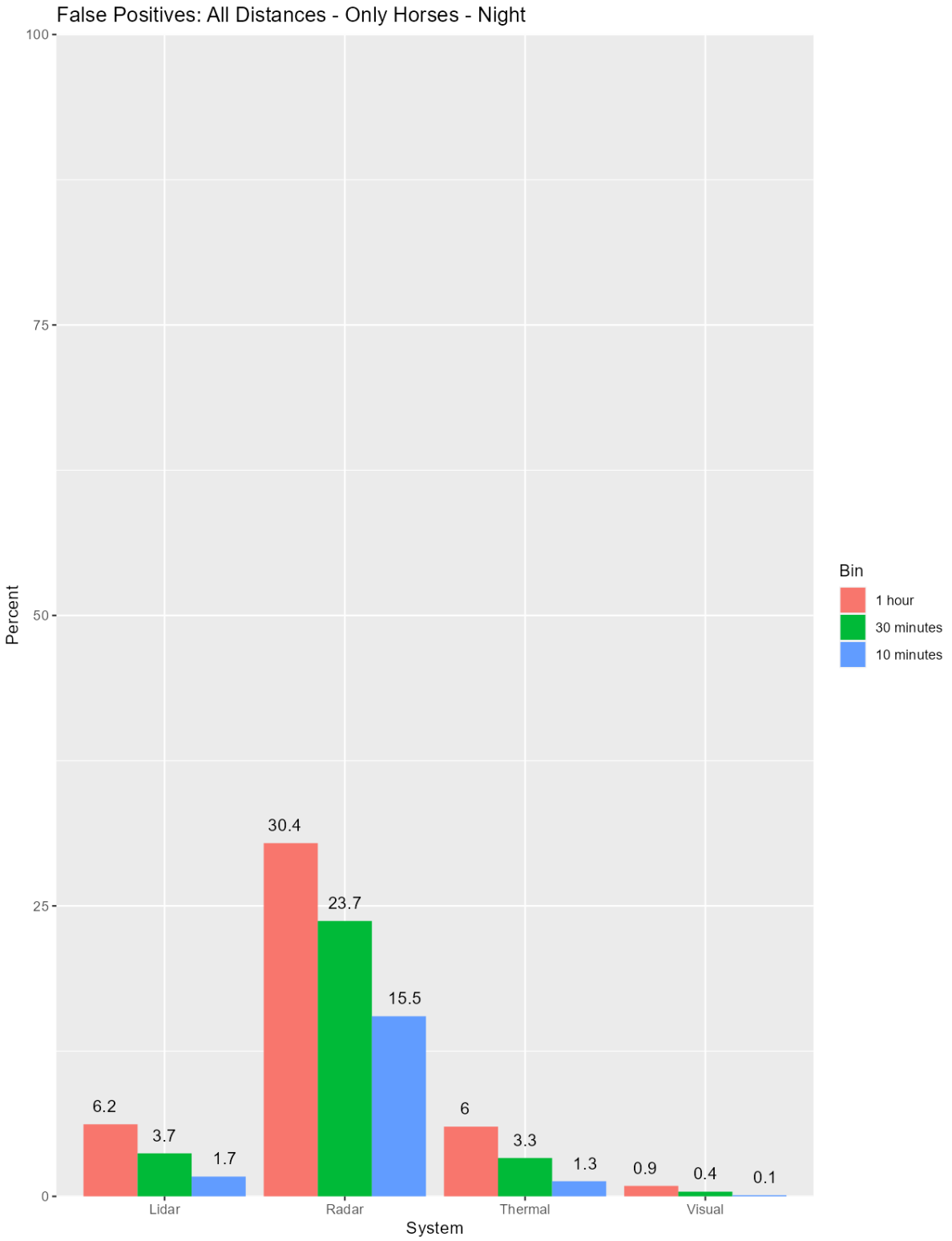


Figure 17. Cycle 3 nighttime false positive percentage of four sensing systems across all distances by temporal aggregation bin

5.4.Summary of Performance Comparison

Across the three data collection cycles, clear and consistent patterns emerge in the performance of the four animal detection systems, LiDAR, radar, thermal camera, and optical camera, with distance to the sensor and time of day being the dominant factors influencing detection effectiveness and false alert behavior.

Distance Effects (All Cycles)

Distance is the strongest determinant of detection performance for all sensing modalities. Across all cycles and both daytime and nighttime conditions:

- Detection performance is consistently high within 300 ft, where most systems achieve near perfect or perfect true positive rates.
- Performance degrades rapidly beyond 500 ft, particularly for LiDAR and optical cameras, which are fundamentally limited by range, resolution, and environmental clutter.
- Radar and thermal systems demonstrate greater resilience at mid-range distances (300–500 ft) but still show reduced effectiveness when far-range (>500 ft) events dominate the baseline dataset.

As a result, all-distance performance metrics are heavily influenced by the proportion of far-range events and should be interpreted cautiously when comparing sensing modalities.

Daytime vs. Nighttime Performance

Nighttime conditions generally improve true positive detection rates, particularly for radar and thermal sensing, while also increasing the risk of false positives for some systems.

- Radar consistently demonstrates the strongest nighttime detection capability, achieving the highest all-distance true positive rates in all three cycles, with particularly robust performance within 500 ft.
- Thermal sensing performs well at night for near- and mid-range detections, but its effectiveness is sensitive to field-of-view configuration and thermal background variability, especially during winter deployments.
- Optical cameras show reasonable daytime performance at short distances but exhibit substantially reduced effectiveness at night, particularly beyond 300 ft.
- LiDAR shows moderate nighttime improvement relative to daytime but remains constrained by range limitations and sensitivity to configuration parameters.

Nighttime operations also tend to increase false positive rates, especially for radar and thermal systems, highlighting the need for careful temporal filtering and alert logic.

System-Specific Performance Trends

Radar

- Strengths: Highest overall detection reliability, especially at night and within 500 ft.
- Limitations: Consistently highest false positive rates, particularly with longer temporal aggregation windows. *It should be noted that validation reliability at longer distances is uncertain; the radar system receives return signals from distances*

approaching 5,000 feet, which may exceed the effective recognition range of the thermal cameras. As a result, some records classified as false positives may reflect true detections of animals that could not be confirmed visually.

- Implication: Best suited as a **primary detection sensor** but requires aggressive filtering or sensor fusion to manage false alerts.

Thermal Camera

- Strengths: Strong nighttime detection capability at close and mid ranges.
- Limitations: Highly sensitive to configuration changes (size filters, field of view, timestamp alignment), leading to variability across cycles.
- Implication: Effective nighttime detection but requires careful calibration and synchronization.

LiDAR

- Strengths: Very low false positive rates across all cycles and conditions.
- Limitations: Limited detection range and sensitivity to algorithm tuning; true positive rates drop sharply when far-range events dominate.
- Implication: Well suited as a confirmatory or filtering sensor, rather than a standalone detector.

Optical Camera

- Strengths: Lowest false positive rates, particularly during daytime.
- Limitations: Poor nighttime performance and limited range effectiveness.
- Implication: Best used for visual confirmation and daytime operations, not as a primary nighttime detector.

Cross-Cycle Observations

- **Cycle 1 (Fall 2023)** established baseline performance but was affected by thermal size-filter issues that inflated thermal true positives.
- **Cycle 2 (Winter 2024)** introduced environmental stressors and data gaps, revealing tradeoffs between increasing true positives and controlling false positives, particularly for LiDAR and thermal systems.
- **Cycle 3 (Fall 2024)** showed improved false positive control overall, but detection performance—especially for thermal sensing—was influenced by intentional field-of-view adjustments and timing offsets.

Overall Implications for Deployment

No single sensing modality provides optimal performance across all distances, lighting conditions, and seasons. Radar and thermal sensing provide the strongest detection capability, particularly at night and within 500 ft, while LiDAR and optical cameras excel at false positive control but have limited standalone detection capability at longer distances. These complementary strengths support a multi-sensor deployment approach; full recommendations on sensor selection and fusion strategies are provided in Chapter 7.

This cross-cycle evaluation underscores the importance of distance-aware alert logic, time-of-day-specific tuning, and redundant sensing strategies when deploying roadside animal detection systems for real-world transportation safety applications.

6. PROJECT PROCESS, CHALLENGES, SOLUTIONS, AND LESSONS LEARNED (2020–2025)

This chapter provides a chronological overview of the project process from its inception in 2020 through the end of 2025. It highlights major milestones, sensor deployments, data collection efforts, and site changes. The chapter focuses on completed activities and emphasizes key engineering challenges and the solutions implemented to overcome them. The narrative is organized by project phase and year for clarity. Following the chronological project history, a **Lessons Learned** section summarizes the key insights gained, which can guide future NDOT research deployments.

6.1.Initial Planning and Power System Design (2020)

Project kickoff: The project began in late 2020 with planning meetings and scope refinement. Early coordination discussions referenced outcomes from prior pilot efforts, including the observation that earlier LiDAR and camera deployments were constrained by limited solar power until supplemental wind power was introduced. This experience reinforced the need for a more robust and redundant power solution for a multi-sensor platform.

Power supply challenge: A critical early challenge was providing adequate off-grid power for continuous operation. Preliminary estimates indicated a total system load on the order of 300–500 W, depending on sensor configuration and computing requirements. A grid connection was considered but was not feasible due to the remote nature of the study area and the lack of permanent utility power.

Solution – renewable and backup power approach: The power system concept was developed around a self-contained DC setup with multiple power sources. The design incorporated solar panels, a wind turbine, and a generator as backup power. This multi-source approach established the foundation for a trailer-based platform capable of sustained field operation, providing a more robust solution than the earlier solar-only pilot systems.

Site selection and stakeholder coordination: Initial candidate locations were considered along USA Parkway in the Tahoe–Reno Industrial Center area. Coordination began with NDOT District II and local stakeholders to evaluate feasible trailer placement, access, and operational constraints. Early site reviews indicated that wild/feral horse activity in the area was influenced by water availability and was sensitive to nearby construction and land-use changes. NDOT District II also provided input on the existing trailer's solar and battery configuration and discussed upgrades required to support the planned sensor suite.

6.2.Site Selection and Initial Deployment (2021)

Reevaluating the site: In early 2021, the team recognized that the originally considered location was no longer ideal. Ongoing construction activity and changes in water resources had reduced wild/feral horse crossings at the initial candidate site. The UNR research team evaluated additional locations along USA Parkway. By mid-2021, the intersection of Electric Avenue and Venice Drive emerged as the preferred deployment location, based on field observations confirming active wild/feral horse presence in that corridor. Selecting a site with confirmed animal activity was essential to the success of the evaluation.

Trailer relocation and power upgrade: During summer 2021, the team secured the permissions needed to stage the NDOT ITS trailer at Electric Avenue and Venice Drive. NDOT

District II supported contractor coordination for trailer relocation and implementation of planned power system upgrades.

Solution – enhanced power infrastructure: The trailer was configured with an upgraded solar array, added wind generation, and an integrated generator backup (with remote-start capability) to improve operational reliability. This enhanced power infrastructure provided much-needed redundancy to support continuous sensing operations and reduced the risk of outages associated with weather variability and seasonal daylight limitations.

Initial sensor installation: With the trailer deployed at the new site, the team proceeded with sensor integration. Prior to full system activation, temporary animal cameras were used to document baseline animal activity and confirm ongoing horse presence. During 2021, UNR integrated two LiDAR units into the platform: a Velodyne mechanical LiDAR and a second LiDAR unit from another vendor that ultimately could not support automated detection due to limitations in its software. The project mitigated this issue by relying on the Velodyne LiDAR, together with UNR-developed processing software, as the primary LiDAR sensing solution. An optical video camera and an edge-computing system were also installed to support animal detection research and system integration testing.

Upgrades and configuration in late 2021: The camera subsystem was improved by transitioning from an AC-powered computing setup to a DC-powered edge computing device, which better aligned with the off-grid power constraints. The team also trained and calibrated the camera's detection model and improved remote connectivity by upgrading communications and networking components. To improve field durability and security, a protective generator enclosure was installed. By the end of 2021, the platform was prepared for expansion to include thermal and radar sensing systems once fabrication of the required equipment enclosures and hardware integration components was complete.

Key challenges and solutions in 2021: The site selection challenge was addressed through direct field observations and stakeholder coordination to ensure the chosen location had active animal crossings. Power limitations were mitigated by a hybrid solar–wind–generator power retrofit that increased the off-grid power capacity. Sensor integration risk was reduced by maintaining functional alternatives (e.g., using the Velodyne LiDAR when the other vendor-provided LiDAR solution proved unusable). These actions positioned the project for an expansion of sensing modalities in 2022.

6.3.Sensor Expansion and Construction Impacts (2022)

Delayed sensor deployment: Installation of the remaining sensors (thermal imaging and radar) was delayed in early 2022 due to hardware availability issues and integration schedule constraints. The sensor deployment was rescheduled multiple times during the first half of the year. The thermal camera and radar systems were ultimately installed in late July 2022. By that time, the platform included optical, thermal, radar, and LiDAR sensing components, although configuration and stabilization of the multi-sensor system required continued field work through the second half of 2022.

Intermediate improvements: During the sensor delivery and installation delays, the team took the opportunity to refine existing subsystems. For example, the sensors' fields of view were adjusted and aligned to cover a common detection corridor. The trailer's power and networking components were also reviewed and tuned to support continuous operation of multiple sensors simultaneously.

Independent evaluation and ground-truth approach: In 2022, the project team formalized an evaluation strategy for comparing the performance of the different sensing systems. We adopted a human-reviewed ground-truth validation approach using thermal video as the baseline reference for animal detections. This decision supported a more rigorous and objective evaluation framework and reduced potential bias associated with using a system's self-reported detections as truth. (It was assumed that the thermal camera, with its continuous video, would capture all wild/feral horse events in the camera's view.)

Construction disruptions to wild/feral horse activity: Not long after the thermal and radar systems were installed, nearby construction activity (unrelated to the project) began to alter animal movement patterns at the site. Field observations indicated that horse crossings declined or shifted outside the trailer's effective coverage area during the construction period. This development reduced the effectiveness of the site for data collection and prompted the team to consider relocation options.

Response – exploring alternative sites: UNR and NDOT conducted additional field surveys in late 2022 to identify new horse crossing locations that might be more suitable. A potential relocation site along USA Parkway was identified, but it was later deemed unavailable due to land ownership constraints and planned development (the landowner, a private company, had other plans for the site). The project team then evaluated alternate locations suggested by NDOT and consulted external stakeholders with regional knowledge of wild/feral horse movement patterns. By late 2022, a promising candidate site along US 50 near the SR 341 junction was identified and preliminarily evaluated for feasibility as a new deployment location.

Power system setback: In the last quarter of 2022, the trailer's aging battery bank suffered a failure. The old batteries had degraded to the point of providing significantly reduced capacity, leading to unreliable overnight operation and unexpected system shutdowns. The UNR team addressed this by replacing the entire battery bank with higher-capacity lithium batteries. This upgrade restored power reliability and supported continued field deployment through the winter. It underscored the importance of monitoring battery health and having a maintenance plan for critical power components.

Key challenges and solutions in 2022: The sensor deployment delays were managed through schedule adjustments and by making incremental improvements to subsystems while waiting for hardware. Construction-driven changes in wild/feral horse behavior required adaptive site planning and close consultation with stakeholders to explore alternative locations; this demonstrated the value of having a mobile platform (trailer) that could potentially be relocated if needed. The battery failure was resolved through a complete replacement and power system refurbishment, which reinforced the need for quality power storage and backup plans. Despite significant external disruptions and operational constraints, these responsive actions enabled the project to continue making progress.

6.4.Power Overhaul and Data Collection Preparations (2023)

Relocation plans and adaptive site decisions: In early 2023, the team prepared to relocate the system to the alternate US 50/SR 341 site if necessary. However, as the nearby construction near Electric Avenue concluded, the wild/feral horses gradually returned to the original corridor. Renewed field observations in spring 2023 confirmed horse activity had resumed at the Electric Avenue & Venice Drive site. In response, the project paused relocation efforts and instead adjusted the existing sensor coverage and trailer orientation to align with the updated animal

movement patterns. This decision avoided unnecessary relocation and minimized downtime, illustrating an adaptive approach to site selection.

Power system stability improvements: Despite the late-2022 battery upgrades, the trailer continued to experience power stability issues into 2023. These included low-voltage shutdown events, inverter cutoffs, and instances where the backup generator did not automatically start as expected, leading to system interruptions. The project implemented a series of engineering fixes to address these issues: the backup generator was replaced with a more reliable unit, charge controller settings were optimized for the new lithium battery bank, and a low-voltage protection device (low-voltage disconnect) was added to prevent over-discharge of the batteries. Additionally, the team discovered some degraded connectors and wiring issues during troubleshooting; these were repaired or replaced to improve overall system stability and resilience.

Pilot testing all sensors: Once the power system had been stabilized, the project conducted multi-sensor pilot tests to verify 24/7 operation of the integrated platform. Short-duration, full-system trial runs were carried out in mid-2023 to confirm that all sensors (optical, thermal, radar, LiDAR) could run simultaneously without issues. These pilot tests were used to check sensor logging performance, data storage, and communication links, and to identify any remaining integration issues before commencing formal, long-term data collection.

Final preparations: By mid to late 2023, individual sensor tests and pilot runs were successfully completed. The platform was then prepared for extended multi-week data collection periods. The team developed operational plans to ensure continuous power during these runs, including active generator monitoring and refueling schedules (with UNR personnel on-site or on call to manage the generator daily if needed). These preparations aimed to mitigate any last-minute failures and to ensure that once data collection started, it could continue uninterrupted for the designated periods.

6.5.Multi-Sensor Data Collection and Validation (Late 2023–2024)

Fall 2023 multi-week deployments: With the system ready, the project executed its first extended multi-sensor data collection in October 2023. This involved running all sensors continuously for a multi-week period to gather synchronized data on animal detections. During this phase, the team refined the camera setup (e.g., adjusting focus and field of view) and verified sensor time synchronization. They also installed physical distance markers in the camera's view to help calibrate detection ranges and facilitate later analysis. Several operational issues emerged and were addressed during this deployment: for example, the optical camera experienced occasional communication disruptions and insufficient buffer storage when connectivity was lost, and there were a few instances of the camera losing focus due to temperature fluctuations. Each issue was handled through prompt troubleshooting and configuration adjustments during field visits. Despite these minor setbacks, the October 2023 collection period achieved a complete multi-sensor dataset, with sustained operations made possible by proactive power management (including daily generator check-ins).

Winter 2024 data collection: To evaluate system performance under inclement conditions, another data collection was conducted in early 2024 (winter months). This run tested the sensors during cold temperatures, short daylight hours, and frequent low-light or night conditions. The winter deployment experienced intermittent disruptions due to severe weather conditions (e.g., snowstorms) and occasional system downtimes, primarily caused by limited site access for

refueling and restarting the generator. However, the team managed to obtain a substantial winter dataset. These data helped assess how weather and seasonal factors might affect sensor performance and reliability, providing insight into any needed adjustments for all-weather operation.

Ground-truth validation and data standardization: Throughout 2024, the sensing system teams and the independent evaluator team concentrated on validation and data management. The assumption was maintained that the thermal video recordings would serve as the ground-truth reference, with structured manual review to identify all horse events. Using this ground truth, the team compared the detections from the optical camera's AI, the thermal sensing triggers, the radar triggers, and the LiDAR data against the timeline events manually extracted from thermal videos to calculate performance metrics (such as true positives, false positives, and false negatives for each sensor). To streamline analysis, the project adopted standardized data formats and timestamp conventions across all sensors. Logs and detection outputs were reformatted into a consistent structure (e.g., combined comma-separated values (CSV) files with synchronized timestamps and common location references) to support cross-sensor comparison and improve interpretability for NDOT's reviewers.

Fall 2024 final data collections: A final full-scale data collection was conducted in October 2024 to wrap up the field data gathering. At the start of this period, a minor issue occurred—a starter battery for the generator's auto-start system failed, causing the generator to not engage on the first night. The team immediately replaced the small battery, restoring the backup power functionality. To ensure a complete dataset despite this brief disruption, the collection period was extended slightly beyond the original schedule. A subsequent late-2024 collection (in November 2024) was also carried out as a supplemental effort, aimed at increasing data robustness and capturing additional wild/feral horse observations under varied nighttime and late-season conditions. By the end of 2024, the project had amassed several multi-week datasets across different seasons for use in the performance evaluation.

6.6.Transition to Analysis and Reporting (2025 - 2026)

With field deployments complete by the end of 2024, project activities in 2025 shifted to data processing, performance evaluation, and preparation of final deliverables. The team (including the independent evaluator) applied the standardized data formats and ground-truth validation methods to compute detection performance measures for each sensor modality. They analyzed system effectiveness, identifying strengths and weaknesses of the optical, thermal, radar, and LiDAR components in detecting wild/feral horses. Based on these findings, implementation guidance and recommendations were developed for NDOT.

The final reporting in 2026 documented the results, key performance metrics, and recommendations from the project. It also compiled operational lessons learned and best practices for NDOT's consideration in future deployments. By February 2026, the project concluded with a comprehensive report summarizing the multi-year research effort and providing insights for potential next steps in intelligent animal detection and warning systems.

7. RECOMMENDATIONS ON ROADSIDE ANIMAL SENSING AND DRIVER WARNING SYSTEMS

7.1. Sensing Technologies and Sensor Fusion

Adopt a Multi-Sensor Detection Strategy: Deploy multiple complementary sensor types rather than relying on a single technology. Each sensing modality has distinct strengths – for example, LiDAR and optical cameras offer high accuracy and trajectory tracking, thermal and radar sensors excel in darkness and adverse weather, and cameras provide cost-effective visual verification. Using a combination of sensors ensures more consistent animal detection across varied lighting and weather conditions and allows cross-validation of events (e.g., using camera footage to confirm a radar trigger), leading to greater overall reliability.

7.2. Deployment Strategy and Infrastructure

Optimize sensor placement and coverage: Carefully plan the physical placement of animal sensors to maximize road coverage and detection performance. Factors like mounting height, lateral offset from the road, and sensor tilt angle should be determined via site-specific analysis or pilot testing. Field studies from the project showed that sensor installation parameters significantly affect scanning range and data quality; for instance, LiDAR units were tested at different heights and angles to minimize occlusion and extend detection range. If a single sensor cannot cover the target road segment (due to curves, terrain, or range limits), consider using multiple sensors with overlapping fields of view to cover blind spots. Ensure each sensor is mounted securely on a stable platform (to avoid wind-induced vibration) and housed in weatherproof enclosures, as stability and environmental protection are critical for long-term detection accuracy.

Adapt to wild/feral horse behavior and environmental changes: Plan deployments to be flexible in response to changing animal movement patterns and habitat conditions. Recognize that wild/feral horse crossing “hotspots” may shift over time due to factors such as construction, fencing, development, or water resource changes. Consider using mobile or re-deployable sensor platforms (e.g., trailer-mounted units) that can be relocated if herds or migration paths move to a different area. It is also wise to perform periodic wild/feral horse activity monitoring (through field observations, trail cameras, or consultations with wildlife experts) to verify that sensors remain focused on active crossing locations. Building this adaptability into the deployment strategy will ensure the system continues to provide coverage as wild/feral horse behavior evolves.

Ensure reliable power and communications: Provide a robust off-grid power and data connection infrastructure for remote sensing sites. Many road sections in wild/feral horse habitat areas lack readily available utilities, so equip sensor installations with sustainable power sources like solar panels coupled with battery storage, potentially augmented by wind turbines or backup generators for redundancy. Design the power system with ample capacity and energy management to maintain 24/7 operation through nighttime and poor weather – for example, use high-capacity batteries and low-power electronics to accommodate several overcast days without sunlight. For communications, use wireless links (cellular, radiofrequency, or satellite) to transmit detection events to driver warning signs or central monitoring systems, avoiding the need for expensive hardwired lines. Engineers should ensure the communication channel is secure, robust, and low-latency so that once an animal is detected, the warning signal is activated

immediately on the roadway. It is also recommended to implement fail-safes like on-site data buffering or dual network carriers to prevent data loss during temporary network outages.

7.3.Driver Alert Systems

Deploy clear and effective roadside warnings: Use driver-facing warning interfaces that are highly visible, unambiguous, and only activate in the presence of detected animals. Best practices from prior deployments favor flashing signs or beacons with easily recognized animal symbols (e.g., a deer or horse silhouette) over text-only messages, as drivers more quickly understand and respond to symbolic warnings. Place these warning signs at appropriate distances upstream of the crossing zone to give motorists adequate time to react – in many cases, multiple sequential signs (for example, one at 1500 ft and another at 600 ft before the hazard) have been used to provide progressive advance notice. Use advisory signals such as flashing lights with a "Slow Down" message or animal icon rather than changing the regulatory speed limit, to avoid legal and compliance issues that arise with dynamic speed limit enforcement. Calibrate the detection-to-warning logic to minimize false triggers and prevent alarm fatigue; alerts should activate only for real wild/feral horse events and be attention-grabbing yet not so startling that they alarm drivers. By employing familiar traffic warning formats and thoughtful placement, the system can effectively prompt drivers to reduce speed and prepare to stop when animals are on the roadway.

Engage the public and plan for connected vehicle alerts: When new animal warning systems are deployed, accompany them with driver outreach and education. Agencies have found it valuable to inform the local community about how the system works and what the flashing signs mean (e.g., via public meetings, press releases, or temporary roadside plaques explaining "Wildlife Detection System in Use – When Flashing, Animal on Road"). This outreach helps build driver trust that the warnings are credible, so they are more likely to heed the alert. In parallel, NDOT should anticipate emerging vehicle technology integrations: for example, connected vehicle systems could broadcast animal hazard alerts directly to in-vehicle displays or navigation apps in the future. As connected vehicle infrastructure becomes more common, leveraging cellular V2X messages to deliver animal-on-road warnings inside vehicles will further improve driver reaction times. Planning for these advancements (such as ensuring the detection system can output a standard alert message format for traffic management centers or connected vehicle broadcasts) will position NDOT to upgrade seamlessly when the opportunity arises.

7.4.Data Collection and Evaluation

Validate system performance with ground-truth data: Incorporate a rigorous evaluation plan that benchmarks the detection system against independent ground-truth observations. In this study, thermal video cameras were used to continuously record wild/feral horse activity and served as one option for a ground-truth baseline. Other options include independent day/night optical cameras and statistical comparison among sensor outputs. NDOT should similarly deploy a validation sensor or method – such as an optical or thermal camera or human observers – to log actual animal crossings and then compare those records against the automated sensor detections. Engage independent reviewers or a third-party evaluator to analyze the ground-truth data and the system outputs, in order to calculate detection rates, false positives, and false negatives for each sensor modality. This process provides a quantified measure of system effectiveness and confidence that the driver alerts are based on accurate detections. Planning for ground-truth data

collection and validation analysis from the outset of the project ensures that performance can be objectively assessed and communicated to stakeholders.

Standardize data formats and pipeline: Use consistent data formats and robust data management practices across the sensing and warning system. At the start of the project, define a standardized format for logging detection events and wild/feral horse observations (e.g., common timestamp conventions, unified CSV or database schemas for all sensors). Enforcing this consistency means data from LiDAR, radar, cameras, and other devices can be easily merged and compared, greatly simplifying analysis and multi-sensor fusion efforts. Establish an automated data pipeline to handle the volume of information collected: for example, implement local data storage with scheduled uploads to a central server or cloud repository to back up data regularly. The system should be designed to cache data locally if connectivity is lost and to prevent storage overflow (for instance, by alerting operators when disks are near capacity). Treat the collected data as a critical asset – conduct routine data offloads, maintain clear file naming and metadata documentation, and use secure, redundant storage. Such standardization and planning will not only protect valuable project data but also enable efficient processing and objective comparisons of sensor performance across vendors or locations.

7.5.Maintenance and Operations

Plan for maintenance and long-term reliability: Develop a maintenance program to keep the sensing and alert system operational in challenging field conditions. Remote roadside equipment will be exposed to weather extremes, dust, and animals, so design for durability and serviceability. Schedule regular maintenance checks to clean sensors (e.g., removing dust, snow, or debris from LiDAR and camera lenses) and to update or recalibrate system software for seasonal environmental changes (such as adjusting detection algorithms for summer foliage vs. winter snow cover). Field experience from the pilot deployments showed that power systems and electronics can and will fail unexpectedly (for instance, batteries degrading, solar charge controllers, or even a connector burning out), so **prepare for component failures**. Use high-quality, weatherproof housings to protect sensitive hardware and include safeguards like surge protectors and battery charge controllers to enhance reliability. Keep critical spare parts on hand or readily available – for example, spare sensors, cables, batteries, and networking gear – to enable rapid replacement if a unit fails in the field. It is also advisable to implement remote monitoring of system health (battery levels, device status notifications) where possible, and to have technicians conduct on-site inspections periodically to catch issues such as water intrusion, animal damage, or calibration drift before they escalate. By budgeting for maintenance and designing the system with robustness in mind, NDOT can ensure the animal detection and warning system remains effective over its intended lifespan.

Coordinate with vendors and stakeholders throughout deployment: Successful implementation of an animal sensing and alert project requires strong coordination between the agency, technology vendors, researchers, and other stakeholders. Establish clear lines of communication and assign responsibilities early: for example, designate leads for each major subsystem (one point-person each for power supply, sensing hardware, communications, data management, etc.). Hold regular coordination meetings or calls (e.g., weekly or biweekly) to review progress, share observations, and troubleshoot issues collaboratively – in the pilot project, frequent team consultations helped resolve system malfunctions and refined evaluation methods by combining insights from NDOT engineers, university researchers, and the equipment suppliers. Develop a protocol for information sharing so that any field changes or problems (such

as a sensor firmware update or a network outage) are communicated to all parties promptly. Likewise, involve the vendors in training staff and developing maintenance procedures; vendor support can be crucial for diagnosing technical sensor issues or integrating their hardware with NDOT's systems. Finally, maintain thorough documentation of the deployment – including configuration settings, maintenance activities, and decisions made – and ensure knowledge transfer at project milestones. This documentation will serve as a valuable reference for both current team members and future projects, helping institutionalize the lessons learned and streamlining subsequent deployments of similar advanced animal detection technologies.

8. CONCLUSION AND FUTURE EFFORTS

This chapter summarizes key findings from the three-cycle field evaluation and identifies priorities for future research and deployment. Lessons learned from the project process are documented in Chapter 6; full implementation recommendations are provided in Chapter 7.

8.1.Summary of Key Findings

Each sensing technology demonstrated distinct strengths and limitations in real-world conditions. No single sensor type excelled under all circumstances, but together they provided a more robust detection capability. Key findings for each system include:

LiDAR: The LiDAR system used laser-pulse scanning to generate real-time 3D point cloud data of the roadside environment, enabling precise detection and tracking of animals by shape, size, and movement. It was selected for its 360-degree spatial awareness and its ability to analyze vehicle and animal trajectories simultaneously. Strengths include very low false positive rates across all conditions, high spatial accuracy, and consistent performance regardless of lighting. Limitations include a practical detection range of approximately 300 ft under field conditions, higher integration complexity than camera-based systems, and sensitivity to algorithm configuration. Unit cost ranges from $8,000–$15,000; power demand is less than 15 W per sensor plus less than 60 W for the edge computer, or approximately 100 W for a two- to three-sensor system.

Thermal infrared camera: The thermal camera detected animals by their body heat rather than reflected light, making it effective in complete darkness and low-visibility conditions. It was selected for its nighttime capability and its dual role as both a detection sensor and a ground-truth validation tool. Strengths include reliable nighttime performance at close and mid-range distances, insensitivity to headlight glare, and configurable detection zones. Limitations include sensitivity to configuration changes (size filters, field of view, and timestamp alignment) that introduced variability across cycles and reduced thermal contrast in hot ambient conditions. Unit cost ranges from $3,000 - $8,000; power demand is approximately 14 W per camera plus up to 65 W for associated interfaces and processing hardware; effective detection range is approximately 300 - 1,000 ft with reliable recognition within approximately 300 - 500 ft.

Radar: The radar system detected moving objects via radio-wave reflection, offering the longest range and all-weather, day-and-night operation of any sensor tested. It was selected for its ability to cover large areas from a single unit and to distinguish slow-moving animals from faster vehicles. Strengths include a detection range of up to 4,200 ft, insensitivity to darkness, fog, or precipitation, and the ability to simultaneously track up to 500 targets. Limitations include an inability to visually confirm detections, the highest false positive rates among all systems tested, and the need for careful tuning to suppress environmental noise. Unit cost ranges from $50,000 - $65,000; power demand is approximately 45 W for the radar unit, or approximately 150 W for the combined thermal and radar system including shared processing and communication components. At approximately $7 - $15 per foot of coverage, radar offers the lowest cost-per-foot of any sensor evaluated despite its higher unit cost.

Optical Camera: The optical camera system used AI-based computer vision running on an edge-computing device to detect and classify animals in real time from live video. It was selected for its low cost, species-level classification capability, and compatibility with existing ITS infrastructure. Strengths include the lowest unit cost of all systems tested, the lowest false

positive rates, visual confirmation of detections, and a power draw of only 31 W. Limitations include strong dependence on ambient lighting - performance drops sharply at night and in adverse weather - making it unsuitable as a standalone 24-hour detection system. Unit cost ranges from $800 - $1,200; power demand is approximately 31 W; effective detection range is approximately 300 - 500 ft during daytime conditions. At approximately $2 - $4 per foot of coverage, it is the most cost-effective sensor for daytime applications.

8.2.Lessons Learned from Deployment

Beyond sensor performance metrics, the project provided numerous engineering and operational insights over its multi-year span (2020–2025). Deploying a mobile, solar-powered ITS trailer with diverse sensors in a remote environment posed challenges that yielded lessons to inform future efforts. Major lessons learned include:

Power challenges and energy management: Reliable off-grid power was both crucial and challenging. Early in the project, a single-source solar power setup proved insufficient – limited sun (especially in winter) caused low power yield and sensor downtime. The team addressed this by adopting a hybrid power system (solar panels plus a wind turbine and backup generator) to meet the ~300–500 W power demand of the multi-sensor platform. Even with this setup, battery maintenance was critical: all original batteries failed during the project due to deep discharge and age, underscoring the need to budget for battery replacements in long deployments. Protective circuitry (low-voltage disconnects) was added to prevent over-depleting batteries, which taught the importance of safeguarding energy storage. Regular power monitoring and alerts were instituted so the team could respond quickly to outages (for example, receiving notifications of low voltage and dispatching maintenance to refuel generators or replace failed components).

> **Lessons learned:** design redundant, multi-source power systems for remote sensor installations, include ample battery storage and automatic cutoff protection, and implement real-time monitoring with contingency plans (spare generators, on-call technicians) to maintain continuous operation.

Hardware reliability and maintenance: The harsh roadside environment (extreme temperatures, dust, wind, vibration) tested the durability of all equipment. Several hardware failures occurred – for instance, a radar unit arrived DOA (dead on arrival) due to shipping damage, a generator's starter battery died unexpectedly, and some electrical connectors and cables degraded or burned out over time. Although the optical camera was deployed the longest of any single sensor element (4 years), it is possible that its lens and CMOS sensor degraded during that time. These incidents highlighted the value of robust hardware selection and proactive maintenance. The team learned to keep critical spare parts on hand (such as an extra radar sensor, backup batteries, spare cables and networking gear) so that failures could be addressed with minimal downtime. Weatherproof enclosures and protective housing were essential – for example, a custom environmental cabinet was used to shield the thermal camera and radar, and the generator was secured in a ventilated cage. Regular on-site inspections proved useful to catch issues like loose connections or water intrusion before they caused system outages.

> **Lessons learned:** expect that field equipment "anything that can fail, will fail." To achieve high system uptime, use industrial-grade components, protect them from the elements, schedule periodic inspections, and maintain an inventory of spares or a rapid procurement strategy for replacements.

Wild/feral horse behavior and site selection: The project underscored that choosing a deployment site for animal detection is not a one-time decision – it requires flexibility and continuous validation. Initially, two highways were identified based on historical wild animal crossings. However, environmental changes (construction activities, water sources moving, new fencing) drastically altered animal movement patterns. For example, wild/feral horses virtually abandoned the first chosen site after nearby construction began, forcing the team to relocate the equipment. A successful adjustment was made by conducting field surveys and consulting local wild/feral horse experts to confirm active crossing locations; this led to selecting the Electric Avenue & Venice Drive site, where horses were observed crossing regularly. Even then, horse activity fluctuated seasonally and with land use changes, so the mobile trailer approach proved valuable – the system could be redeployed if needed to follow the animals. Stakeholder engagement was another crucial factor: coordinating with state and county agencies, private landowners, and wild/feral horse groups early on helped secure access permissions and updated information on animal hotspots.

> **Lessons learned:** wild/feral horse crossing events are dynamic, so projects should plan for possible relocations or multiple trial sites. Perform thorough site assessments (including direct wild/feral horse observation or trail cameras) before and during deployments to ensure the sensors cover active crossing areas. Maintain close communication with local stakeholders (transportation districts, landowners, wildlife agencies, and even advocacy groups) to anticipate changes (e.g., planned developments or migration shifts) that could affect site suitability.

Sensor integration and data validation: Bringing together four different sensing systems (LiDAR, radar, thermal, and video) on one platform was an ambitious engineering task that taught the team how to manage integration complexity. Rather than activating all sensors at once, the project followed a phased integration – adding one sensor at a time, resolving its issues, then layering the next. This approach isolated problems and prevented complete system failures. For instance, when the first radar malfunctioned, a replacement was installed without impacting the other sensors, and when the software for one of the two LiDAR units integrated in 2021 proved unusable for automated detection, the Velodyne VLP-32C LiDAR was adopted as the primary LiDAR sensing solution. Because this occurred before the first data collection cycle in October 2023, all LiDAR results reported in this study reflect the Velodyne unit (see Section 2.6 and Section 6.2). Careful calibration was needed so that all sensors "agreed" on the detection zone; the team physically measured and aligned fields of view (placing markers in camera view for distance calibration, aligning LiDAR and radar coverage to the road). After any hardware or software change, all settings must be re-checked. To evaluate performance objectively, independent ground-truth data was critical. The project chose recorded continuous thermal video as a reference, and independent reviewers manually annotated this footage to log actual animal crossings. Comparing each sensor's detections against this ground truth option enabled calculation of false negatives and false positives, though the assumption of thermal imaging as the best reference was not tested.

> **Lessons learned:** multi-sensor deployments benefit from step-by-step integration, thorough calibration, and independent validation. Future projects should allocate time for pilot testing of each component, maintain documentation of sensor configurations (to avoid human error), and include a plan for gathering ground-truth observations (e.g.,

optical or thermal camera recordings or on-site observers) to verify and tune the system's detection performance.

Implementation guidance based on these lessons is provided in Chapter 7.

8.3.Recommendations for Future Efforts

Building on the findings and lessons learned, the study offers several recommendations to enhance roadside animal sensing and driver warning systems going forward. These recommendations aim to improve detection accuracy, expand deployment impact, integrate new technologies, and promote sustainable, standardized implementation:

Advance AI and sensor fusion: Continue research and development in artificial intelligence and multi-sensor fusion algorithms to improve detection accuracy and reduce false alerts. Recommendations on specific sensor combinations and fusion strategies for NDOT deployments are provided in Chapter 7. Future research should focus on enhanced machine learning models that can classify species, predict animal behavior, and leverage edge computing for faster on-site processing.

Expand and integrate deployments: Transition from short-term pilot tests to expanded pilot implementations or permanent deployments in high-risk animal collision zones. A key next step is to deploy full integrated warning systems – not just sensing equipment, but also permanent flashing signs or dynamic message signs that activate when animals are detected. These installations should be treated as demonstration projects to gather long-term effectiveness data (multi-year collision and driver response statistics) and to refine system operations under real traffic conditions. Wherever feasible, favor permanent pole-mounted or roadside units with grid power for reliability, using mobile solar-powered trailers primarily for temporary studies or where fixed infrastructure is impossible. An expanded deployment program might start with several sites known for frequent deer, elk, or horse crossings, deploying multi-sensor RADS and warning signs, and closely monitoring results. Such scaled-up trials will help validate that the collision reductions observed in small pilots can be sustained and replicated across different environments. They will also illuminate practical considerations for statewide adoption, such as public acceptance, maintenance needs, and cost-benefit outcomes.

Strategic site selection, power, and maintenance planning: When moving toward broader deployment, carefully select sites and design supporting infrastructure for sustainability and effectiveness. Use data-driven criteria for site selection, such as crash history, documented animal corridors, and terrain suitability for sensors, to target locations where RADS will yield the greatest safety benefit. For each site, invest in a robust power solution (preferably tied into the electrical grid or a well-engineered solar/wind hybrid system with ample battery backup) to ensure the system remains continuously operational. Plan the demand of the sensors used to fit the power available. Plan for maintenance from the start: establish maintenance schedules for cleaning and inspecting sensors, battery replacements, and periodic testing of communications and warning signs. It may be advantageous to develop maintenance contracts with vendors or dedicated crews, including performance measures (e.g., require a certain uptime percentage and timely repairs). Additionally, maintain flexibility to reposition or adjust the system if animal movement patterns change – for instance, modular designs or trailer-mounted components can be moved without starting from scratch. By approaching deployments with a holistic plan encompassing site selection, power reliability, and long-term maintenance, agencies can avoid

many of the pitfalls uncovered in this research and ensure each installation delivers sustained safety improvements.

Animal detection and warning systems move from experimental trials to wider use; there is a growing need for standards and knowledge sharing. Transportation agencies, wildlife agencies, and researchers should collaborate to develop uniform guidelines on system design, installation, and performance evaluation. This could involve establishing standards for detection accuracy, false alarm rates, and response times, as well as standardized signage and communication protocols (so a warning system in Nevada functions similarly to one in another state). National bodies like AASHTO or the Transportation Research Board could lead the creation of best-practice manuals, covering topics such as recommended sensor combinations for various scenarios, ideal signage layouts, and maintenance best practices. Inter-agency partnerships are also key: issues of animals crossing roads often span jurisdictional boundaries, so pooling resources and data (for example, a multi-state database of wildlife detections and collisions) can help identify priority sites and effective strategies. Regular forums or working groups (regional or national) on wildlife-vehicle collision mitigation should be used to exchange lessons learned, new research findings, and technology updates. By fostering collaboration across highway agencies, wildlife departments, and technology providers, the deployment of RADS can be accelerated and optimized with a consistent approach, ultimately saving more lives – both human and animal – on our roadways.

GLOSSARY OF TERMS

Aggregation Window - A defined time interval over which sensor detection events are grouped or combined for analysis purposes.

Algorithm - A set of computational rules or instructions used by a sensor system to process data and make detection decisions.

Animal-Vehicle Collision (AVC) - A crash involving a motor vehicle and an animal on or near the roadway, resulting in property damage, injury, or death to humans or animals.

Artificial Intelligence (AI) - Computer-based systems that use machine learning models to identify and classify objects, such as animals, from sensor data.

Break-the-Beam Sensor - A detection system that triggers an alert when an animal physically interrupts an infrared or laser beam stretched across a known crossing point.

Calibration - The process of adjusting a sensor's settings to ensure accurate and consistent detection performance under field conditions.

Computer Vision - A field of artificial intelligence in which software interprets and classifies visual information from cameras or other imaging sensors.

Data Collection Cycle - A standardized period of continuous multi-sensor monitoring used in this study; three 14-day cycles were conducted in October 2023, February 2024, and October 2024.

Deep Learning - A type of machine learning that uses layered neural networks to recognize patterns in data, used here for animal classification in optical camera footage.

Detection Event - A discrete instance in which a sensor system records the presence of a moving object within its field of view.

Detection Range - The maximum distance at which a sensor can reliably identify the presence of an animal or object.

Detection Zone - A defined area within a sensor's field of view configured to trigger driver warning alerts when an animal is present.

Driver Warning System - A roadside or in-vehicle system that alerts motorists to the presence of animals near the roadway, typically through variable message signs or flashing lights.

Dual-Reviewer Validation - A quality-control process in which two independent reviewers separately examine ground-truth video footage to confirm or refute animal presence events, reducing individual bias.

Edge Computing - On-device data processing performed at the sensor location in real time, without transmitting raw data to a remote server. This reduces latency and bandwidth requirements for roadside deployments.

Electromagnetic Sensor - A detection system that generates a localized electromagnetic field around a buried cable and triggers an alert when a large animal disturbs that field while passing nearby.

Exclusionary Fencing - Physical barriers installed along roadways to prevent animals from accessing the travel lanes, typically combined with designated underpasses or overpasses to maintain wildlife movement corridors.

False Negative (FN) - A missed detection: an animal presence event that was confirmed in the ground-truth record but was not captured by the sensor system.

False Positive (FP) - An erroneous detection: a sensor alert that was triggered in the absence of confirmed animal presence, often caused by vegetation movement, precipitation, or passing vehicles.

Field of View (FOV) - The total observable area monitored by a sensor, typically described as an angle (degrees) or a coverage radius (feet).

Frequency-Modulated Continuous-Wave (FMCW) Radar - A radar type that continuously transmits and receives signals at varying frequencies to detect, locate, and track moving objects. Used in this study for long-range animal detection.

Ground Truth - An independently verified record of actual animal presence events, established in this study through continuous dual-reviewer thermal video review, used as the baseline against which sensor detections are evaluated.

Infrared Radiation - Electromagnetic energy emitted as heat by warm-bodied animals. Thermal cameras detect infrared radiation to produce heat-based images, enabling detection in complete darkness.

Intelligent Transportation System (ITS) - A category of technology-based tools used to improve the safety, efficiency, and performance of surface transportation networks. In this study, an NDOT ITS trailer served as the multi-sensor deployment platform.

Inter-Rater Reliability - A statistical measure of the degree of agreement between two or more independent reviewers evaluating the same data, used here to validate the dual-reviewer ground-truth process.

LiDAR (Light Detection and Ranging) - An active sensing technology that emits laser pulses and measures return times to generate precise three-dimensional point cloud data of the surrounding environment, enabling detection and tracking of objects by shape and movement.

Long-Wave Infrared (LWIR) - The infrared wavelength range of approximately 7–14 micrometers (μm) detected by the thermal cameras used in this study. LWIR cameras are well suited for detecting body heat from warm-blooded animals.

Mobile Deployment Platform - A transportable system, such as the NDOT ITS trailer used in this study, that allows sensors to be rapidly installed, relocated, and operated at roadside locations without permanent infrastructure.

Multi-Sensor Fusion - The integration of detection data from two or more sensor types to improve overall accuracy, reduce false positives, and extend coverage beyond what any single sensor can achieve alone.

Passive Infrared (PIR) Sensor - A motion-sensitive detector that responds to changes in infrared radiation within its field of view, commonly used in simple animal detection systems as a low-cost trigger mechanism.

Point Cloud - A three-dimensional dataset consisting of thousands of spatial measurement points generated by a LiDAR sensor scan, used to detect and classify objects by their shape, size, and movement.

Power over Ethernet (PoE) - A networking standard that allows electrical power to be transmitted through a standard Ethernet cable alongside data, used in this study to power and communicate with the thermal camera system.

Precision - In detection performance analysis, the proportion of sensor detections that correspond to actual animal presence events (i.e., true positives divided by all detections).

Recall - In detection performance analysis, the proportion of actual animal presence events that were successfully detected by the sensor (i.e., true positives divided by all confirmed events). Also referred to as detection rate or sensitivity.

Recognition Range - The shorter distance, within the overall detection range, at which a sensor can not only detect but reliably identify and classify an object (e.g., distinguishing a horse from a vehicle or vegetation).

Roadside Animal Detection System (RADS) - An integrated system of sensors and associated software deployed along a roadway to automatically detect the presence of large animals and trigger driver warning signals.

Sensing Radius - The effective circular coverage area around a 360-degree sensor such as radar or LiDAR, measured as the distance from the sensor at which reliable detection is maintained.

Solar-Wind-Battery Power System - An off-grid power configuration used in this study combining solar panels, a wind turbine, and a battery bank to supply continuous power to the roadside sensor trailer.

Temporal Aggregation - The process of combining or summarizing detection data across a defined time window to reduce noise and improve the reliability of performance metrics.

Thermal Infrared Camera - A passive imaging sensor that detects heat emitted by objects and converts it into a visual image. Unlike optical cameras, thermal cameras do not require visible light and are effective at night and in low-visibility conditions.

True Positive (TP) - A correct detection: a sensor alert that corresponds to a confirmed animal presence event in the ground-truth record.

Variable Message Sign (VMS) - An electronic roadside sign capable of displaying dynamic messages, used in animal detection and driver warning systems to alert motorists when animals are detected near the roadway.

YOLO (You Only Look Once) - A real-time deep learning object detection algorithm used by the optical camera system in this study to identify and classify animals and vehicles from live video streams. Version 5 (YOLOv5) was used.

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APPENDIX 1: LITERATURE REVIEW ON ROADSIDE ANIMAL SENSING AND DRIVER WARNING SYSTEMS

Collisions between vehicles and large wildlife and livestock (deer, moose, elk, etc.) are a serious roadway safety and ecological issue worldwide. In the United States alone, deer-vehicle collisions number in the millions annually, causing billions of dollars in damage and hundreds of human fatalities each year [2, 3]. These incidents also result in substantial wildlife mortality; for example, in California, more than 48,000 deer are killed in vehicle collisions each year, representing over 10 percent of the state's deer population [2]. Similar problems exist globally, from Europe (where wildlife-vehicle collisions have risen in frequency) to Australia (collisions with kangaroos) and Asia. Collisions peak in low-visibility conditions (dusk, night, fog) and during animal migration or breeding seasons, when wildlife movements and vehicle traffic often intersect [2].

Traditional mitigation measures like static *"Deer Crossing"* signs, animal silhouette signs, or reflectors have shown limited effectiveness, as drivers often become habituated and ignore them [2]. More effective are exclusionary measures such as fencing that, by itself, or when combined with wildlife underpasses/overpasses to facilitate cross roadway movements, can reduce WVCs by over 80% on major highways [2]. However, fencing and grade-separated crossings are expensive and usually limited to high-priority road corridors (e.g., major highways). This leaves many secondary roads and rural highways, where WVCs are also common, without mitigation [4]. In this context, roadside animal detection and driver warning systems have emerged as a promising solution to dynamically warn drivers when large animals are on or near the road. These systems use various sensors to detect wildlife in real time and then activate warning signals (flashing signs, alarms, or in-vehicle alerts) to prompt drivers to slow down and avoid a collision [5].

Over the past 15 years, substantial research, including peer-reviewed studies and government agency trials, has evaluated a wide range of sensing technologies for wildlife detection and driver warning. Results have been encouraging: properly implemented detection-warning systems have reduced collisions with large animals by roughly 50 - 90% in many trials [3, 5]. For instance, a detection/fencing system in Arizona reduced elk-vehicle collisions by 97% [7], and several European installations reported about 80% fewer crashes with deer [5]. At the same time, these systems face challenges such as sensor false alarms, high installation/maintenance costs, and reliance on driver compliance. Many projects remain experimental or pilot-scale, highlighting a need for further validation and refinement[4, 5]. This section presents a structured literature review of roadside animal detection and driver warning systems, with an emphasis on large-animal detection in the U.S. context while drawing on global examples. We examine the technologies used, case studies of deployments, their effectiveness and limitations, integration with driver warning system interfaces, and future directions for research and implementation.

This literature review categorizes the sensing technologies into major types: radar, infrared (IR) thermal cameras, standard visible-light cameras (with computer vision), passive infrared/motion sensors, laser or microwave "break-the-beam" sensors, inductive loop or electromagnetic field sensors, and others (e.g., acoustic detectors). For each category, information was compiled on detection capabilities, environmental constraints, and deployment examples. Case study learnings were gathered from different regions with emphasis on U.S. deployments (e.g., in Colorado, Idaho, California, Florida), but also notable efforts in Canada and Europe (Sweden, Switzerland, etc.).

Overview of Sensing Technologies

Modern wildlife detection systems have employed a variety of sensor technologies, each with distinct advantages and limitations. Broadly, these systems fall into two detection strategies [5]: "area coverage" sensors that monitor a zone for the presence of animals (e.g., radar, thermal imagers, optical sensor, or passive IR sensors), and "break-the-beam" sensors that detect an animal when it crosses a specific line or beam (e.g., active infrared or laser tripwires). Many deployments use the area-cover approach for broader range, while some early systems used break-beam pairs along known crossing points.

Radar: Radar-based detection is one of the most widely tested approaches in recent years. These systems use Doppler microwave radar units mounted roadside to sense large animals moving within a certain range. Radar can operate day or night and in various weather conditions. A notable example is the system deployed on US Highway 95 in Idaho, which used a Doppler radar to continuously scan a 370 ft road segment [8]. Radar's strengths include long range and insensitivity to lighting, radar detection had a wide coverage and performed reliably even at night or in fog where other sensors struggle [3, 8]. Modern radar units can also track multiple targets, detect very small movements, locate the animal in space with good precision and filter out vehicles (by speed or size), focusing on large, slow-moving objects like animals.

However, radar can be prone to false positives from movement of vegetation or precipitation and may have difficulty detecting stationary animals. The Idaho system, for instance, logged some "possible false positives" (up to 24% of detections), likely due to small animals or environmental factors triggering the radar. Overall detection reliability was high, for example, the Idaho radar correctly detected 97.5% of all deer/elk that entered the road, with only 2.5% false negatives. In controlled tests, all elk were detected, and 98% of deer triggered the system in time to warn drivers. These results show that radar can meet stringent detection criteria. Regular maintenance (e.g., recalibrating radar aim, clearing foliage) is needed to sustain performance. They can also be used in tandem with other sensors (e.g., thermal or optical) to fuse data and reduce false alarms [10, 11]. Radar systems also require a power source and are among the more expensive sensors; an estimate from Idaho put the cost around $60,000 per 820 ft of instrumented roadway [10], with about $3,000 annual maintenance for that section. Despite cost, radar's all-weather, 24-hour capability and proven reliability have made it a leading choice in recent pilot programs.

Infrared (IR) thermal cameras: Thermal cameras detect the body heat of animals and are highly effective at night and in low-light conditions. These cameras produce a heat-image and, coupled with image-processing algorithms or AI, can identify warm-bodied animals against cooler backgrounds [2]. Thermal systems can "see" wildlife beyond headlight range and aren't blinded by darkness. A low-cost thermal camera system tested in Europe demonstrated substantially faster detection of roadside deer at night compared to visual scanning [12]. In a U.S. research project, a thermal imaging system with computer vision was developed to detect deer; it achieved near 100% detection accuracy in field tests with processing at 10 Hz [13]. This system could reliably spot deer even in total darkness or obscuring weather, as thermal contrast makes deer stand out when their body temperature differs from the environment. In another research project in Arizona, USA thermal sensors connected to animal-activated signs in combination with exclusionary fences reduced elk-vehicle collisions by 97% and notable changes in reduced driver speed and increased driver alertness during its nine-year evaluation [7]. In a study sponsored by Washington State Department of Transportation, a thermal sensor

combined with AI-supported analysis achieved rapid (<1 second) and accurate detection and classification of deer, elk, mountain lion, and black bear at I-90 crossing structures [2].

Thermal cameras, however, can be costly and generate large data streams that require advanced processing, often an on-site computer or edge AI device. They also have a finite range and field of view, typically effective to a few hundred meters. False negatives may occur if an animal is partially hidden (e.g., behind vegetation) or if ambient temperature is close to body temperature (reducing contrast) [14]. False positives can be triggered by *"pockets of hot air"* or other heat sources moving in the wind. Nonetheless, modern thermal imaging paired with deep learning is very promising. They can also be used in tandem with other sensors (e.g., radar or optical) to fuse data and reduce false alarms [10], [11].

Optical cameras: Standard optical cameras (video or still-image) have been used to detect animals using computer vision techniques. These are often cheaper than thermal cameras and can leverage the rapid advances in vision-based object detection (e.g., algorithms trained to recognize deer in dashcam footage). Some systems use low-light cameras with infrared floodlights to enable 24-hour operation [16]. One example is a wildlife detection system in Sweden (Skåne County) that uses video cameras with IR lighting and motion triggers: a series of cameras monitor an unfenced road segment, and when an animal is detected on either side of the road, a warning sign with a deer icon is activated for drivers. In that pilot, the camera system continuously tracked animals crossing a 90-ft "fauna passage" opening in roadside fencing, and recorded over 300 animal crossing events in one year [4]. Vision-based detection in that project proved accurate for large ungulates and contributed to a 66% reduction in WVCs at the site (compared to nearby reference roads).

The upside of camera-based systems is the rich information (images can confirm species, group size, behavior) and potential integration with machine learning classification. They can also cover a specific zone quite precisely. The downside is sensitivity to lighting, weather, and obstructions. Rain, fog, or snow can degrade video image quality; likewise, tall grass or undulating terrain might hide animals from view. Like all sensor systems with automated processing, optical camera systems also require data transmission and processing capability on-site (or high-bandwidth links to a remote computer), which can complicate installation. Camera-based wildlife detection is rapidly advancing thanks to AI. They can be used in tandem with other sensors (e.g., radar or thermal) to fuse data and reduce false alarms [10, 11]. Some commercial solutions now market AI-driven camera towers specifically for wildlife, claiming high detection rates by day and moderate performance at night with IR illumination [2], [10].

Passive infrared (PIR) motion sensors: These are essentially the same kind of sensors used in security lights – they detect changes in infrared radiation (heat) within their field of view, indicating a warm object moving. Passive IR sensors (sometimes called pyroelectric sensors) were among the earliest deployed technologies for animal detection due to their low cost and power needs. Typically, a PIR detector is mounted on a post and creates a cone-shaped detection zone; when a large warm animal enters that zone, the sensor triggers. PIR sensors are "area cover passive" sensors [5] and require a temperature differential between the animal and background. They work best at night or at cool periods (when animal's body heat contrasts with ambient air). Several animal detection installations in the 2000s used PIR sensors, but results were mixed. They tend to have a shorter range (on the order of tens of meters), and can be prone to false triggers from sunlight heating moving foliage, wind-blown warm air, etc. [14]. As noted in a test

comparing multiple technologies, passive IR systems struggled in hot summer conditions, as they could not clearly distinguish animals from a hot background, leading to higher error rates.

On the positive side, passive IR detectors are inexpensive and simple. A network of PIR motion sensors can be deployed and linked to a warning sign system with relative ease. When an animal was sensed by a node, data was sent to a gateway and could trigger warnings. Over one month of testing, the false-trigger rate was only about 2-3%, which is quite low and likely due to careful tuning and filtering of the PIR signals. The detection range was limited, about 30-50 ft per sensor for a human-sized heat source, so multiple sensors were needed to cover a stretch of road. This illustrates that PIR can play a role in low-cost deployments but may be best for covering small areas such as known crossing hotspots or integrating as one component of a multi-sensor system.

“Break-the-Beam” sensors (Active Infrared and Laser): These systems consist of a transmitter and receiver pair positioned across a section of road or at the roadside, forming an *invisible beam*. When a large animal passes through and breaks the beam, the system detects interruption. Active infrared beams or laser beams have been used in some early warning systems. For instance, a system in California on State Route 3 used a set of four break-the-beam sensors spaced along a 0.7-mile segment [3]. When any beam was broken (by objects or an animal crossing), warning lights would flash to alert drivers. Break-beam sensors have a very defined detection line – meaning if an animal crosses at a slightly different spot (under or over the beam, or outside its range), it won’t be detected. Thus, they often require multiple beams at different heights and locations to be effective.

The benefit of break-the-beam is its binary reliability under controlled conditions: if aligned properly, anything substantial crossing the beam will trigger a near-instant detection. They are relatively immune to small movements of vegetation or gradual temperature changes. However, maintaining alignment is critical – wind or ground movement, and excess vegetation can misalign the transmitter/receiver and cause false triggers or missed detections [14]. The California State Route 3 system experienced numerous “false positive” activations caused not by animals but by vehicles turning into side roads and inadvertently cutting through the beam path [3]. Engineers noted that proper placement (and possibly using loops to detect vehicles and invalidate those triggers) was needed to avoid such issues. Environmental factors like heavy snow and intense sunlight can also obstruct or refract the beam, leading to downtime (one test saw a 40% system downtime during a snowstorm due to beam blockage by snow/ice).

Overall, break-beam systems can work well for chokepoint crossings (e.g., a narrow passage where animals funnel through). They have been used in Europe in combination with fencing: fencing directs animals to a gap where a break-beam sensor watches that gap. If an animal crosses there, the beam break triggers roadside flashing signs. This effectively creates an at-grade “wildlife crosswalk”. Such a system in Switzerland (installed in the 1990s) reportedly reduced deer collisions by 80% [3]. The downside is limited versatility – beams only cover fixed lines and may miss animals that approach the road but turn away or run parallel without crossing the beam line (those still pose a hazard yet would not trigger the system). Modern implementations often prefer area sensors (radar/camera) over simple beam breakers, except in very controlled crossing designs.

Inductive loop and magnetic sensors: These refer to sensors embedded in or on the ground that detect changes in electromagnetic fields caused by large objects. Standard inductive loops (used in traffic lights) detect large metal masses (vehicles) and do *not* detect animals (since animals

cannot be magnetized). However, specialized electromagnetic intrusion sensors have been adapted from security applications to detect humans or animals moving near a buried cable. One such system is the Senstar® OmniTrax or *Perimitrax,* a buried coaxial cable sensor that creates an electromagnetic field and detects disturbances. A collaborative project in Colorado tested an electromagnetic cable running along US 160 to detect deer/elk; it was the first of its kind for this purpose [18]. The system proved challenging to calibrate, and initial versions had reliability problems. In controlled testing with proxy animals (horses, llamas) at a Montana facility, the buried cable system detected large mammals but also produced some false triggers and had sensitivity to variations based on animal size and distance [18].

Inductive or magnetic sensors benefit from being invisible and protected (buried underground) and not affected by weather directly. They also can cover long linear distances (OmniTrax cables can run hundreds of meters protecting a perimeter). But they require careful tuning to the target species' size and movement. They may miss slower or stationary animals (if an animal stands still, the disturbance might decay). And installation involves significant construction for trenching along the roadside for the cable. These factors have limited the adoption of buried electromagnetic sensors in wildlife detection, though they remain a part of the toolbox. Newer magnetic anomaly detectors (small magnetometer nodes) have also been proposed: they could detect large animals by the magnetic distortion caused by the animal's body or by a collar tag. As of this review, such approaches appear largely experimental or theoretical for wildlife; no large-scale field results were found in the literature.

Each technology can be paired with driver warning mechanisms to form a complete Animal Detection and Driver Warning System. Next, we examine real-world case studies and applications of these technologies, both internationally and in the U.S., to understand how they perform and the documented outcomes.

Case Studies and Applications

In the past 15 years, dozens of pilot installations of wildlife detection and warning systems have been implemented worldwide. Here we highlight several notable case studies. The focus is on large-animal detection (deer, elk, moose) and on studies that reported performance results.

United States – Montana Test Bed (2007–2009): A seminal study by the Western Transportation Institute (WTI) in Montana evaluated multiple animal detection technologies side-by-side in a controlled test bed [14]. Nine different systems (from various vendors) were installed along a fenced course where researchers could lead horses, llamas, and sheep (surrogates for wildlife) through the detection zones. Technologies included break-the-beam IR, microwave radar, passive IR, and others. This comparative study yielded important insights and set tentative performance benchmarks: researchers concluded an animal detection system should detect 91% or higher percentage of large animals and keep false detections lower than 10% in order to be considered reliable. They also suggested a well-implemented system could reduce wildlife-vehicle collisions by 71% or more. In the tests, 5 of 9 systems met the reliability targets (detection rate and false alarm rate) under test conditions. However, experiences showed that system robustness (resisting environmental wear, maintenance needs, power issues) was a limiting factor for widespread deployment. This Montana test bed informed later field trials, and WTI continued to refine certain systems (e.g., calibrating the Senstar electromagnetic cable sensor, which was part of this test, before deploying it in Colorado).

United States - Colorado (US 160, 2008–2012): Along a 2-mile stretch of US 160 between Durango and Bayfield, Colorado Department of Transportation and WTI installed a buried electromagnetic cable detection system with driver warning signs [18]. This road had frequent deer and elk collisions. The system initially used *Perimitrax*® and later *OmniTrax*® buried cable sensors from Senstar Corp., running parallel to the road to detect large animals approaching the pavement. When the system sensed an intrusion, it activated flashing beacon signs warning "Wildlife on Road when Flashing." The Colorado installation faced growing pains - extensive fine-tuning was required, and the first version was replaced with an updated model in 2010 due to performance issues. Over the short monitoring period after deployment, collision data were too sparse to determine the effectiveness in reducing crashes. Reliability testing indicated the system could detect large animals (horse/llama) in most cases, but some false positives occurred, possibly from small animals or environmental noise. By the project's end, researchers noted that more years of data and possibly complementary sensors (e.g., cameras to verify detections) would be needed to establish its efficacy. The Colorado trial demonstrated the potential of buried sensors but also highlighted the need for backup systems and the difficulty of debugging an unseen underground sensor in the field. It underscored that such systems were still experimental and required further research and development.

United States - Idaho (US 95, 2015–2016): In northern Idaho, near Bonners Ferry, a Doppler radar-based animal detection system was deployed along a 0.5-mile segment of Highway US 95, a wooded rural highway with frequent deer and elk crossings [8]. This project, completed in 2017, is one of the most thoroughly documented modern trials. The system used a single radar unit to cover a 370 ft stretch. When the radar detected a large animal approaching or on the road, it wirelessly activated amber flashing lights atop warning signs on both approaches, with the message "WILDLIFE DETECTION – SLOW DOWN" posted for drivers [9]. To evaluate effectiveness, researchers analyzed vehicle speeds with the system on vs. off, and cross-checked radar detection logs with thermal camera footage that was continuously recorded (to independently verify animal presence and any missed detections).

Results from Idaho were positive on multiple fronts: Vehicle speeds dropped when the warning signs flashed, on average 0.7 to 4.4 mph lower in the radar-activated zones, with the largest reductions at night in winter [9]. While a few mph may seem small, even a 3-4 mph speed reduction can meaningfully improve a driver's reaction and braking distance when an animal is on the road. About 76% of all animal crossing events in the detection zone were correctly detected by the radar (the remainder likely involved animals at the very edge of the zone or moving in a way that didn't trigger Doppler). False positives were harder to quantify; researchers labeled some events "possible false positives" if the radar triggered but thermal cameras showed no animal. Many of those could have been animals in foliage that the thermal didn't capture. The warning lights were active only 2.5% of the time on average, indicating the system wasn't constantly over-triggering. An important outcome: for 90% of deer observed, the warning sign was on for at least part of the time the deer was on the road (and for 75% of deer, it was on for the entire crossing), giving drivers a chance to react. All elk that entered the roadway were detected and warned for. The Idaho trial did not run long enough to measure a statistically significant drop in collisions (the road section was short, so few crashes occurred in the before/after period). But the speed reductions and high detection reliability strongly suggest improved safety. The system's cost ($387,000 per mile plus ongoing maintenance)) is a noted factor; even so, Idaho DOT considered it a potential model for other wildlife-rich corridors.

United States - Arizona (State Route 260, 2007-2015): Arizona Game and Fish Department led a Federal Highway Administration (FHWA) funded study to evaluate the addition of exclusionary fences for elk, where one end of the fence was connected to a series of wildlife underpasses and the other ended at a "crosswalk" [7]. At the crosswalk a thermal sensor driven animal-activated detection system installed by CrossTek LLC., intended to alert motorists of animals approaching the road. It was a placeholder for a future permanent wildlife crossing and fence project ultimately funded in 2026. The detection system included a series of signs (a) a static sign that read 'Test Area-Elk Crossing 1,500 ft Ahead', (b) a variable message sign (VMS), 920 -1,050 ft (depending on lane direction) from the crosswalk that displayed 'Caution Elk Detected', and (c) an activated warning sign with a silhouette of an elk at the crosswalk with flashers. During the nine-year evaluation, the combination of the fencing and detection system reduced collisions with elk by 97%. Motorist response to the animal-activated warning signs indicated a decrease in motorists by 13%, and a 5.5-fold increase in motorist alertness when activated versus deactivated. Additionally, Of the 392 groups of elk that approached within 45ft of the highway, motorist alert signage was activated appropriately 96% of the time and false negatives occurred just 4% of the time when elk were in the crosswalk. In the case of smaller white-tailed deer, 49 groups were detected by the animal activation detection system (AADS), which triggered motorist alert signage 98% of the time with just 2% false negatives. The AGFD team recorded 13 wildlife species with time lapse visible light cameras aided by infrared illuminators, comprised of 1,719 individuals, and overall, elk crossed the road 34% of the times they entered the detection zone. Interestingly, increasing traffic volume reduced the frequency of successful highway crossings at the crosswalk by elk and white-tailed deer.

United States - California (State Route 3, 2010–2012): A Caltrans-funded project in far-northern California (Trinity County) tested a break-the-beam infrared animal detection system on a mountainous two-lane highway (State Route 3) known for deer collisions [3]. Four sets of IR beam emitters and receivers were installed in a series, covering about a 0.8-mile stretch. When any beam was broken, flashing beacon signs would light with an "ANIMAL ON ROAD" warning. This experiment revealed both the promise and pitfalls of such systems in practice. On one hand, over a year of monitoring, the system undoubtedly detected some deer crossings and prompted drivers to slow (public surveys indicated drivers did perceive and respond to the warning when it was active). However, many false triggers frustrated both drivers and residents: the majority of activations (over 90%) turned out to be caused by vehicles entering or leaving driveways that intersected the beam paths, rather than by wildlife [3]. Locals grew skeptical as the signs flashed at times with no deer to be seen, illustrating the "cry wolf" problem. Researchers acknowledged this as a design flaw: the beam system could not distinguish a deer from a turning car. They suggested adding roadway loops at the side roads to detect vehicles and cancel those alerts. Additionally, the system had periods of downtime due to technical issues and harsh conditions. At one point, heavy snow buried the emitters, taking the system offline until maintenance cleared it [3]. Despite these issues, the project provided valuable lessons. A key finding was driver behavior: when the signs flashed, many drivers did slow down (data showed a modest speed reduction, though not as extensively measured as in Idaho). Furthermore, a driving simulator study associated with this project found that participants who saw an activated animal warning braked earlier and avoided crashes more often than those without a warning. The simulator study also tested sign formats, finding graphic deer symbol signs were more effective than text "CAUTION" signs at catching driver attention, especially at dusk/night. By the end of the trial, Caltrans researchers recommended several upgrades (such as filtering out non-wildlife

triggers and improving public education about the system's purpose) before such a system could be made permanent [3].

United States - Florida (US 41, 2012–2015): In Collier County, Florida, a unique motivation for deployment was the endangered Florida panther. On a 1.3-mile stretch of US 41 (Tamiami Trail) skirting Big Cypress National Preserve, an area with panther road fatalities, authorities installed a Roadside Animal Detection System (RADS) in 2012. The RADS used solar-powered sensors and wireless links to activate large electronic message signs reading "Wildlife Crossing / Slow Down" when animals were detected. The exact sensor technology was a combination: it included passive IR motion sensors covering the roadsides and microwave detectors (reports mention multiple sensor types to improve detection). The system targeted not only panthers but also black bears, deer, and even alligators that frequent the area. An evaluation published in 2016 found mixed results [20]. On the positive side, vehicle speed data showed reduction during tourist season when many drivers were unfamiliar with the road. The RADS activation led to an average speed reduction of about 2 mph, while local drivers (off-season) showed less response, likely due to habituation. A public survey indicated many drivers were unaware of the system's purpose or whether it was functioning, suggesting outreach was insufficient. Importantly, chronic maintenance problems plagued the system: weather and technical malfunctions frequently took sensors offline ("chronic system malfunctions" are noted). As a result, the warning signs were not consistently activated when they should have been, and conversely sometimes triggered erratically. In terms of collisions, panther road deaths did not drop to zero, but given the very low baseline (a few per year), it was hard to draw conclusions. The Florida study echoed California's in recommending robust public education (so drivers trust and understand the warning) and careful placement of signage to avoid clutter and ensure clear sightlines. It also highlighted sign design: researchers tested picture-based vs. text-based signs in a simulator and found the panther image sign yielded better driver response at night, aligning with Caltrans' findings on symbol effectiveness. Florida's experience illustrates the difficulties of deploying a complex Animal Detection and Driver Warning System in a challenging environment - everglades ecosystem with thunderstorms, heat, and limited infrastructure, and the importance of reliability: even the best driver warning is moot if the system is frequently down or crying wolf. Nonetheless, it was a pioneering attempt to protect not just common species but an endangered carnivore on a busy public highway.

United States - Washington (I-90, 2023 - 2025): Washington State Department of Transportation (WSDOT) sponsored development of a rapid wildlife detection and classification system supported by AI and "sitting on top of" their current monitoring system for several wildlife crossings across I-90, Snoqualmie Pass (Srinivas et al., 2025). This is the largest and best-monitored wildlife crossing/fencing system in the US, with >2 million still images and videos collected per year from motion-triggered thermal video and still-optical cameras. In collaboration with WSDOT biologists, engineers, and IT specialists, an AI-supported animal detection and classification system was positioned within the workflow of the monitoring system on servers in a maintenance station near the crossings. The hardware device and algorithm were similar to the system deployed for the current NDOT study. Based on the vendor's report, the detection model achieved 98% (bobcat) to 100% (deer/elk) accuracy across three animal groups (deer/elk, bobcat, and coyote) and successfully filtered 98.63% of false positives in real-world thermal videos collected at the 61.5 Overcrossing South on the I-90 corridor. The filtered detections were passed to a lightweight classification model trained on real thermal imagery, which achieved species-level classification accuracies of 93% (bobcat and coyote) and 97%

(deer/elk). This two-stage system substantially reduced manual review while maintaining high identification performance. The underlying AI system was developed for both optical and thermal imagery, making it appropriate to use across sensor types [15].

Canada - Alberta (Trans-Canada Highway, Banff, 2008 - 2009): Banff National Park is famous for its extensive wildlife fencing and crossing structures along the Trans-Canada Highway, which have reduced WVCs by 80%–96% for ungulates. While Banff relies on fencing, there was interest in animal detection systems for unfenced sections or during winter when gate openings occur. In a trial near the park, a prototype radar/camera system was tested to detect elk on an unfenced stretch and trigger driver warning systems. One such system reportedly achieved high detection rates, but data are sparse in published literature. A more documented Canadian effort was in British Columbia: the Wildlife Collision Prevention Program in B.C. tested multiple vendor systems in a "comparison testbed" around 2008 - 2009. They evaluated systems including a radar-based sensor, a break-the-beam, and a thermal camera, monitoring each with video to log real detections vs. false triggers. The outcome of that comparison, summarized in a government report, indicated that some systems had false-negative rates as high as 30% while others were more reliable. The stakeholder tolerance for errors was low: officials wanted >90% detection and minimal false alerts. As a result, B.C. was cautious in deploying any single system widely, instead continuing to use fencing on major highways and exploring detection systems for secondary roads. The B.C. comparison did, however, advance understanding of how local conditions (rainforest climate, terrain) affect each technology, guiding future customization.

Europe - Switzerland and Germany: Europe saw some of the earliest animal detection systems. In the late 1990s, Switzerland installed an infrared beam system on a highway that saw heavy deer migration. Kistler (1998) and Römer (2003) reported that this system [21], [22], which flashed wildlife warning lights, achieved an 81-82% reduction in large animal collisions on that segment. Key to its success was likely the combination with fencing (the system covered a known crossing point left open in the fence). Germany also experimented with similar approaches in the 2000s, and by 2010, researchers like Strein (2010) were reporting collision reductions around 50 - 75% from detection warning systems in certain trials [23]. These European deployments often faced the same reliability and driver compliance issues. One finding was that permanent warning signs lose effectiveness as drivers habituate; hence, the value of dynamic signs that only flash when an animal is present (place- and time-specific warnings). Many European countries integrated these systems into a broader road ecology strategy, including reduced speed limits at night in wildlife zones, reflectors, and public awareness campaigns.

Europe - Sweden's Road 108 ADDWS (2019 - 2021): As introduced earlier, this project in Skåne County combined roadside fencing that funnels animals to a 90 ft open crossing, overhead thermal/video cameras to detect animals at that passage, and automatic VMS with a moose symbol that light up when animals cross [24]. Essentially, it functions as an automated at-grade wildlife crossing. In the first two years of operation, the system captured hundreds of crossings (roe deer, red deer, wild boar) on camera and reduced collisions by an estimated 66% compared to pre-installation (while similar roads without the system saw no decline). Impressively, the site went from an average 30 wildlife collisions per year to just 3 in one-year post-deployment. This suggests a very strong effect, likely because drivers heeded the warnings (helped by the clear moose picture sign) and animals also perhaps learned to use the designated crossing. The project's ecological data showed 75% of animals that approached the crossing eventually crossed

successfully at that spot, indicating the fencing + detection system effectively guided wildlife. The Swedish team set performance goals (≥80% collision reduction, etc.) that were slightly missed in the pilot, but they still achieved major improvements. This case exemplifies a comprehensive approach: it addresses both driver response and animal behavior, by using fencing to control where animals cross and technology to alert drivers when they do. It's a model being watched by road ecologists across Europe, and a working group (Infra Eco Network Europe (IENE), a European professional network, ADDWS group) has been formed to exchange knowledge on such systems.

Effectiveness and Limitations

Available literature and field data suggest that animal detection and driver warning systems can be highly effective in reducing wildlife-vehicle collisions, but success depends on both technical reliability and human factors. Effectiveness can be considered in terms of collision reduction outcomes, driver response, and system reliability.

Collision reduction: Reported reductions in crashes with large animals at instrumented sites range widely, from as high as 97% in the best cases to essentially no change in others, with an average reduction of around 82% cited in early meta-reviews. A Swiss system recorded 81% fewer deer collisions after installation; an Arizona DOT project combining fencing with animal detection achieved a 97% decrease in elk collisions; and Sweden's recent pilot reduced ungulate crashes by 66% relative to baseline. The highest effectiveness figures typically come from hybrid approaches that pair detection with fencing to channel animals to known crossing points. Pure detection systems on open roads still show meaningful results, Montana's long-term monitoring found 58-100% collision reductions at two sites, but some deployments have shown no measurable benefit, usually due to technical failures or insufficient data. Overall, reliable systems appear capable of reducing large-animal crashes by roughly 80%, though statistically robust long-term data remain limited.

Driver response: Evidence indicates that active warnings do influence driver behavior. Speed reductions of 1 - 11 mph have been observed when warnings are active, and simulator studies show that warned drivers brake earlier and experience fewer simulated crashes. However, the effect can diminish over time. Local drivers who encounter warnings frequently show less response than unfamiliar drivers, suggesting habituation is a concern. False activations compound this problem, if drivers learn that warnings do not reliably indicate a real hazard, compliance wanes. Dynamic, event-triggered warnings are significantly more effective than static signage, but their credibility depends on minimizing false positives and educating the public on appropriate response.

Reliability and technical performance: A commonly cited target for operational systems is at least 90% detection with no more than 10% false alerts. Many current systems approach or meet these benchmarks, Idaho's radar system achieved 97.5% detection with under 3% false triggers, and Montana's multi-system tests found several technologies consistently exceeding 95% detection with false alarm rates below 1%. Earlier passive infrared systems performed more poorly, missing roughly 30% of deer. False positives arise mainly from non-target moving objects and environmental interference, and while controlled tests report very low false alert rates, real-world performance has sometimes been considerably worse.

Key limitations:

Environmental factors: Weather and terrain can degrade sensor performance. Snow, vegetation movement, temperature inversions, and low-angle sunlight all present challenges for various sensor types. Harsh environments tend to increase error rates, and no single sensor type is immune to all conditions.

Maintenance and power: These systems require ongoing maintenance — cleaning, recalibration, software updates, and component replacement. Several projects underestimated this burden, leading to extended downtime that eroded safety benefits. Remote diagnostics and adequate maintenance budgets are essential; without them, a system can be offline for days before anyone notices.

Cost and scalability: Upfront costs are significant, with multi-sensor systems across even short road segments often running into hundreds of thousands of dollars. These costs are justifiable at high-collision hotspots involving human fatalities or endangered species, and cost-benefit analyses suggest viable payback periods where collision rates are high. However, covering large road networks remains impractical, making strategic deployment at known hotspots the current norm.

Driver compliance: Human response is inherently unpredictable. Some drivers ignore warnings due to skepticism or distraction, while others may develop an unwarranted sense of security in uncovered areas. Agencies consistently treat these systems as supplements to driver caution, and public education campaigns typically accompany deployment. Legal liability concerns around system failures and non-standard signage have also led agencies to use advisory rather than regulatory signs and to seek FHWA experimental status where needed.

Coverage gaps: Detection systems typically cover a defined segment of road, while animals can cross anywhere. Without complementary fencing, animals may simply cross outside the detection zone, diluting effectiveness. Pairing detection with fencing, or ensuring the detection zone encompasses primary crossing areas, is important for maximizing benefit.

In summary, the principal limitations are environmental reliability, maintenance demands, and driver behavior. Many are being addressed as sensor technology matures and agencies gain operational experience. The next section examines how these systems may continue to evolve and what knowledge gaps remain.

APPENDIX 2: RESULTS_ALL THREE CYCLES

Reno crossings - Results for all three data collection cycles

The following results reflect only horse baseline events, rather than reporting for all mammals coyote size and larger (as reported in the original Cycle 1 and Cycle 2 results). Similarly, each data collection cycle has also been standardized, where all three cycles reflect distance groupings of 0, 50, 100, 150, 200, 300, and 500+ ft, rather than 500-1000 and 1000+ ft (as reported in the original Cycle 1 and Cycle 2 results).

Known issues for each cycle:

For detailed notes, please refer to event-specific comments in the "BaselineEvents_AllThreeCycles_ForDevelopers_FebNoData.xlsx" spreadsheet.

Cycle 1:

- Thermal - size filter issue - the system recorded detections for animals rodent size and larger. Thus, true positive results are artificially high.

Cycle 2:

- Baseline footage - In the 14 day analysis period, 108 hours, 9 minutes, and 7 seconds of baseline footage were missing or corrupt. As such, system detections that corresponded with the missing baseline timestamps were removed from comparison.
- Lidar - A detection was recorded for five events at 500+ ft, despite detection limitations of this system. Thus, true positive results may be artificially high. It is unclear if this was a detection zone or size filter issue, or perhaps a different issue entirely.
- Thermal - size filter issue - the system recorded detections for animals rodent size and larger. Thus, true positive results are artificially high.
- **Visual - No data available from February 6-14, 2024, the system was turned off during this period. Thus, detections during this time period were treated as no data.**

Cycle 3:

- Shift in thermal timelapse and thermal detection system field of view - The thermal timelapse and thermal detection system camera was tilted downward compared to previous cycles. This adjustment reduced the likelihood of accurately observing horses beyond 500 ft.
- Lidar - A detection was recorded for three events at 500+ ft, despite detection limitations of this system. Thus, true positive results may be artificially high. It is unclear if this was a detection zone or size filter issue, or perhaps a different issue entirely.
- Thermal - The thermal detection system experienced a lag when recording data to the .csv file. Specifically, by comparing the timestamps from the thermal time-lapse footage and the PTZ camera to those in the thermal detection .csv, it appeared that the recorded times in the .csv were approximately 10 seconds to 1 minute behind the actual observed times in the thermal timelapse and PTZ footage

Results: Day and Night Combined

Baseline summary information for each data collection cycle

Cycle 1 - October 2023: October 13, 2023 at 00:00:00 – October 26 at 23:59:59
Count of baseline events of horses:
<300 ft: 18
<500 ft: 23
>500 ft: 73

Total loiter time of horse events: 49 hours, 12 minutes, and 42 seconds.

Cycle 2 - February 2024: February 1, 2024 at 00:00:00 – February 14, 2024 at 23:59:59
Count of baseline events of horses:
<300 ft: 11
<500 ft: 33
>500 ft: 52

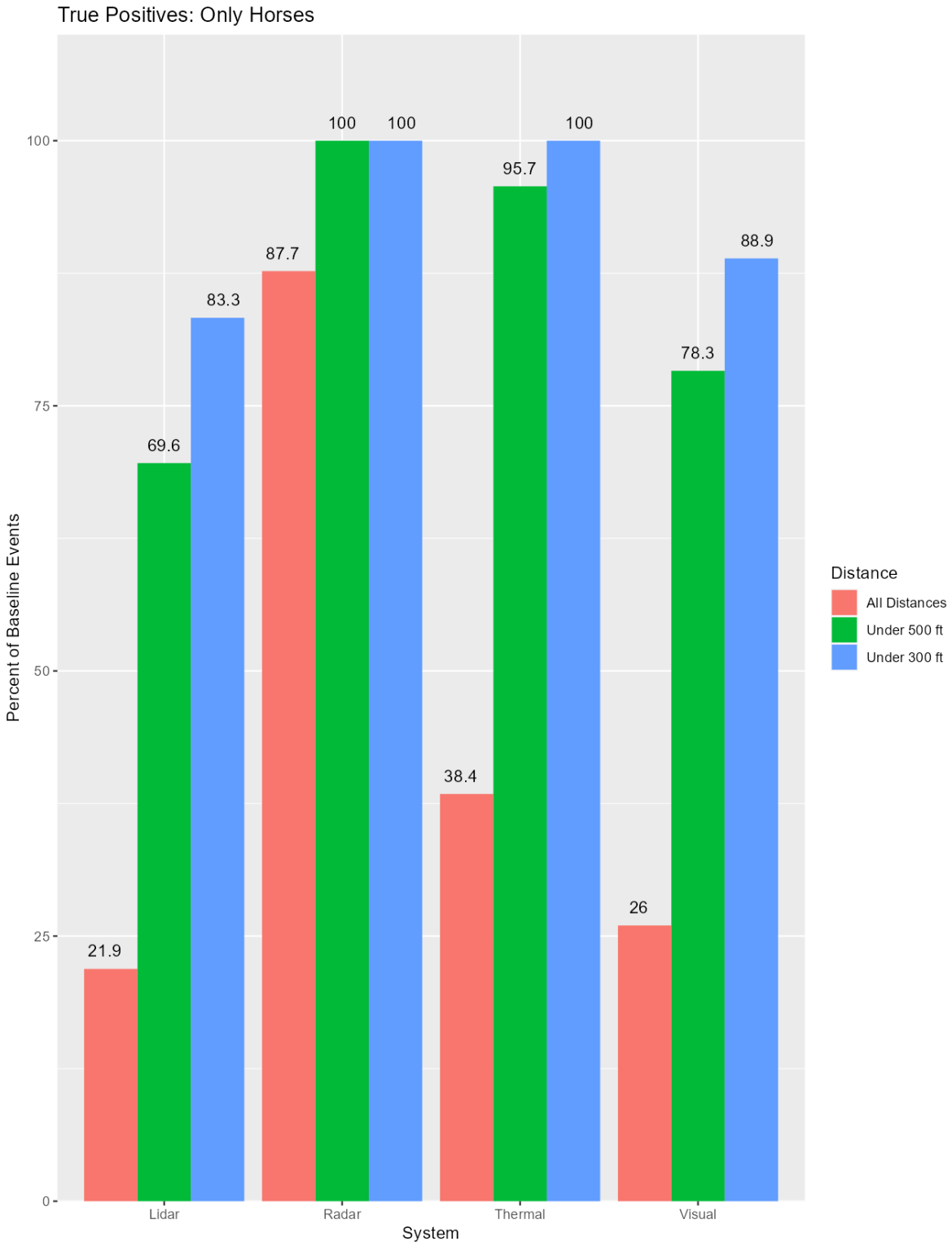
Total loiter time of horse events: 58 hours, 53 minutes, and 59 seconds.

Cycle 3 - October 2024: October 17, 2024 at 00:00:00 through October 30, 2024 at 23:59:59
Count of baseline events of horses:
<300 ft: 21
<500 ft: 23
>500 ft: 62

Total loiter time of horse events: 39 hours, 39 minutes, and 12 seconds.

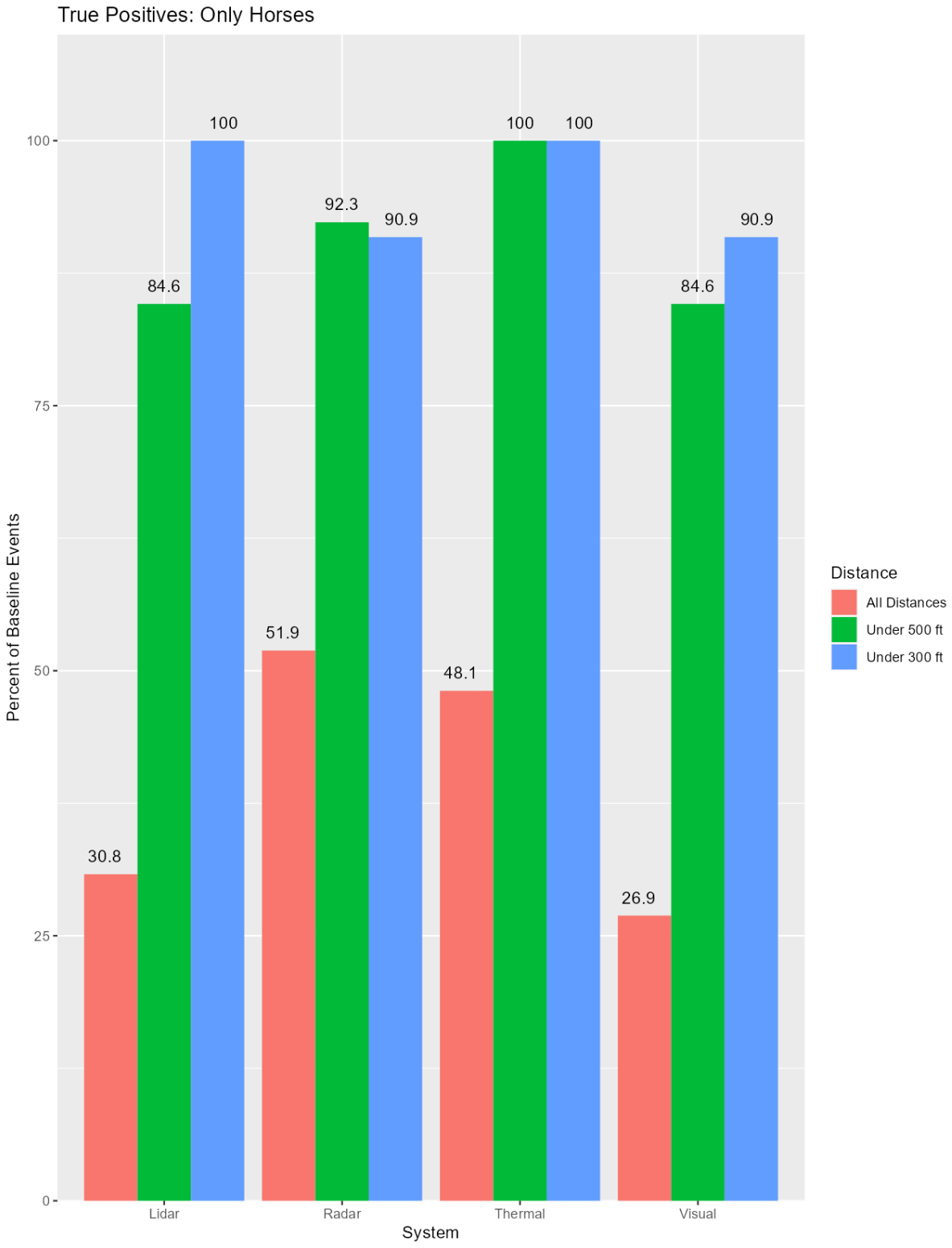
True Positives:

Cycle 1 - Day and Night Combined:



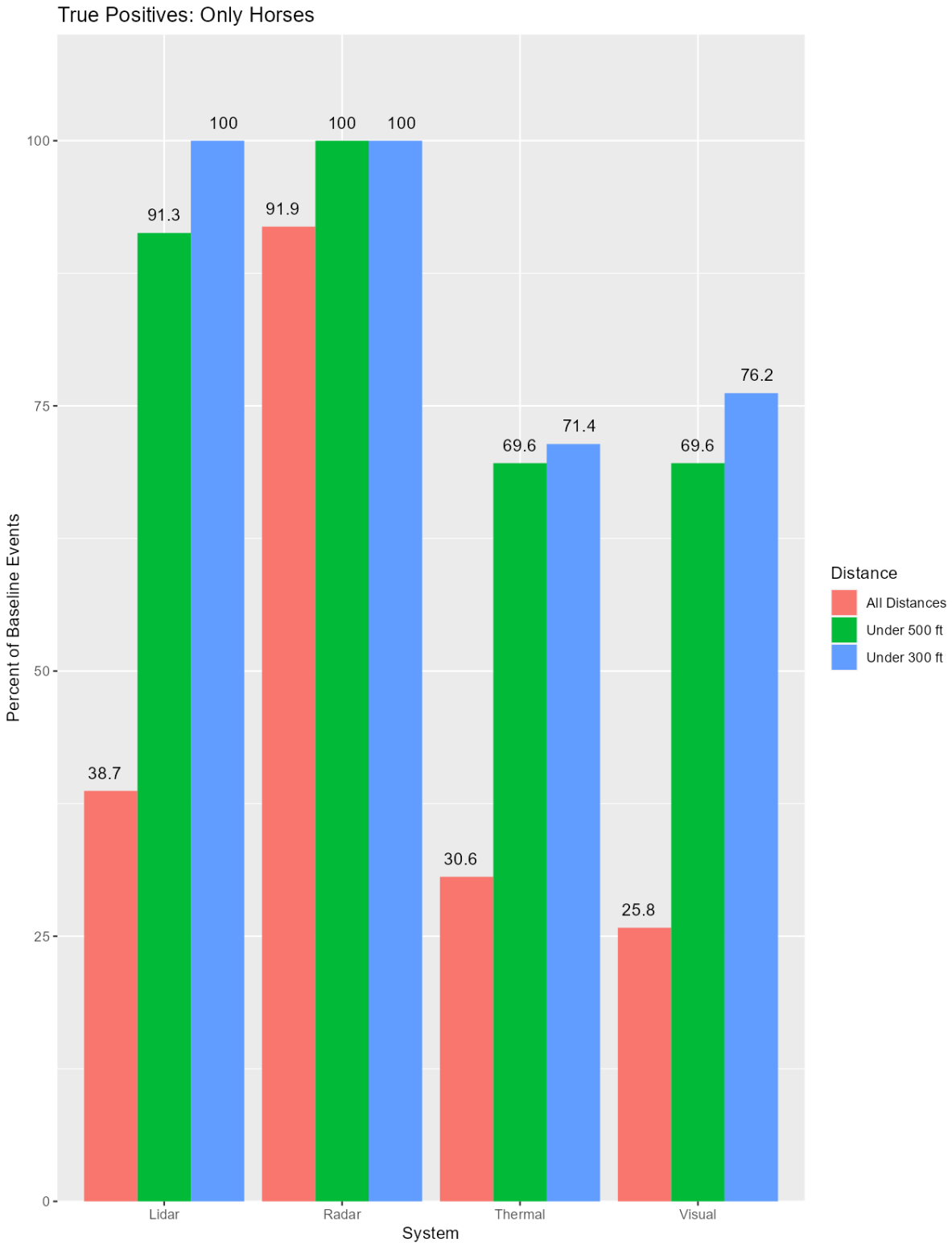
True Positives:

Cycle 2 - Day and Night Combined:



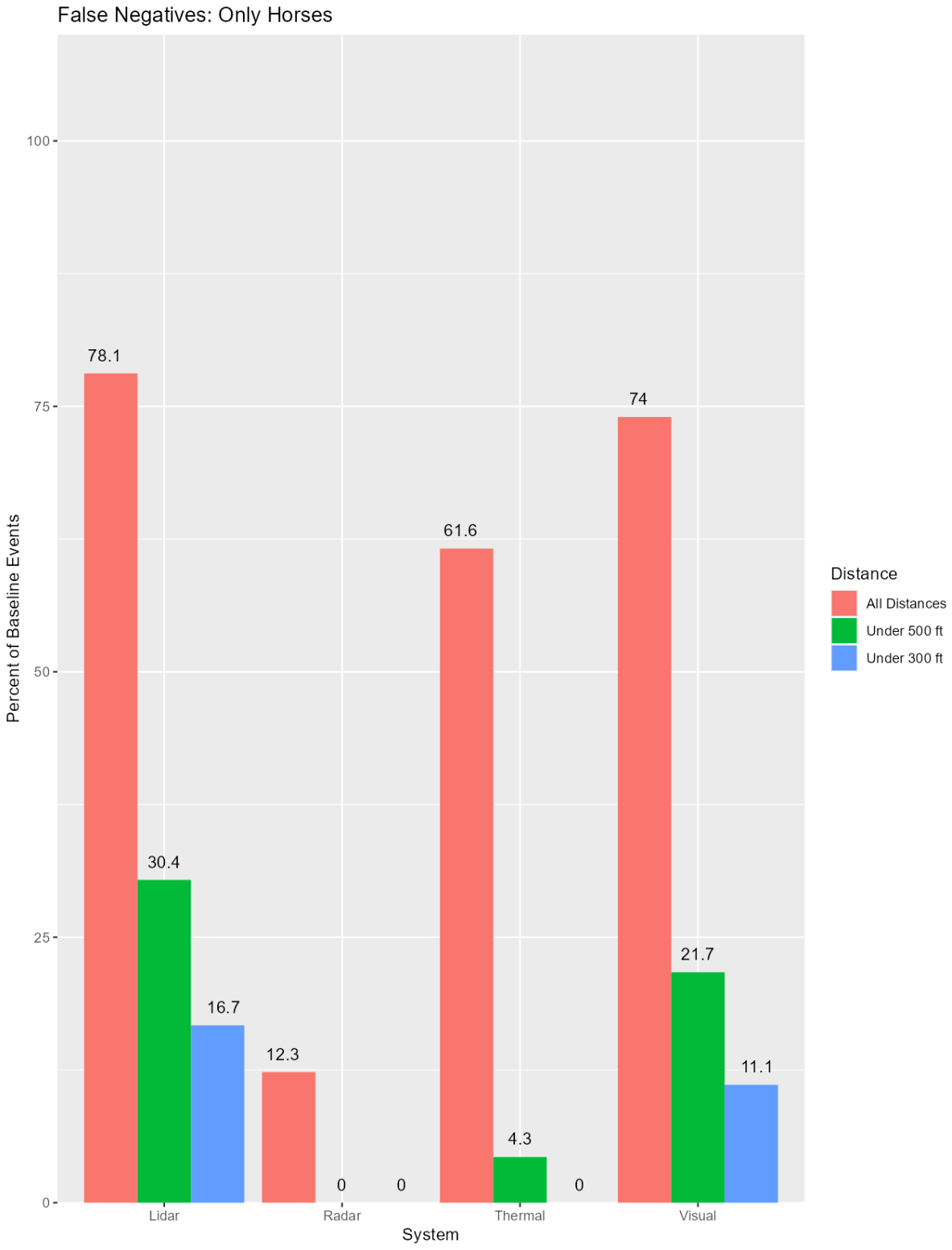
True Positives:

Cycle 3 - Day and Night Combined:



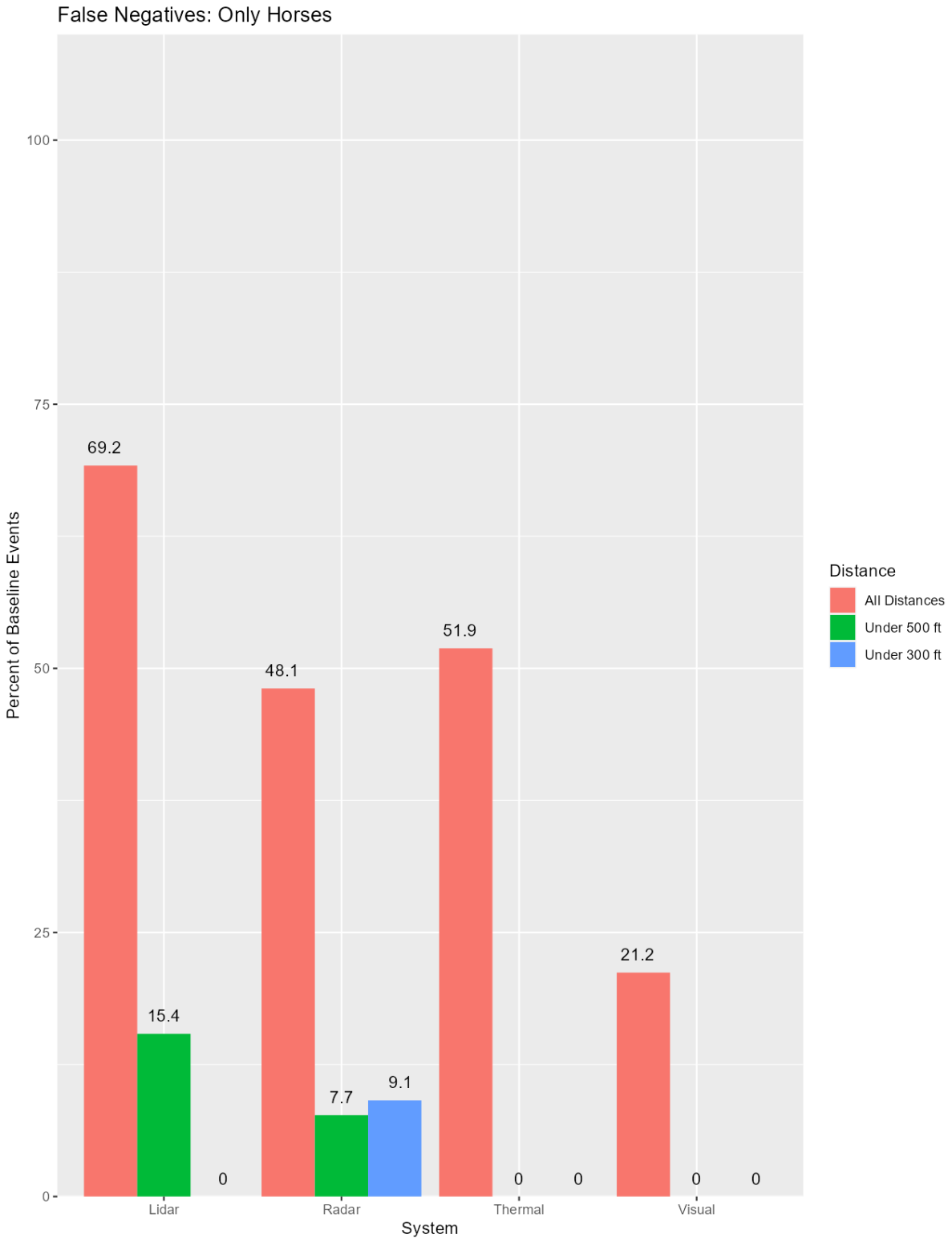
False Negatives:

Cycle 1 - Day and Night Combined:



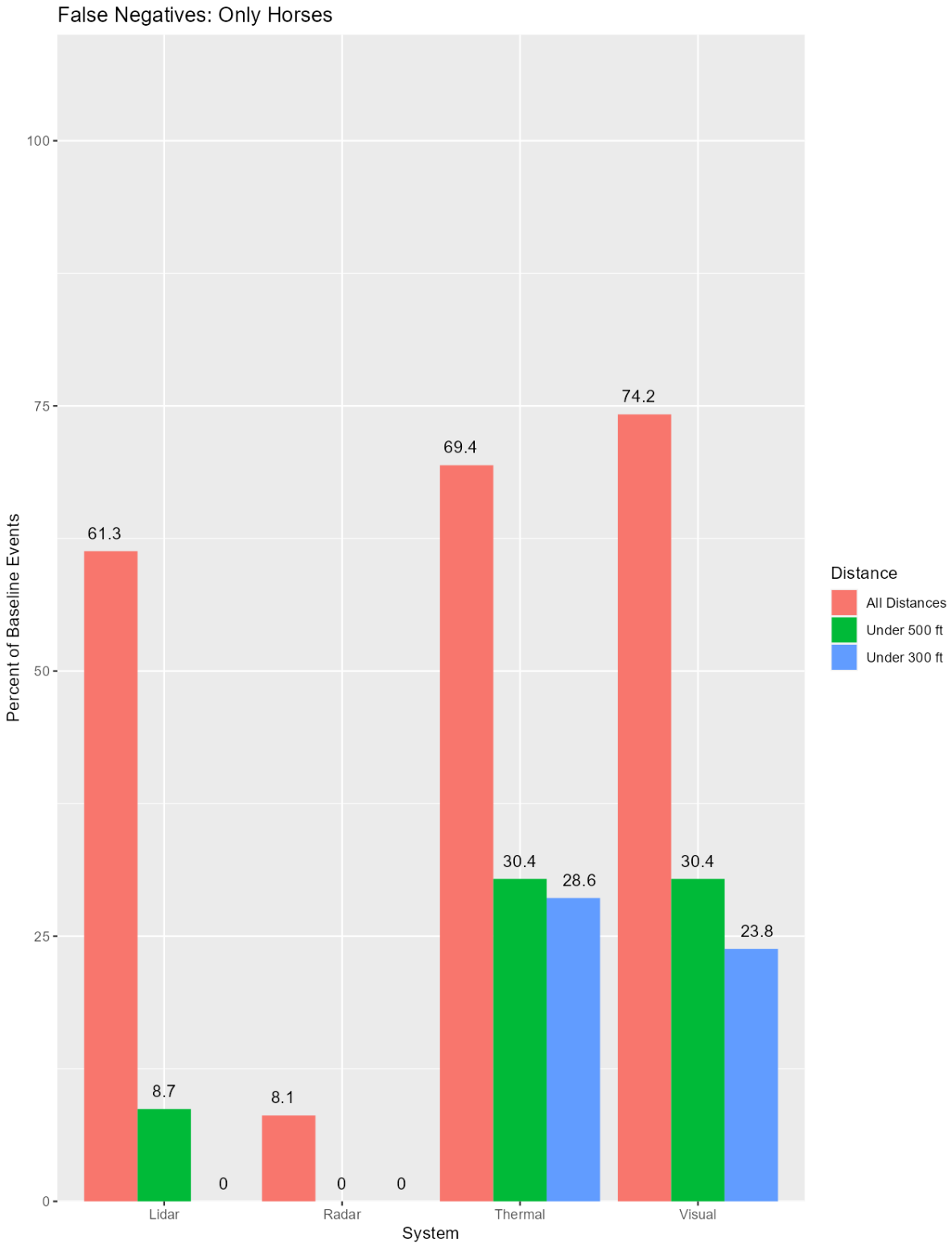
False Negatives:

Cycle 2 - Day and Night Combined:



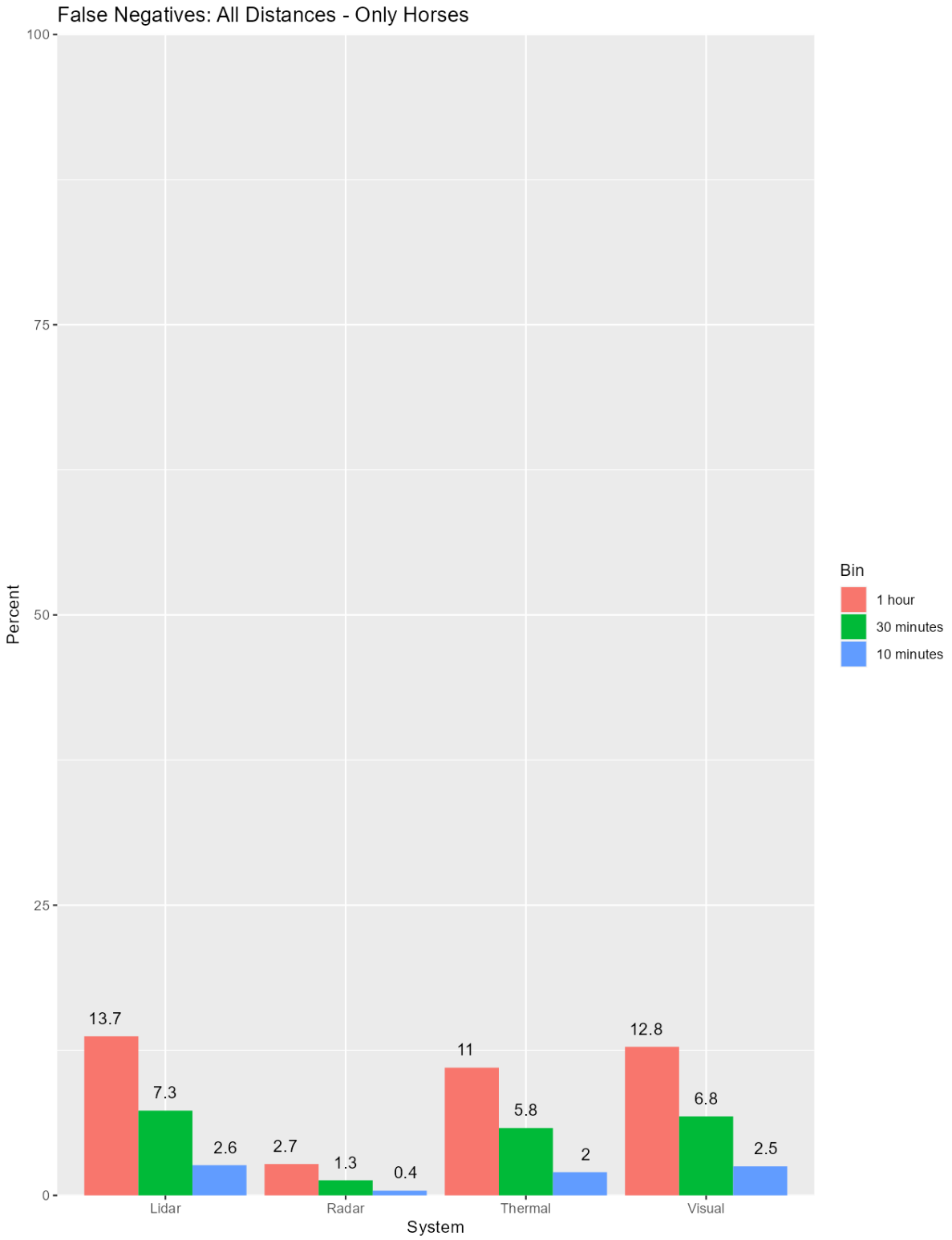
False Negatives:

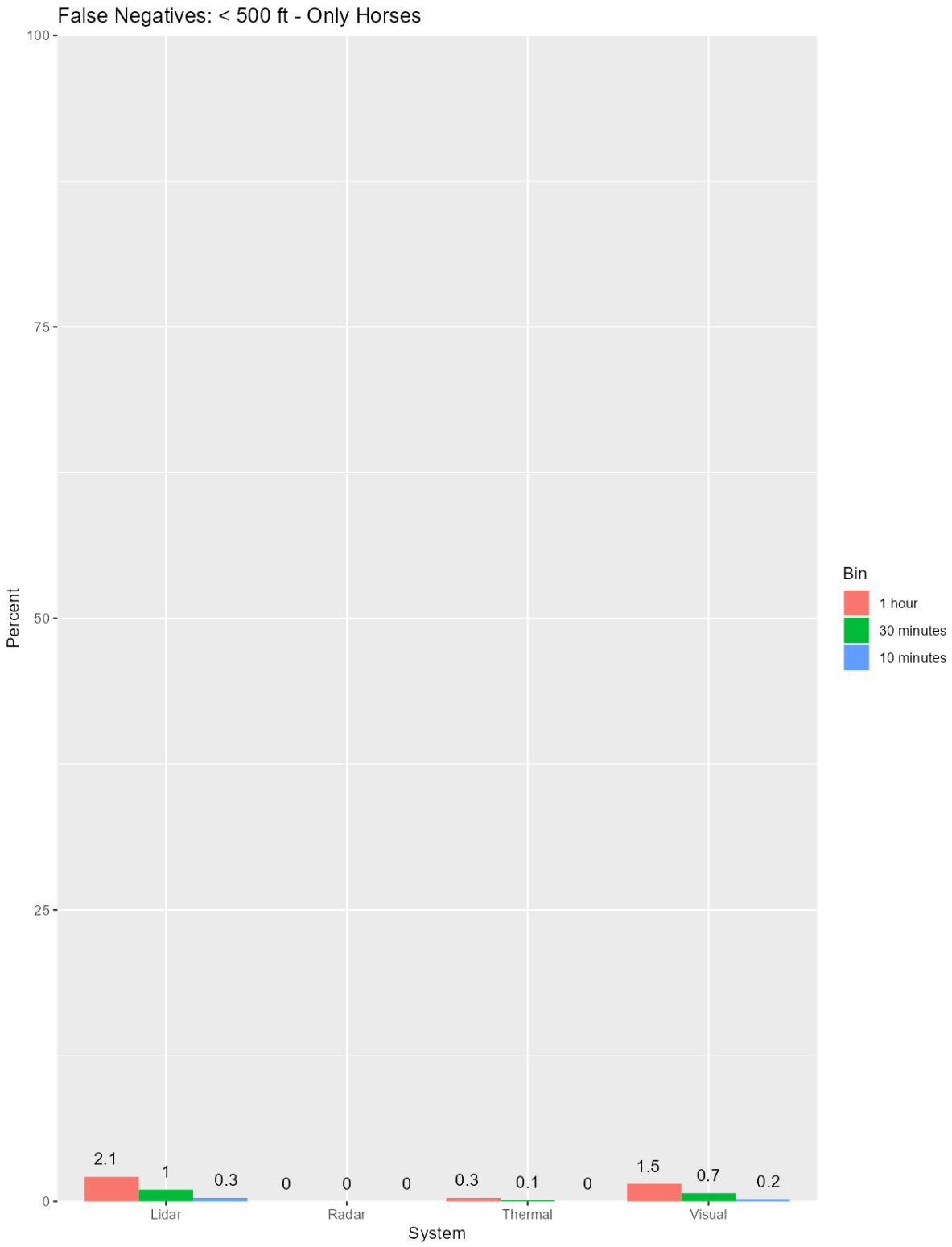
Cycle 3 - Day and Night Combined:

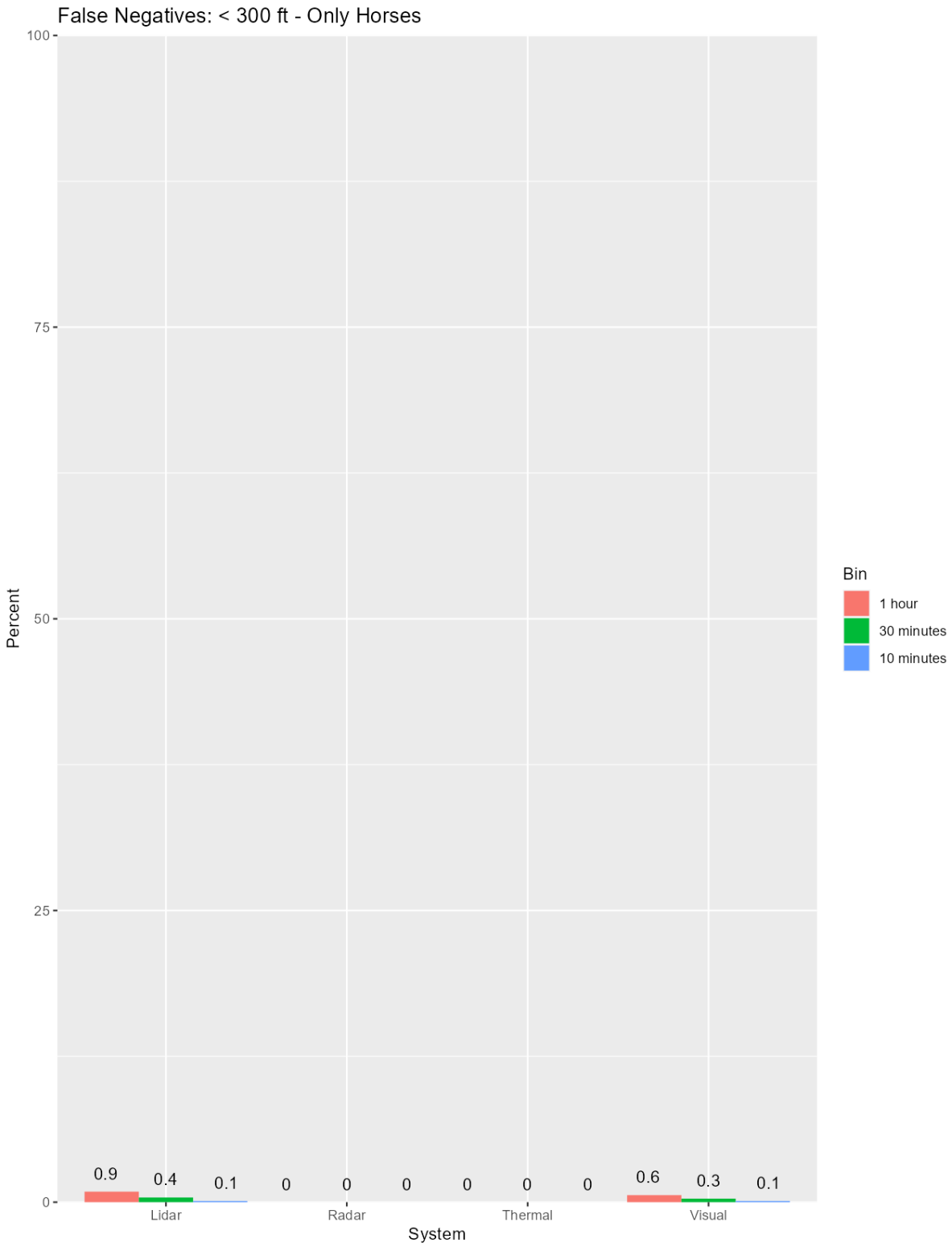


False Negative Time Bins:

Cycle 1 - Day and Night Combined:

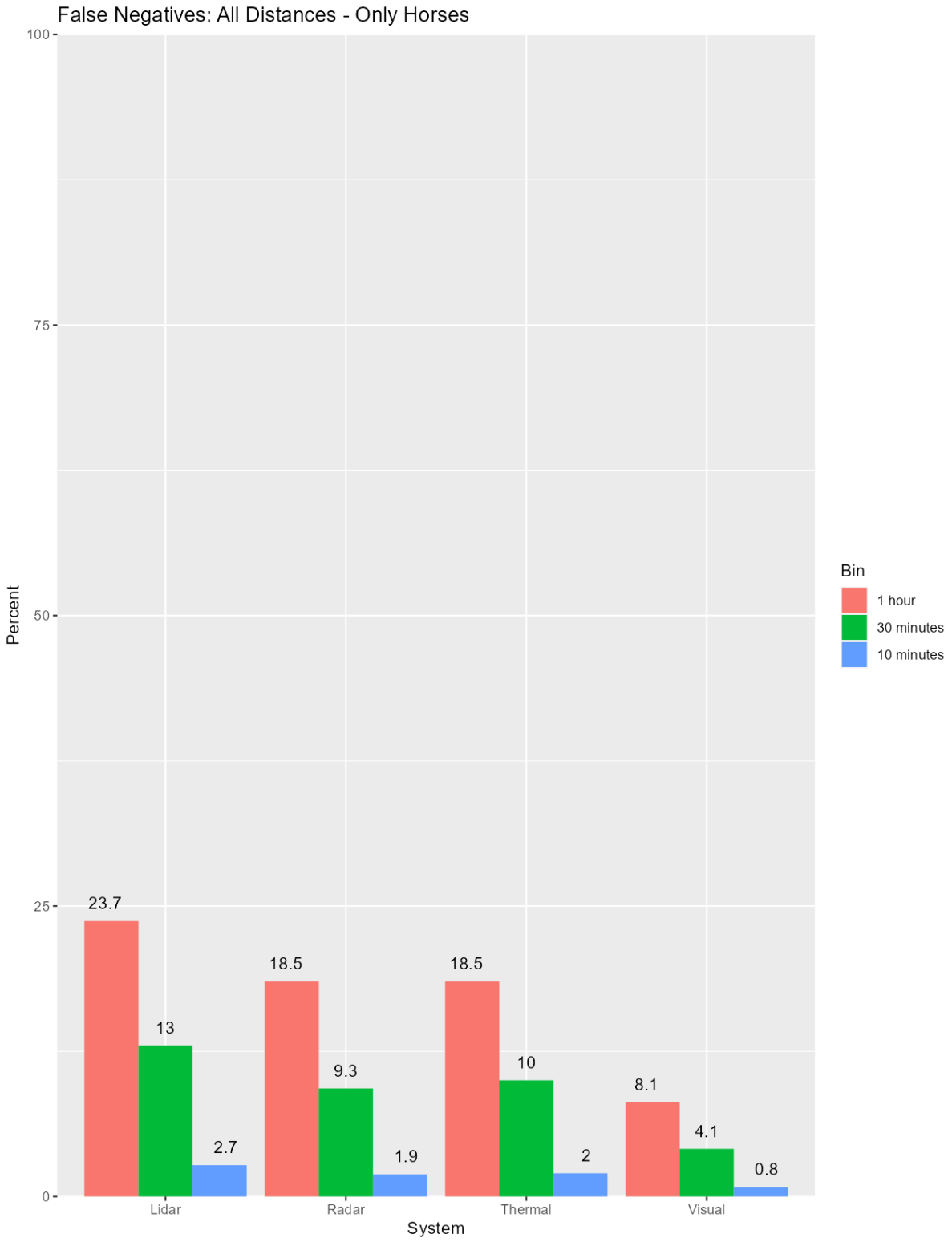


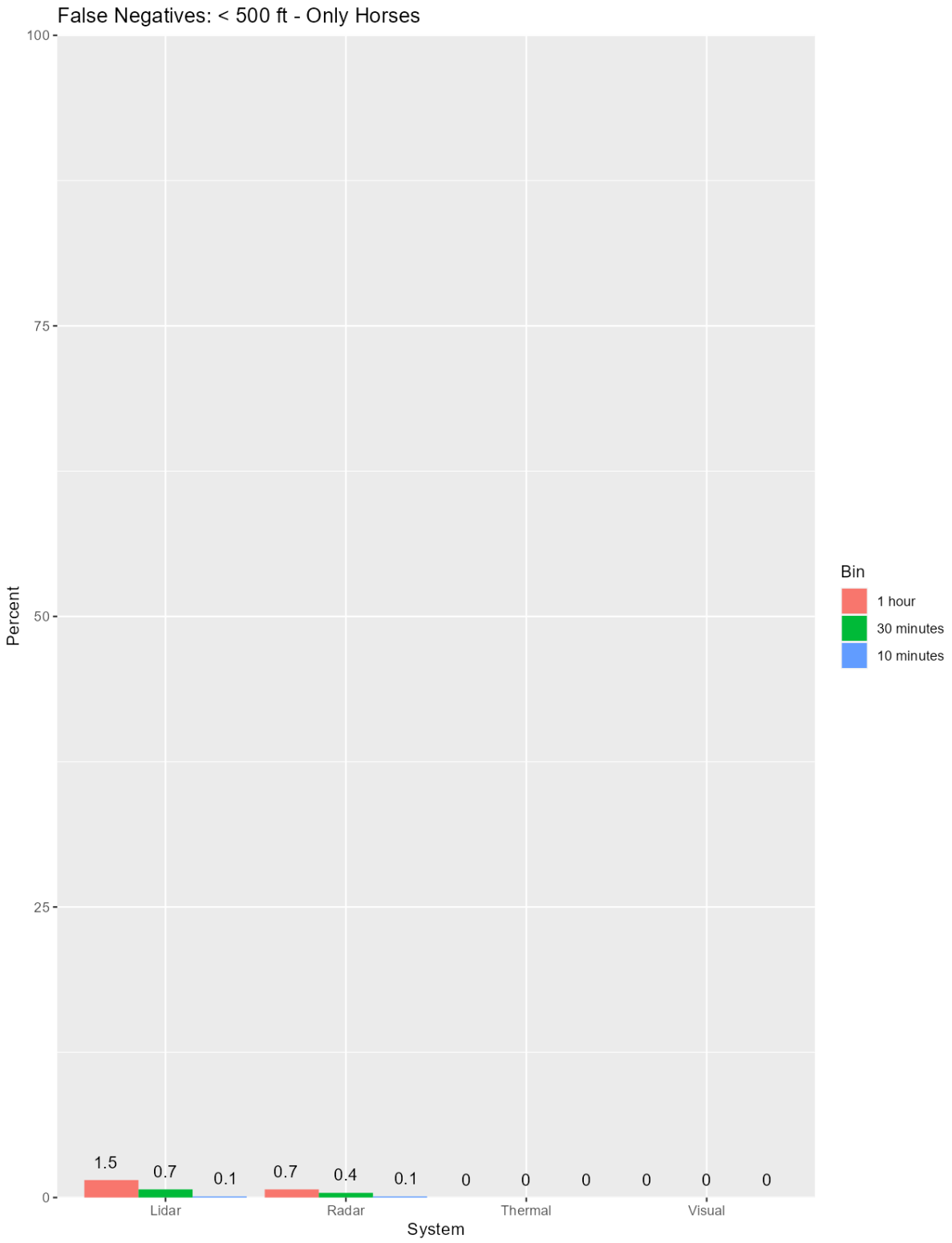

False Negatives: < 500 ft - Only Horses
100
75
50
25
0
Percent
2.1
1
0.3
0
0
0
0.3
0.1
0
1.5
0.7
0.2
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

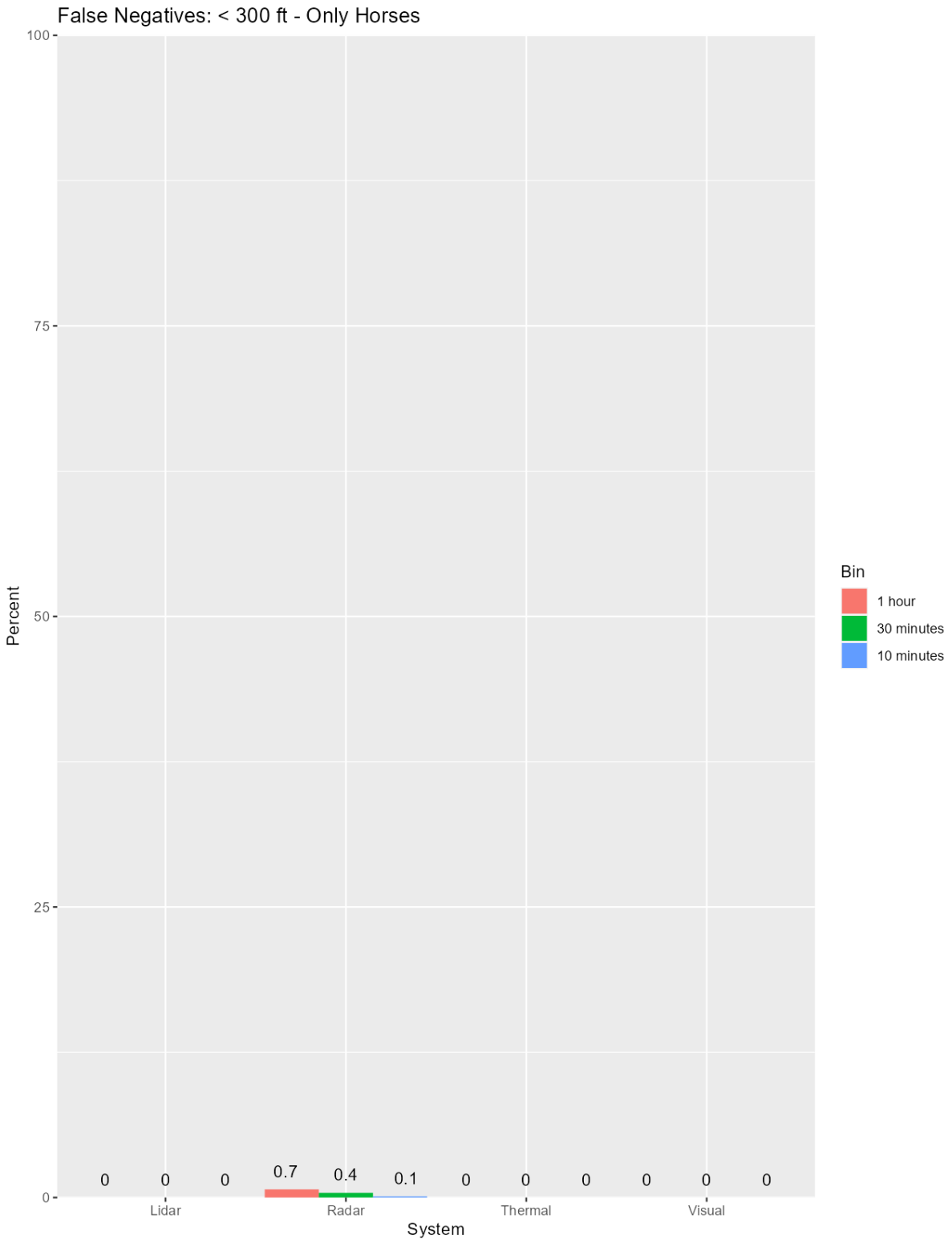

False Negatives: < 300 ft - Only Horses
100
75
50
25
0
Percent
0.9
0.4
0.1
0
0
0
0
0
0
0.6
0.3
0.1
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

False Negative Time Bins:

Cycle 2 - Day and Night Combined:

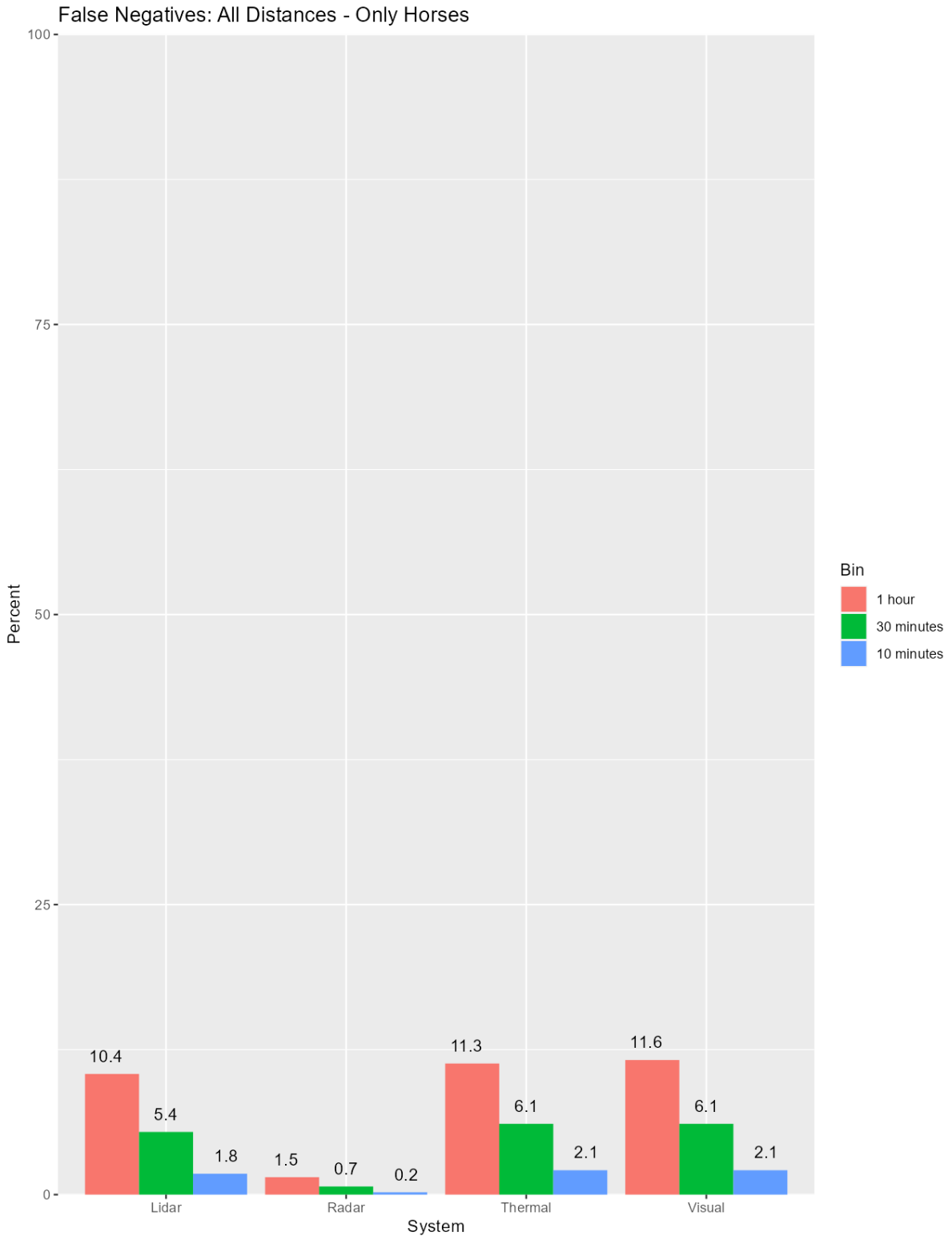


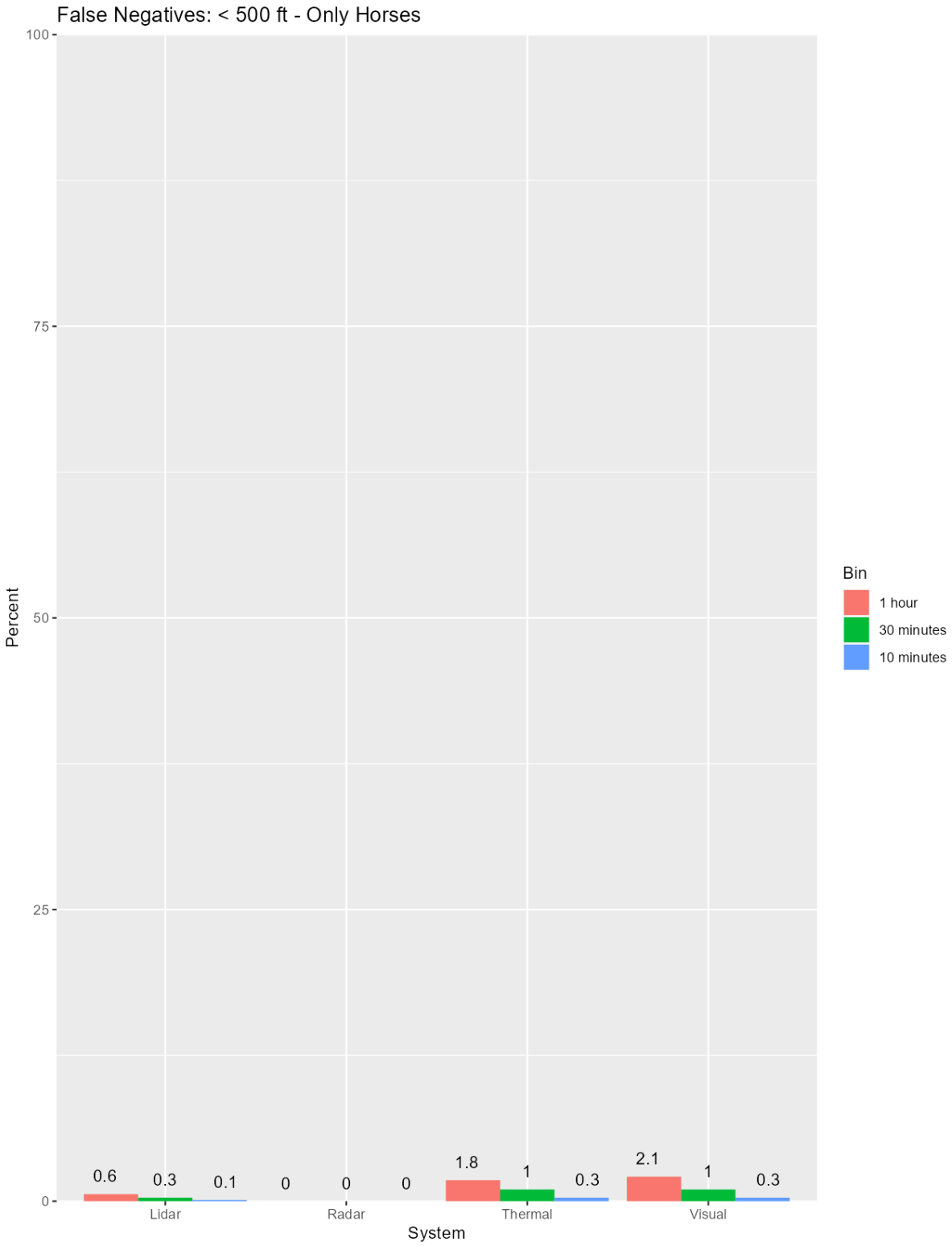

False Negatives: < 500 ft - Only Horses
100
75
50
25
0
Percent
1.5
0.7
0.1
0.7
0.4
0.1
0
0
0
0
0
0
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

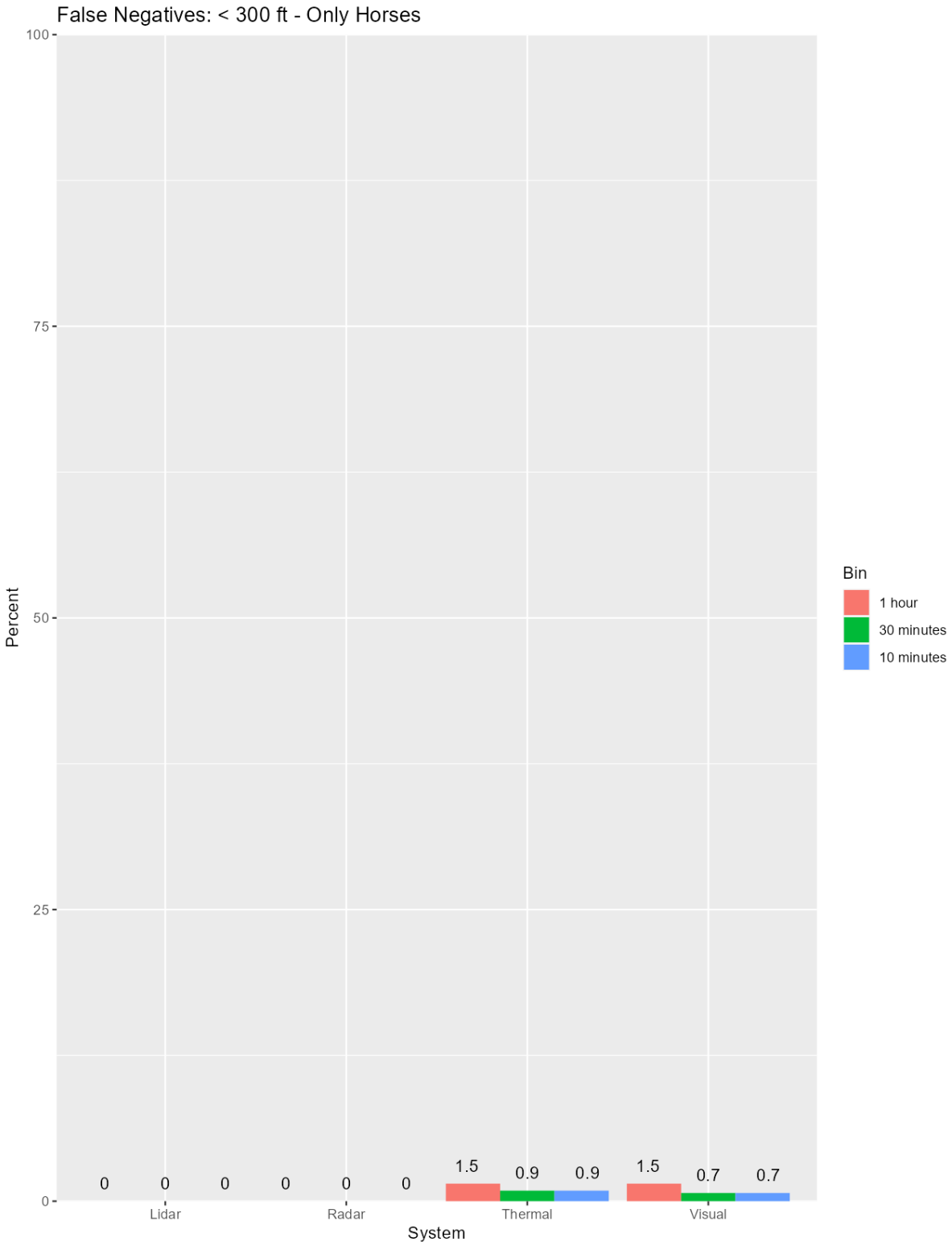

False Negatives: < 300 ft - Only Horses
100
75
50
25
0
Percent
0
0
0
0.7
0.4
0.1
0
0
0
0
0
0
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

False Negative Time Bins:

Cycle 3 - Day and Night Combined:

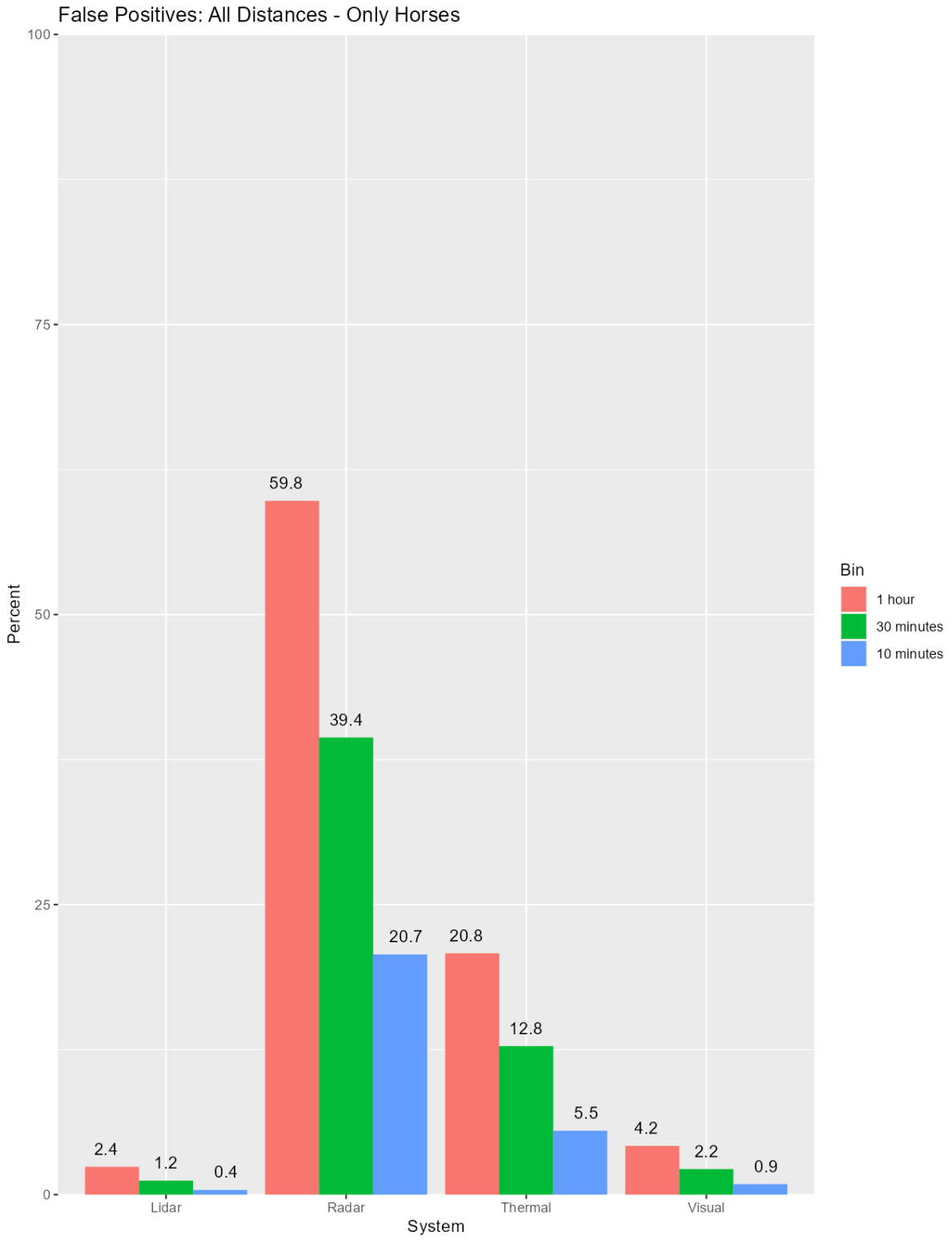


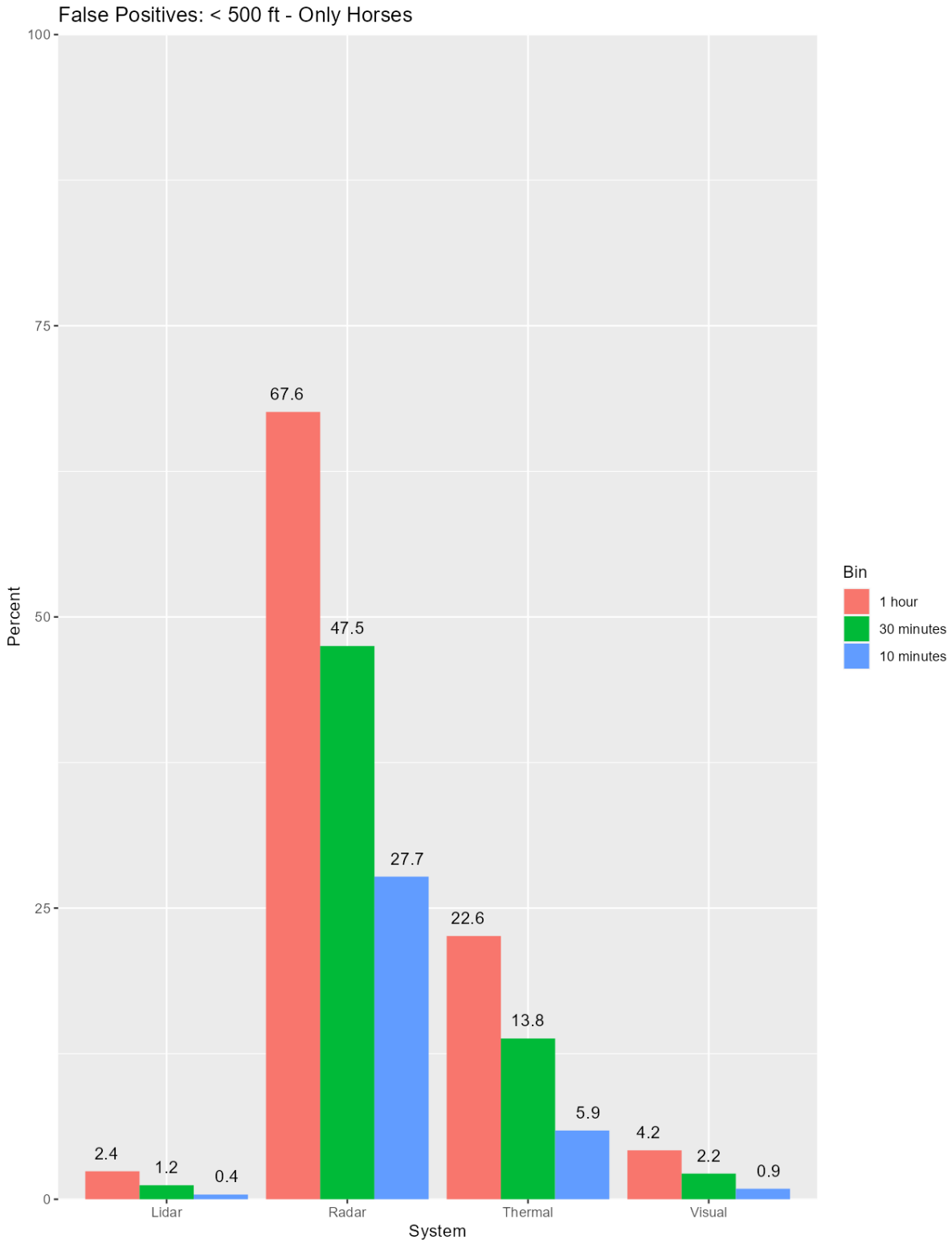

False Negatives: < 500 ft - Only Horses
100
75
50
25
0
Percent
0.6
0.3
0.1
0
0
0
1.8
1
0.3
2.1
1
0.3
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

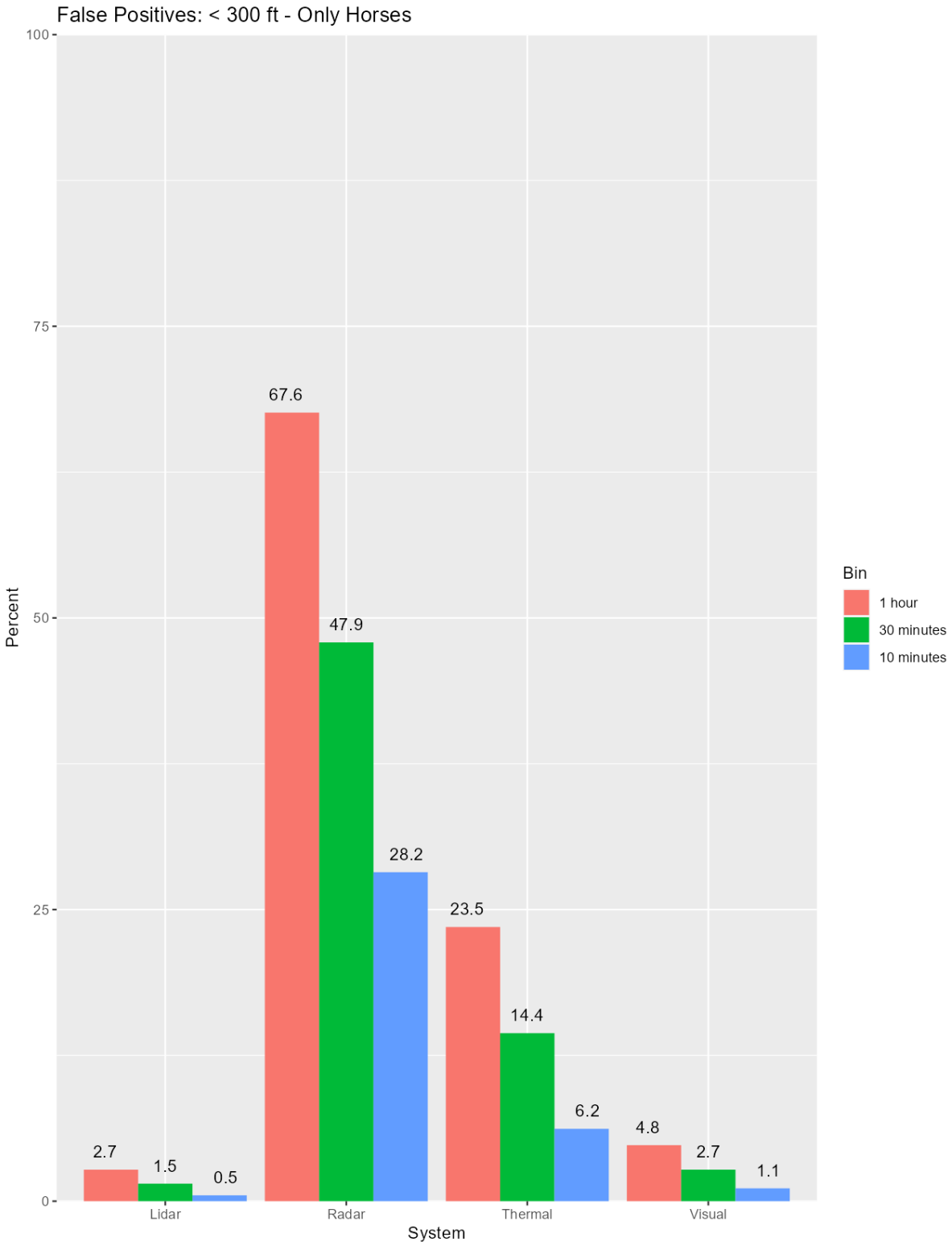

False Negatives: < 300 ft - Only Horses
100
75
50
25
0
Percent
0
0
0
0
0
0
1.5
0.9
0.9
1.5
0.7
0.7
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

False Positive Time Bins:

Cycle 1 - Day and Night Combined:

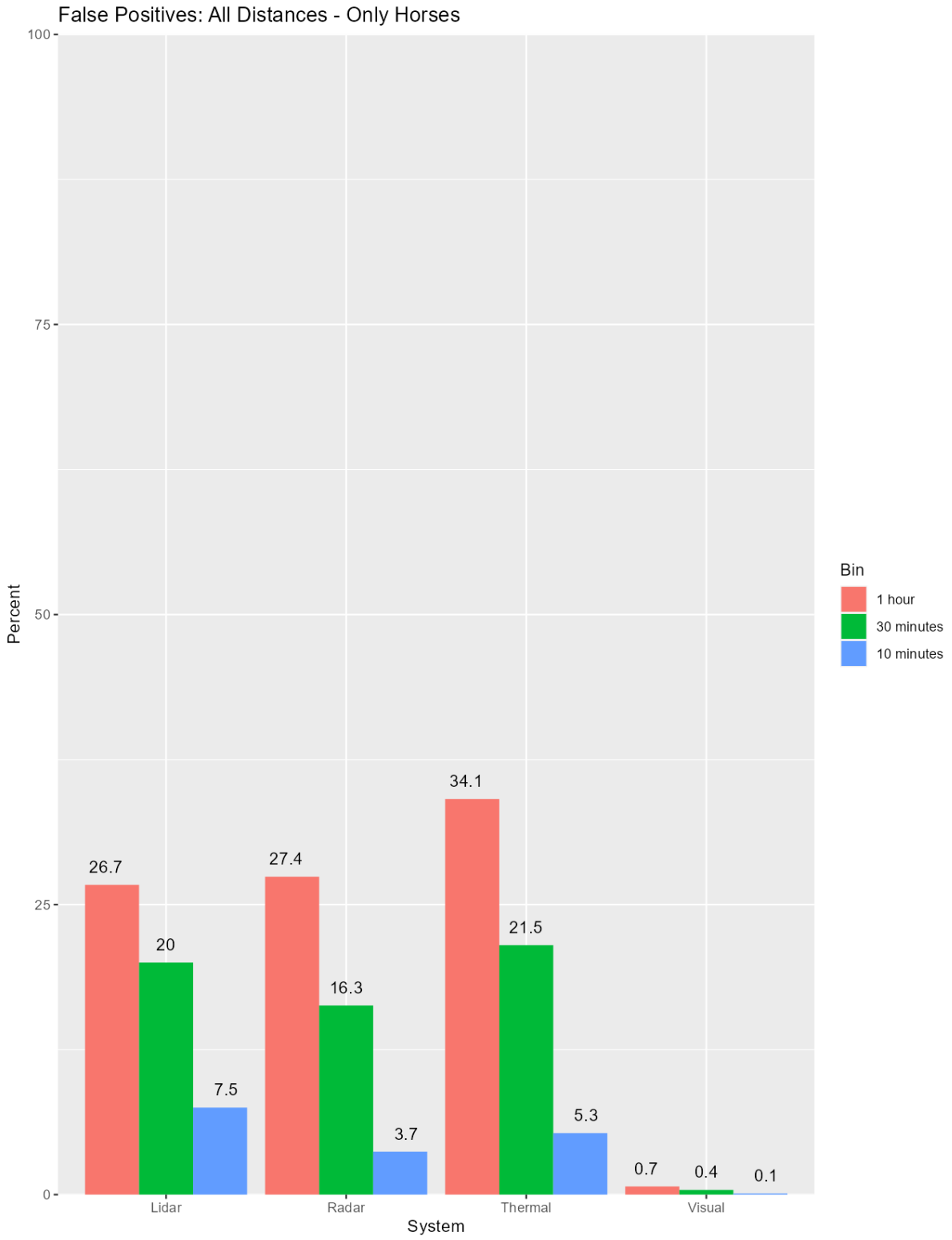


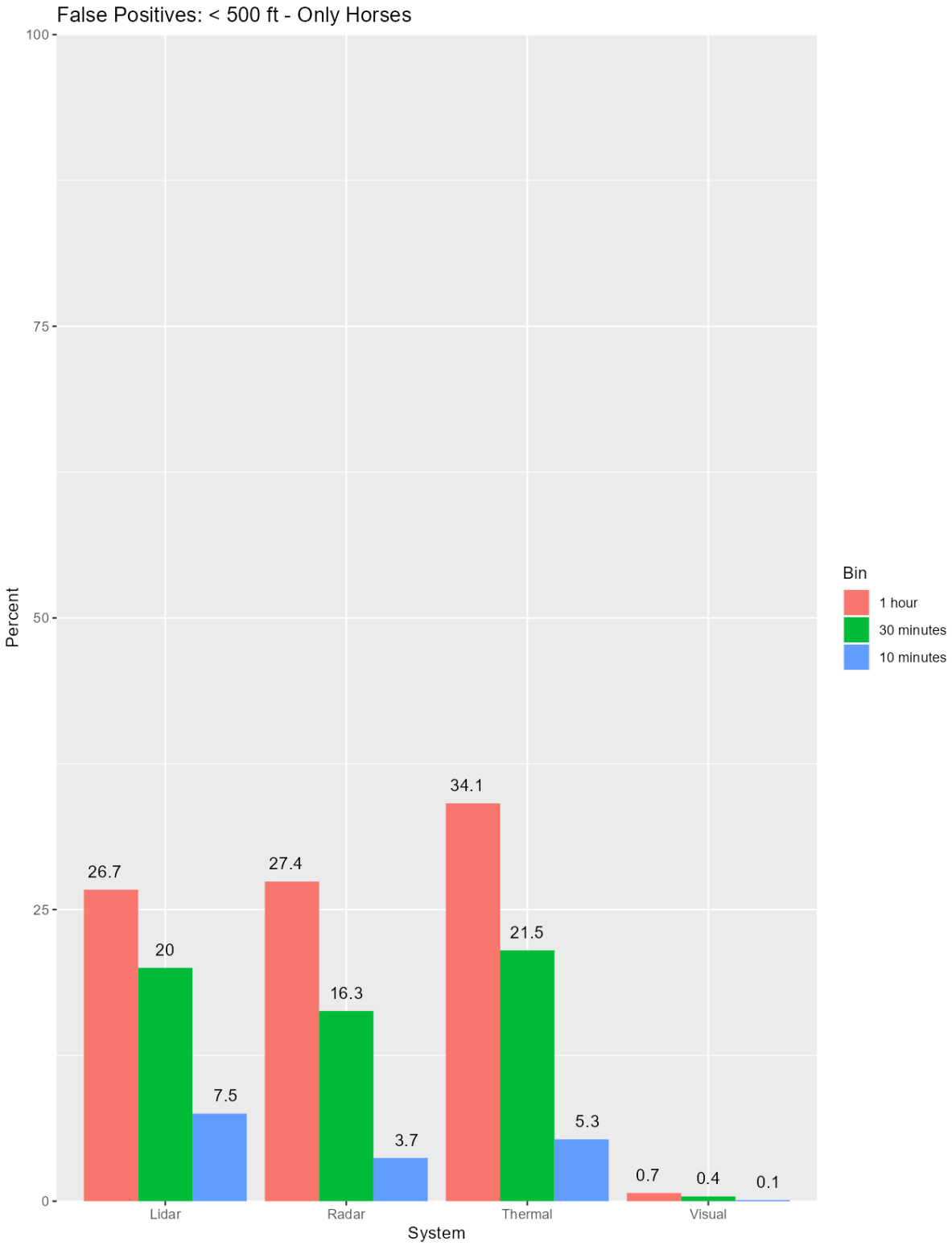

False Positives: < 500 ft - Only Horses
100
75
50
25
0
Percent
67.6
47.5
27.7
22.6
13.8
5.9
4.2
2.2
0.9
2.4
1.2
0.4
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

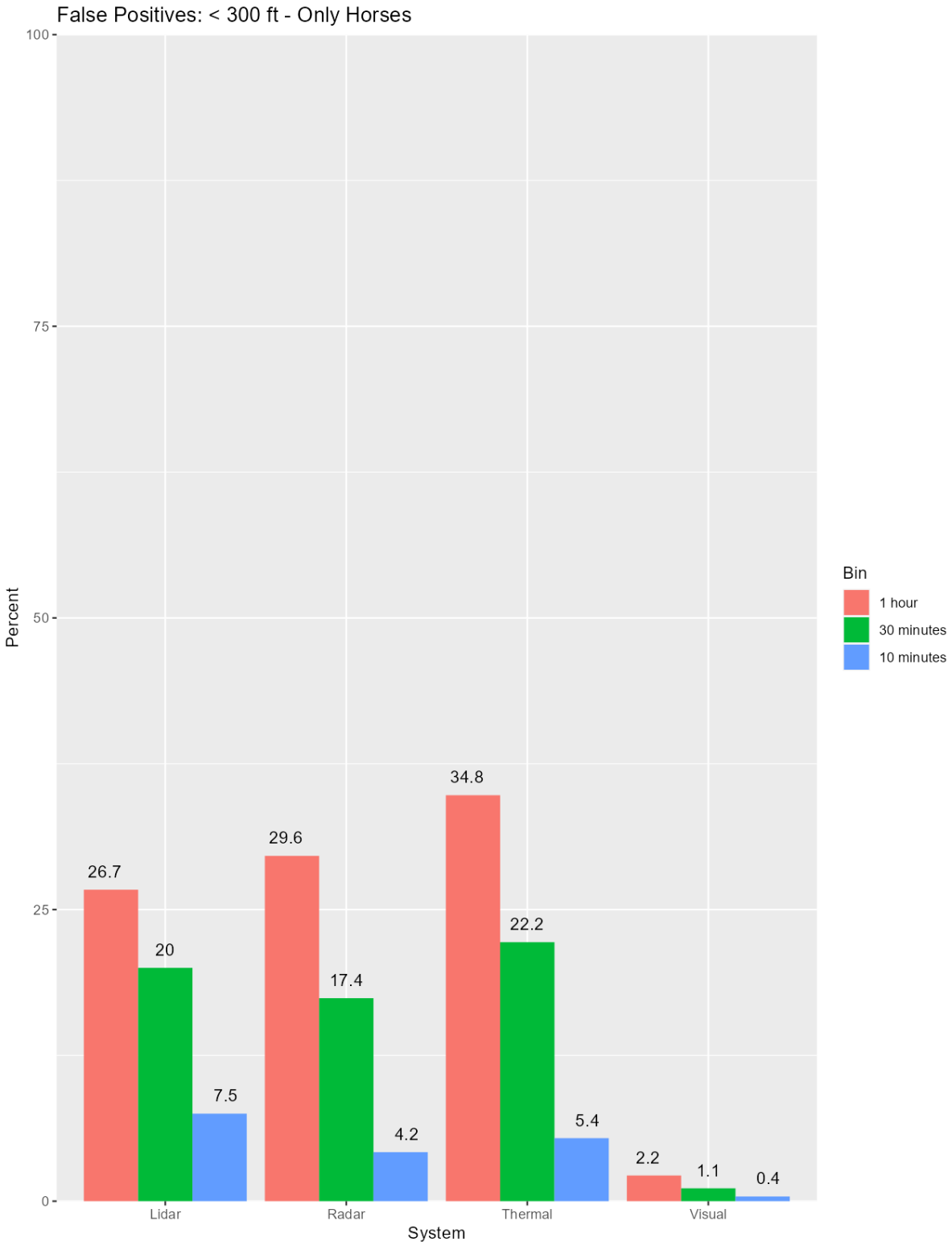

False Positives: < 300 ft - Only Horses
100
75
50
25
0
Percent
67.6
47.9
28.2
23.5
14.4
6.2
4.8
2.7
2.7
1.5
0.5
1.1
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

False Positive Time Bins:

Cycle 2 - Day and Night Combined:

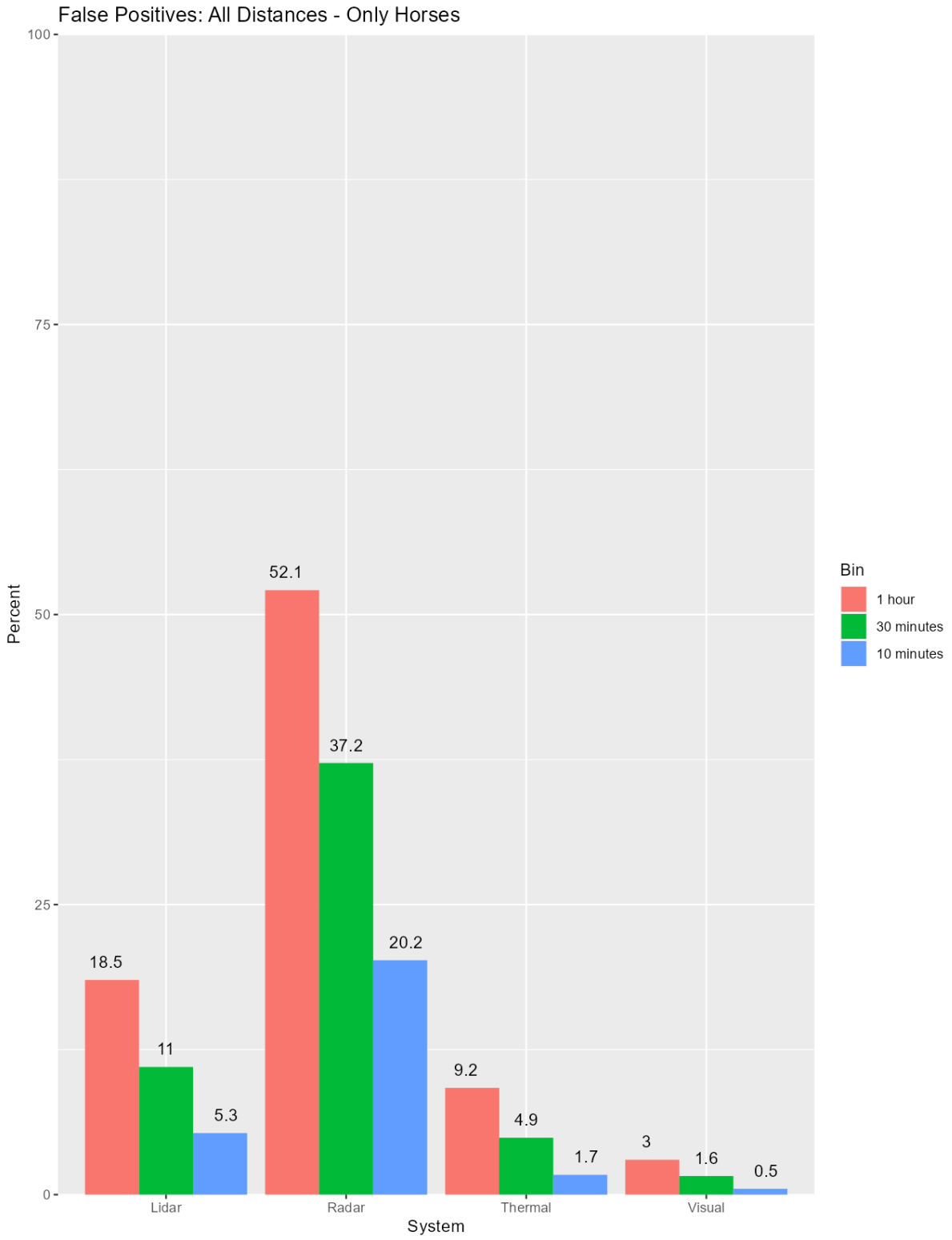


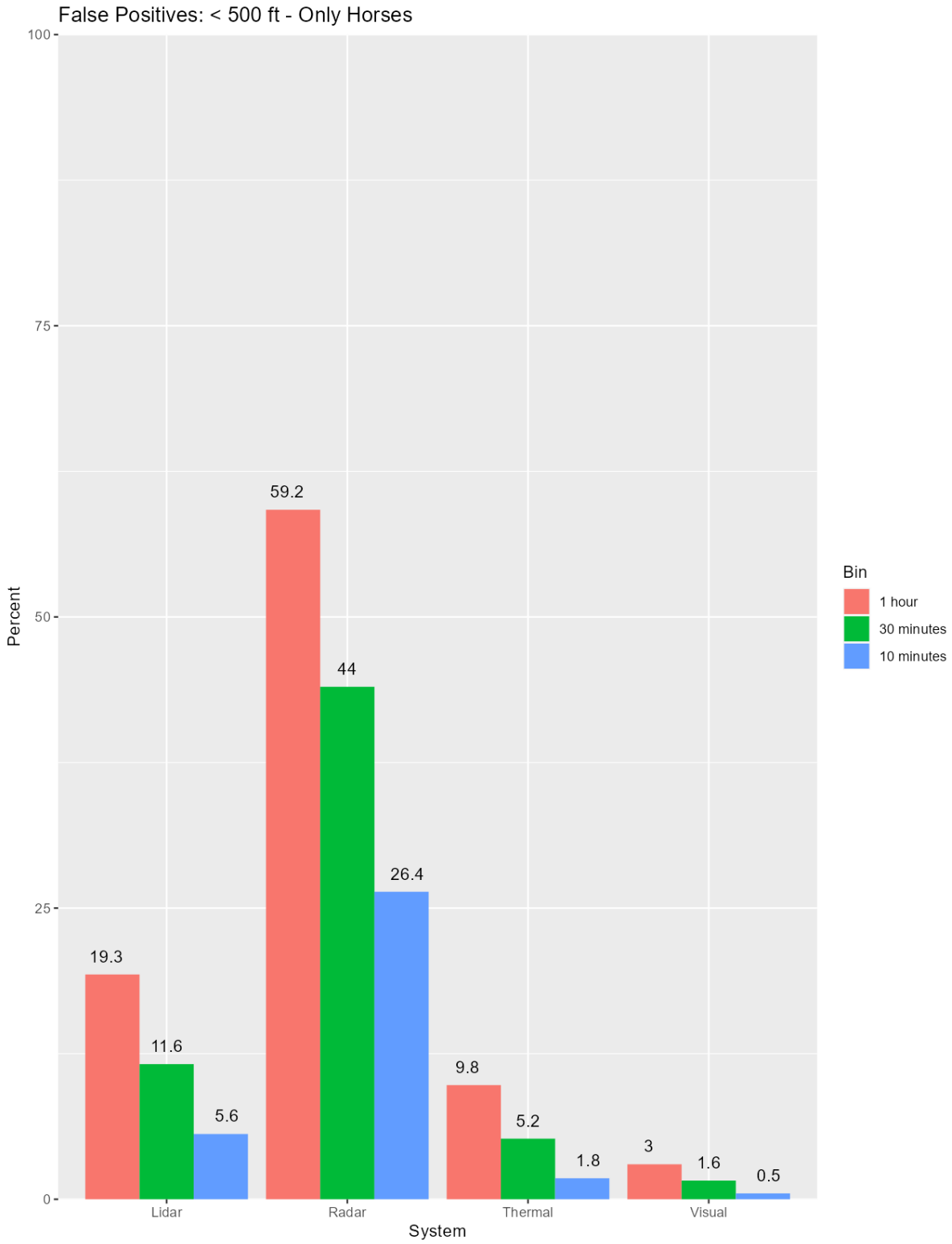

False Positives: < 500 ft - Only Horses
100
75
50
25
0
Percent
26.7
20
7.5
27.4
16.3
3.7
34.1
21.5
5.3
0.7
0.4
0.1
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

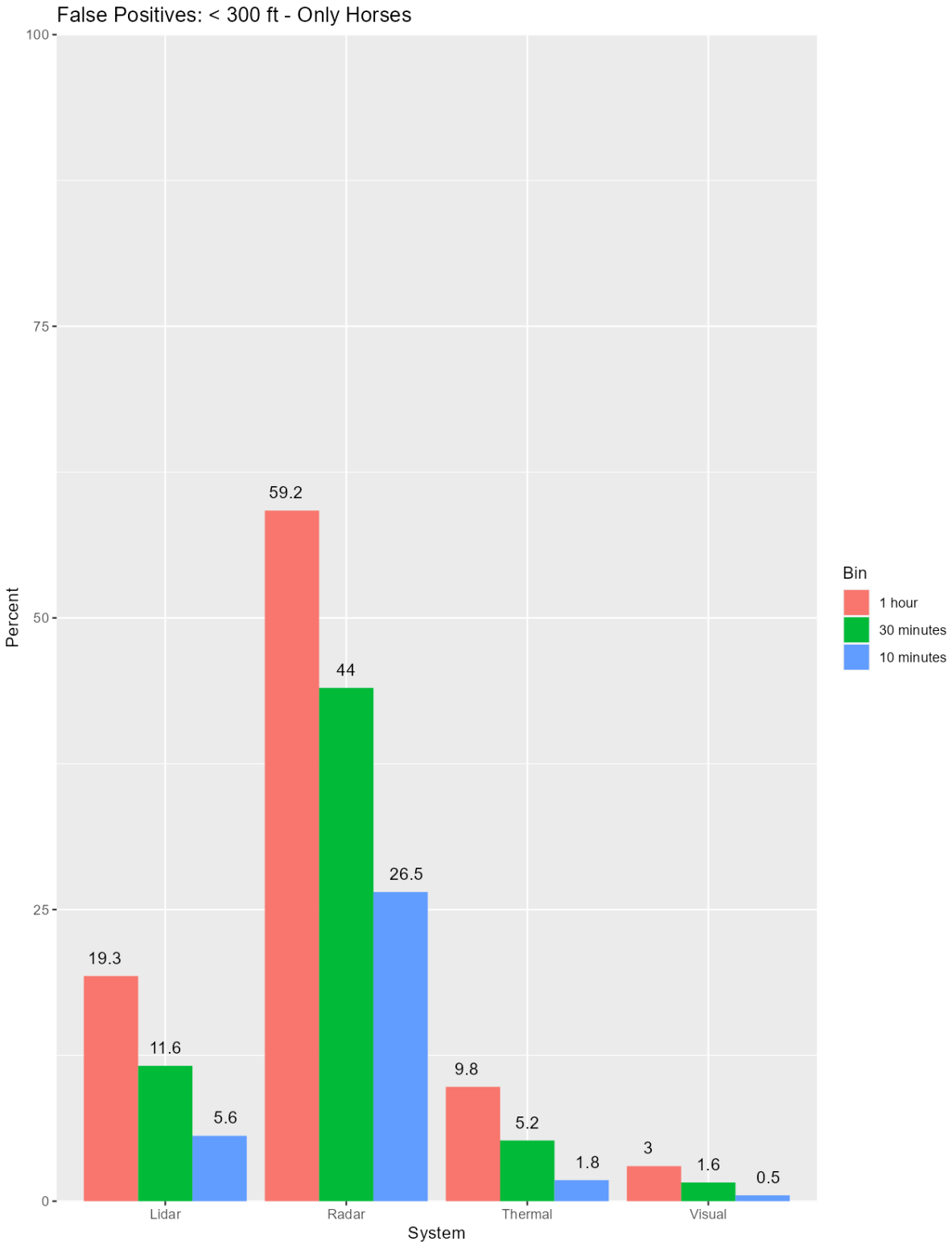

False Positives: < 300 ft - Only Horses
100
75
50
25
0
Percent
26.7
20
7.5
29.6
17.4
4.2
34.8
22.2
5.4
2.2
1.1
0.4
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

False Positive Time Bins:

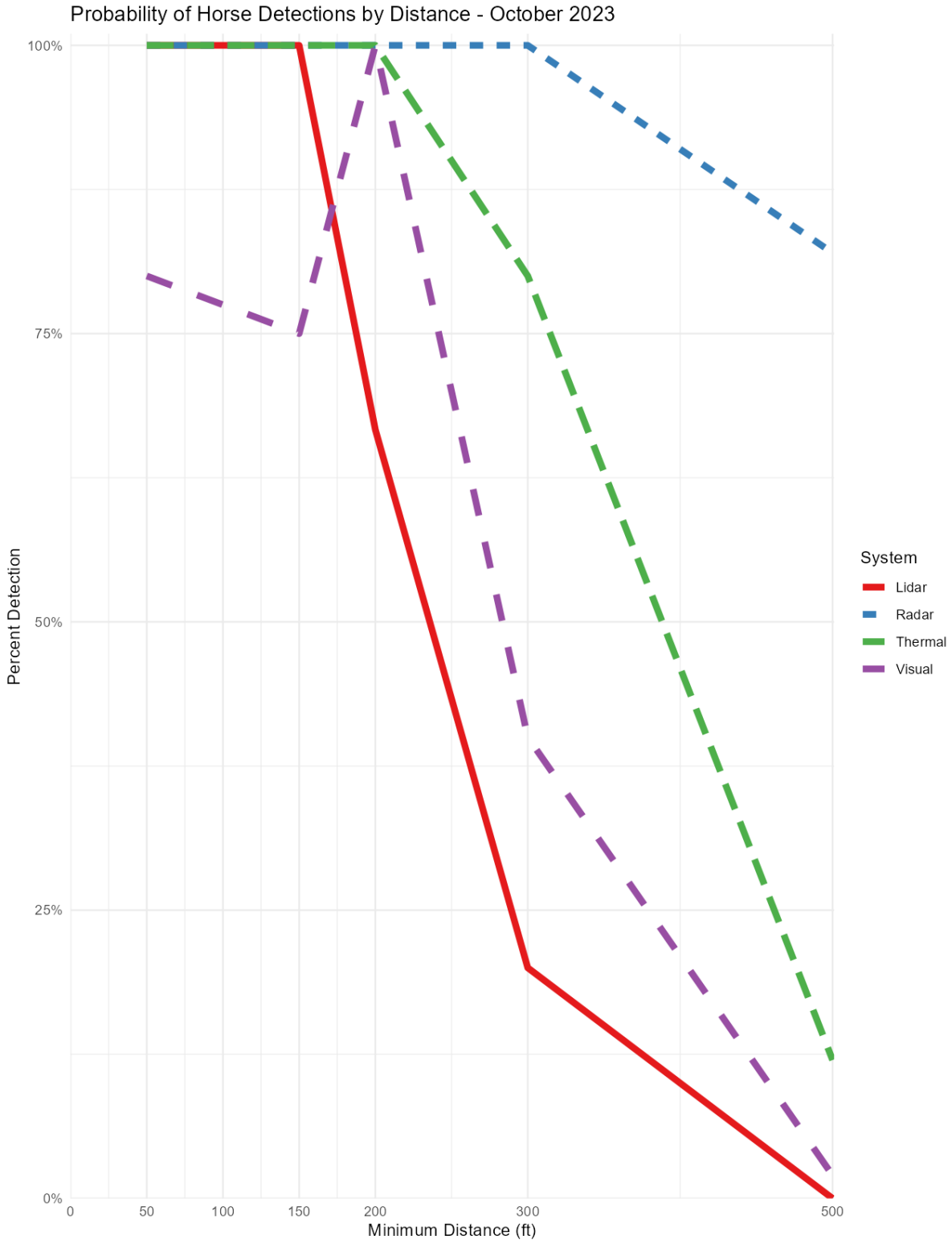
Cycle 3 - Day and Night Combined:



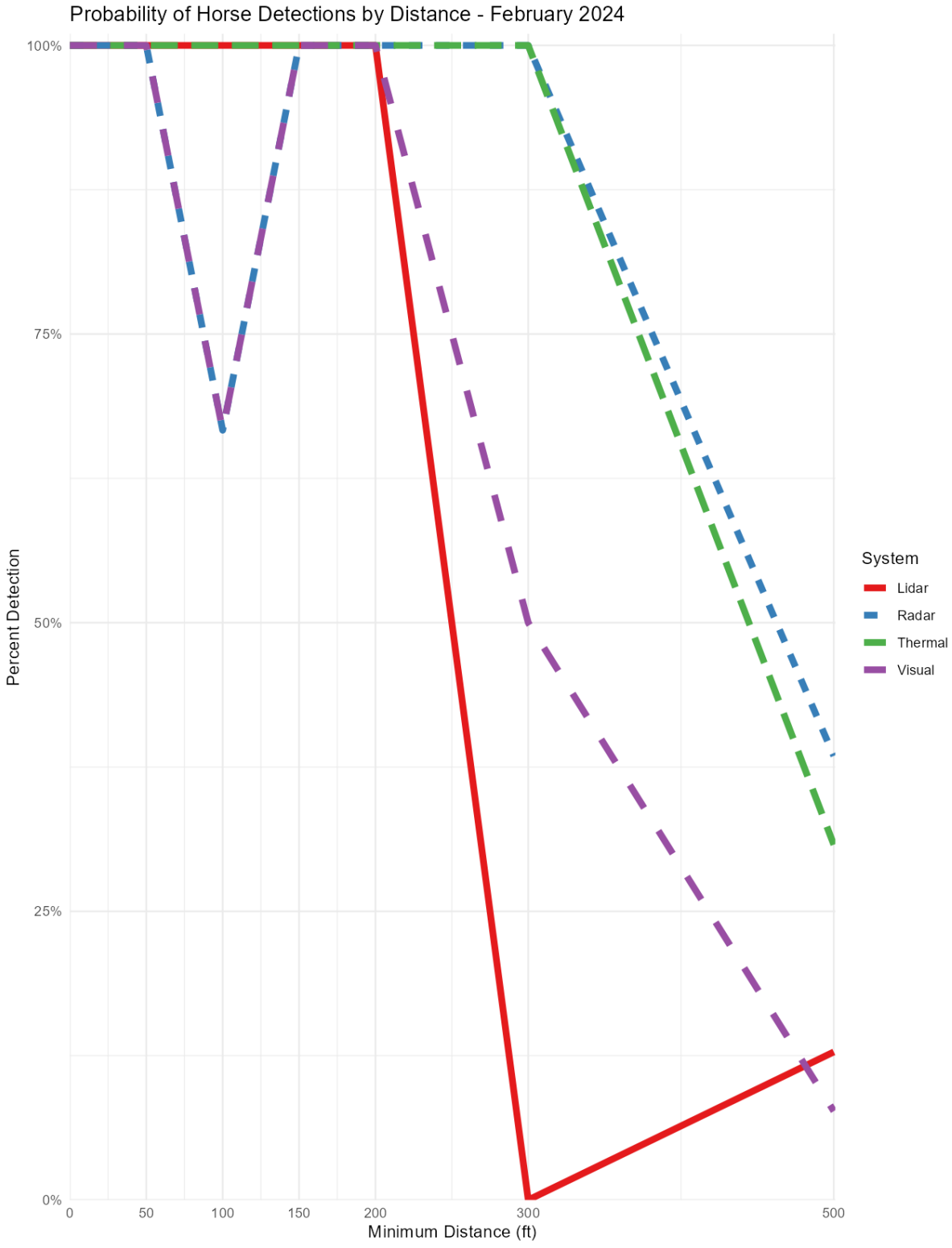

False Positives: < 500 ft - Only Horses
100
75
50
25
0
Percent
59.2
44
26.4
19.3
11.6
5.6
9.8
5.2
1.8
3
1.6
0.5
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes


False Positives: < 300 ft - Only Horses
100
75
50
25
0
Percent
59.2
44
26.5
19.3
11.6
5.6
9.8
5.2
1.8
3
1.6
0.5
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

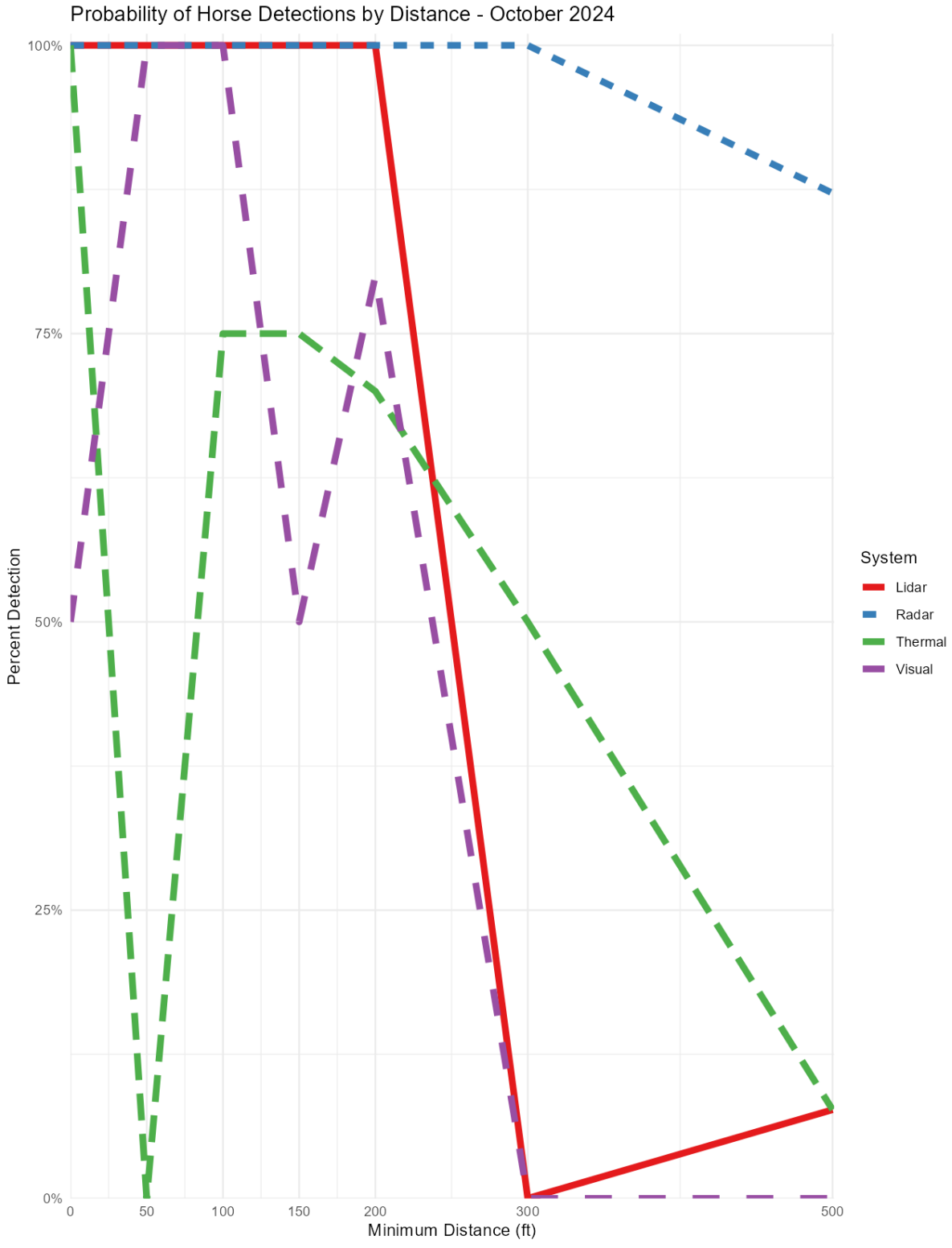
Probability of Detection - Minimum Distance Line Charts
Cycle 1 - Day and Night Combined:



Probability of Detection - Minimum Distance Line Charts
Cycle 2 - Day and Night Combined:

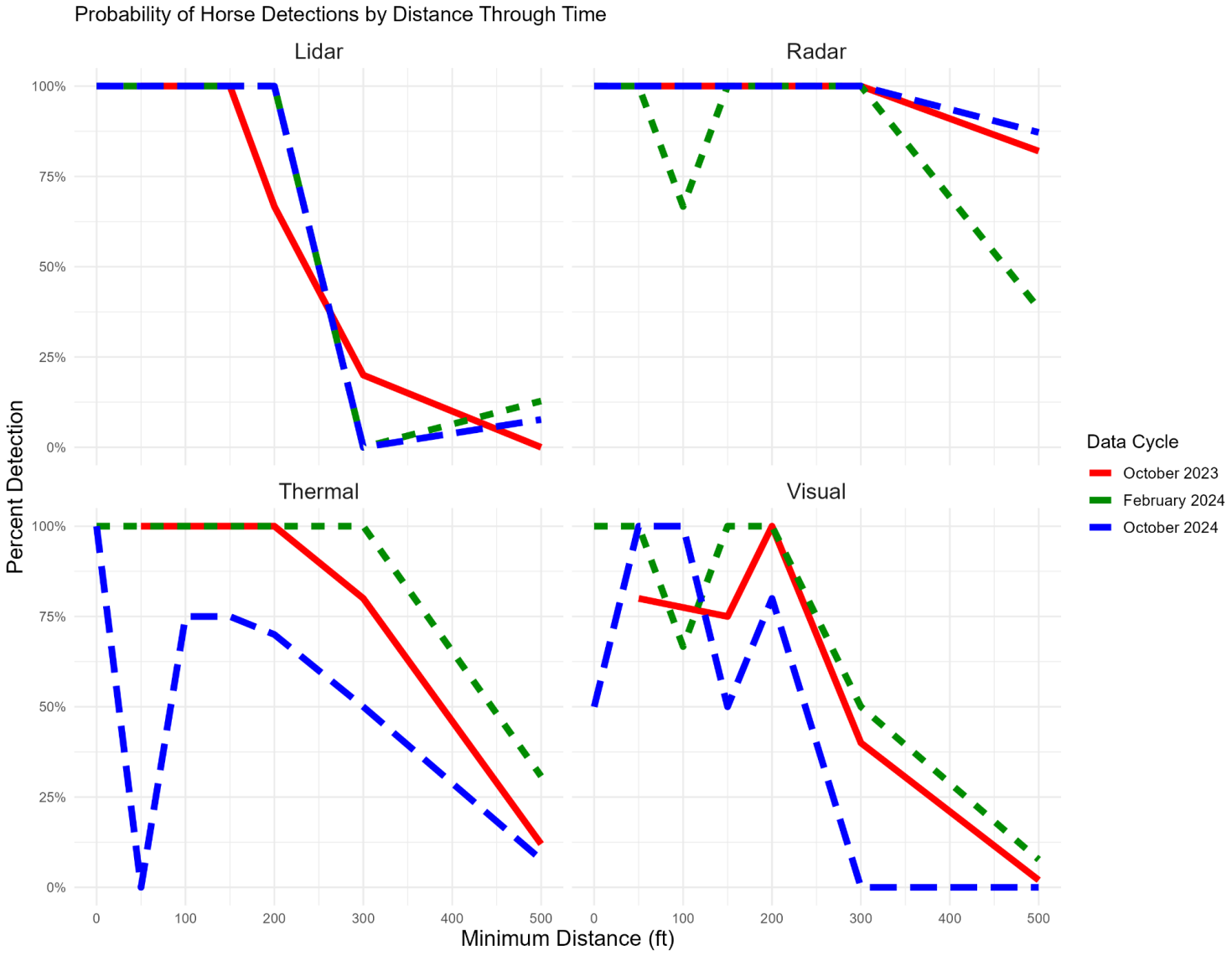


Probability of Detection - Minimum Distance Line Charts
Cycle 3 - Day and Night Combined:



Probability of Detection - Minimum Distance Line Charts

All Three Cycles - Day and Night Combined:



Results: Only Daytime

Baseline summary information for each data collection cycle

Cycle 1 - October 2023: October 13, 2023 at 00:00:00 – October 26 at 23:59:59
Count of baseline events of horses:
<300 ft: 5
<500 ft: 8
>500 ft: 30

Total loiter time of horse events: 19 hours, 09 minutes, and 55 seconds.

Cycle 2 - February 2024: February 1, 2024 at 00:00:00 – February 14, 2024 at 23:59:59
Count of baseline events of horses:
<300 ft: 5
<500 ft: 6
>500 ft: 25

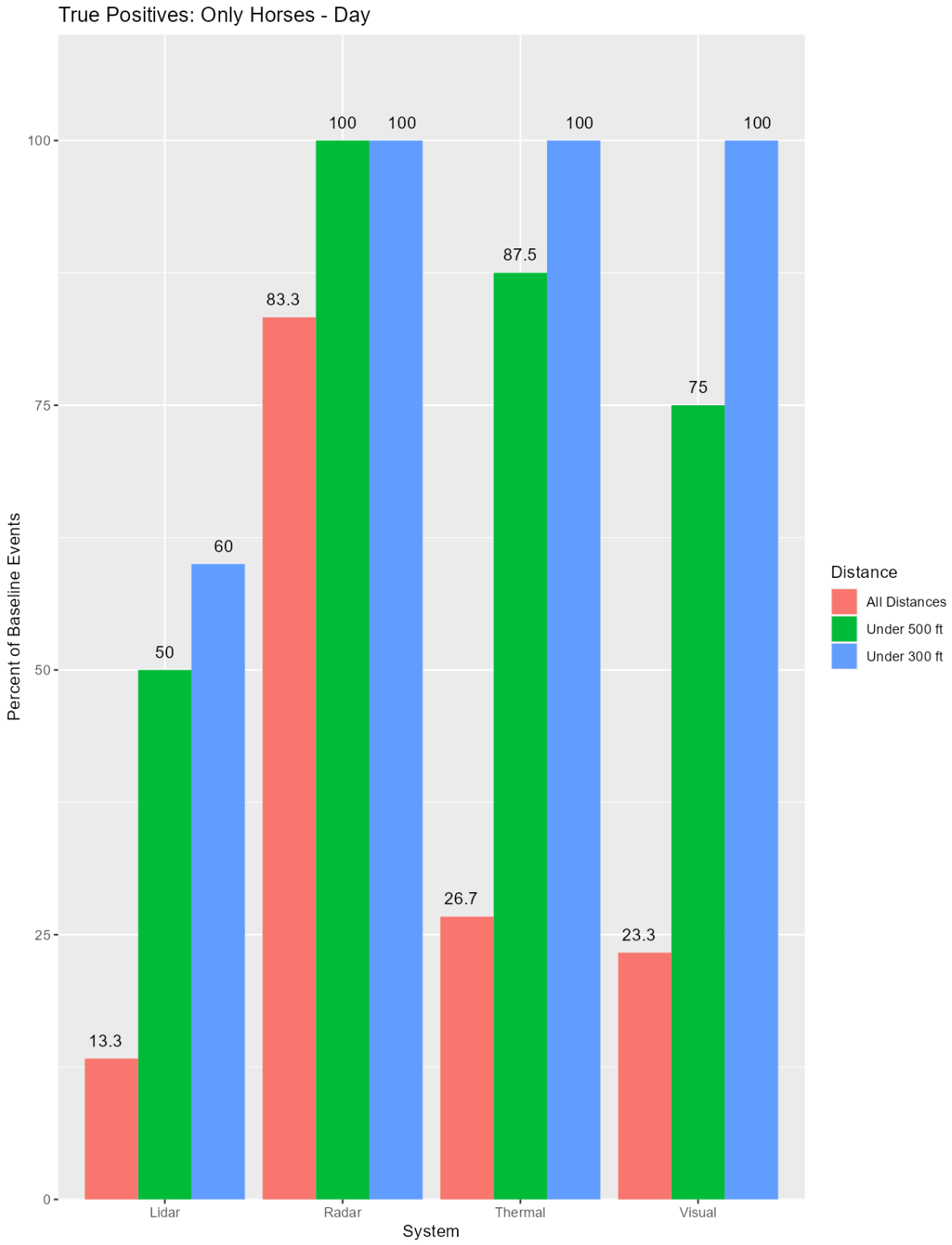
Total loiter time of horse events: 21 hours, 32 minutes, and 15 seconds.

Cycle 3 - October 2024: October 17, 2024 at 00:00:00 through October 30, 2024 at 23:59:59
Count of baseline events of horses:
<300 ft: 15
<500 ft: 15
>500 ft: 26

Total loiter time of horse events: 15 hours, 56 minutes, and 54 seconds.

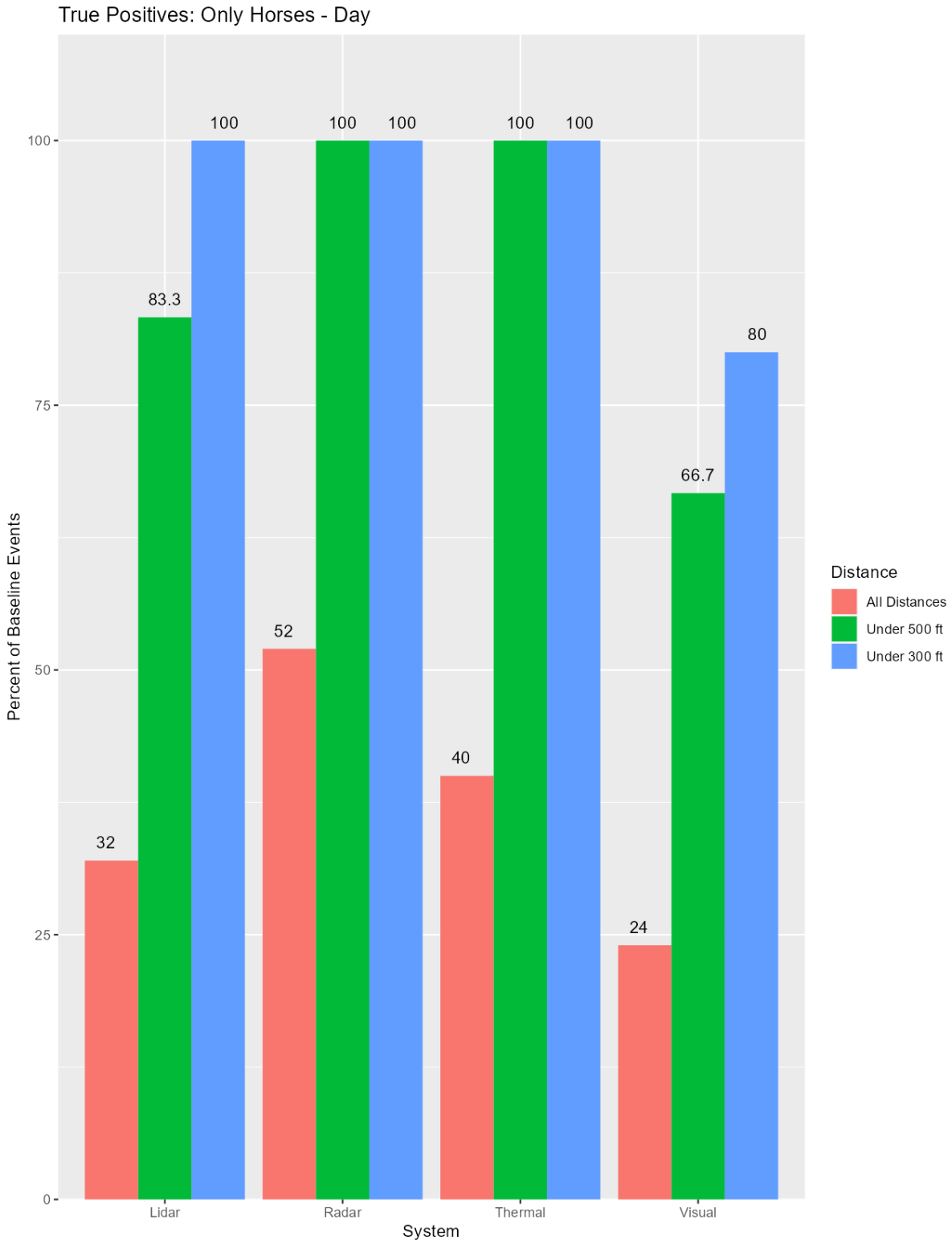
True Positives:

Cycle 1 - Day:



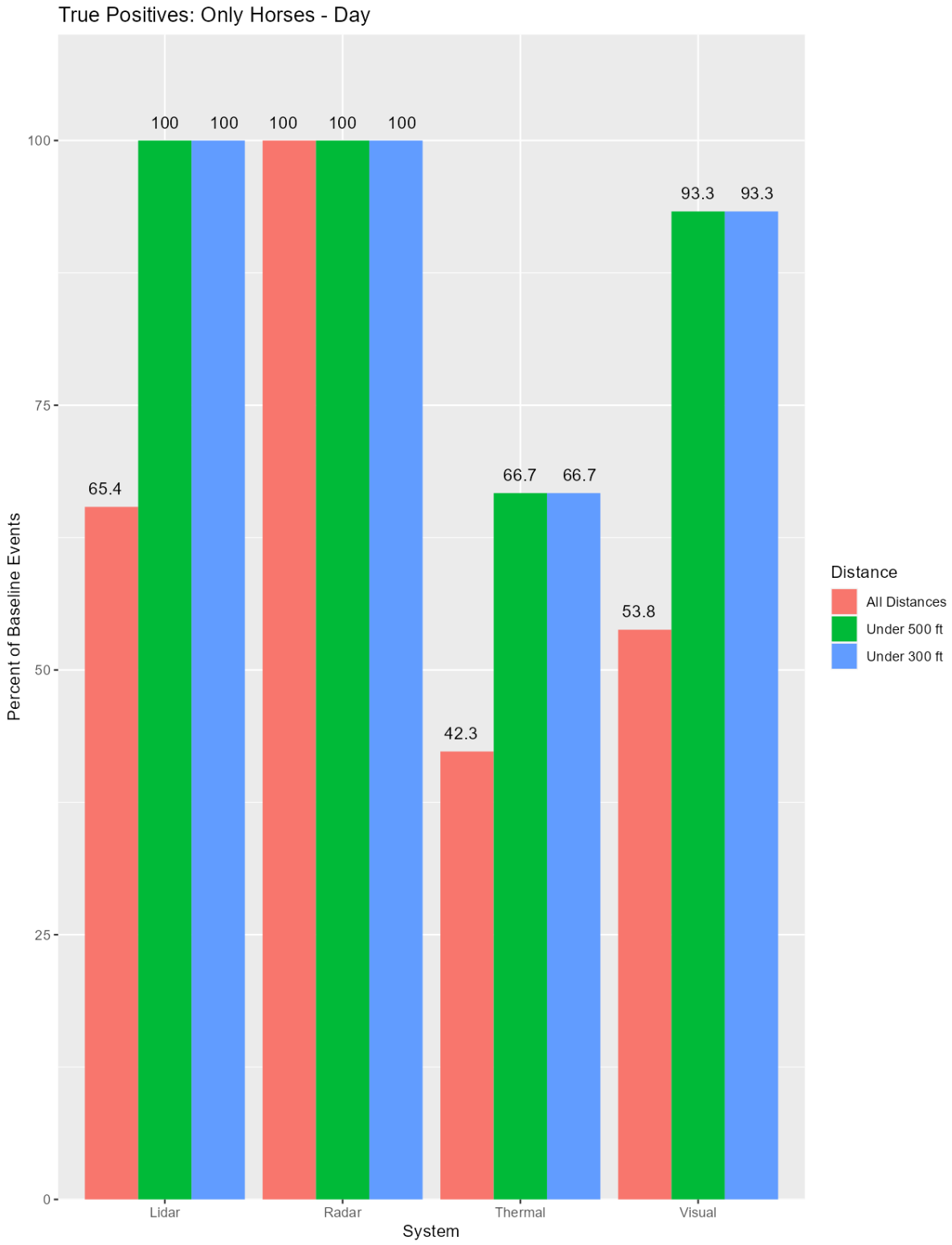
True Positives:

Cycle 2 - Day:



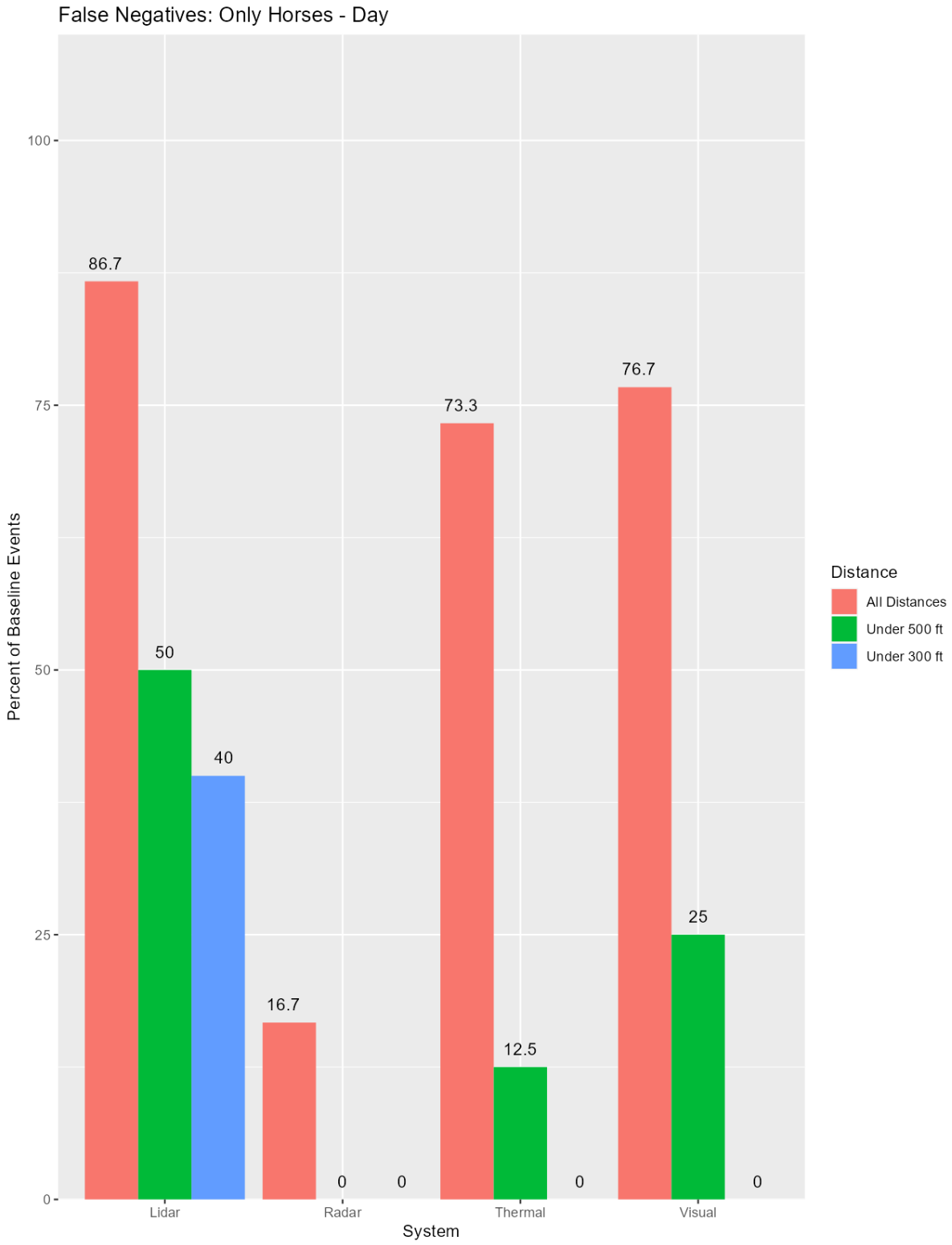
True Positives:

Cycle 3 - Day:



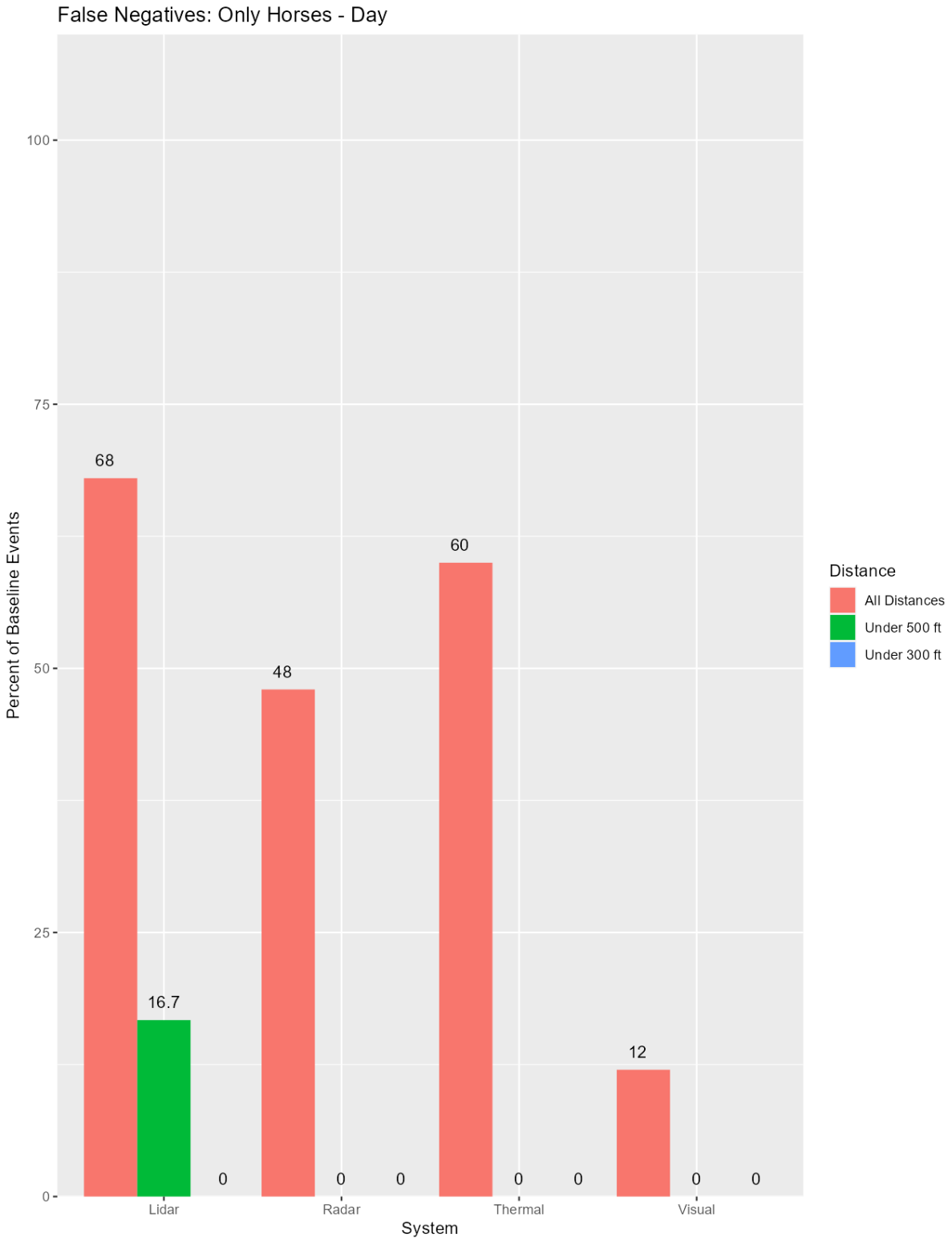
False Negatives:

Cycle 1 - Day:



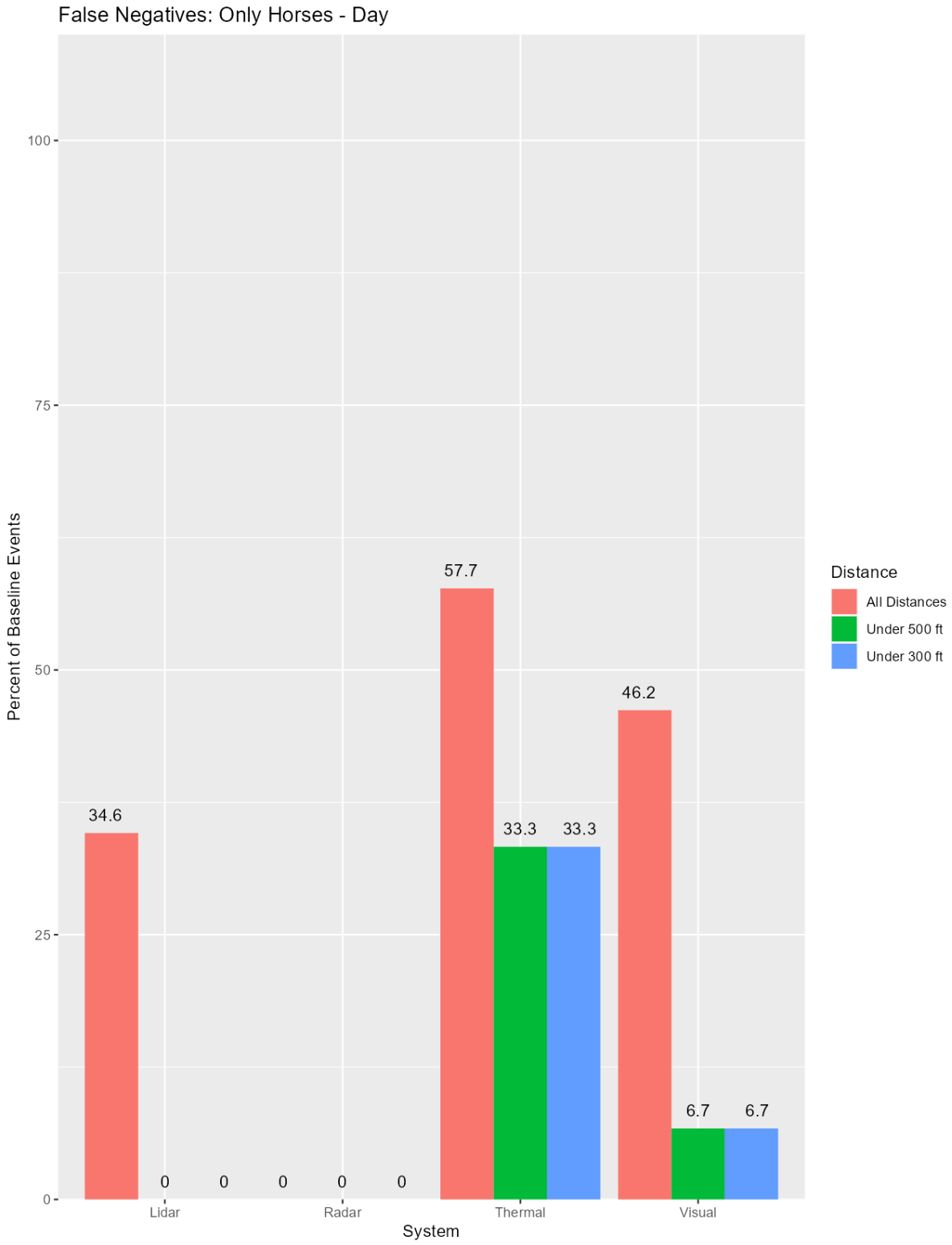
False Negatives:

Cycle 2 - Day:



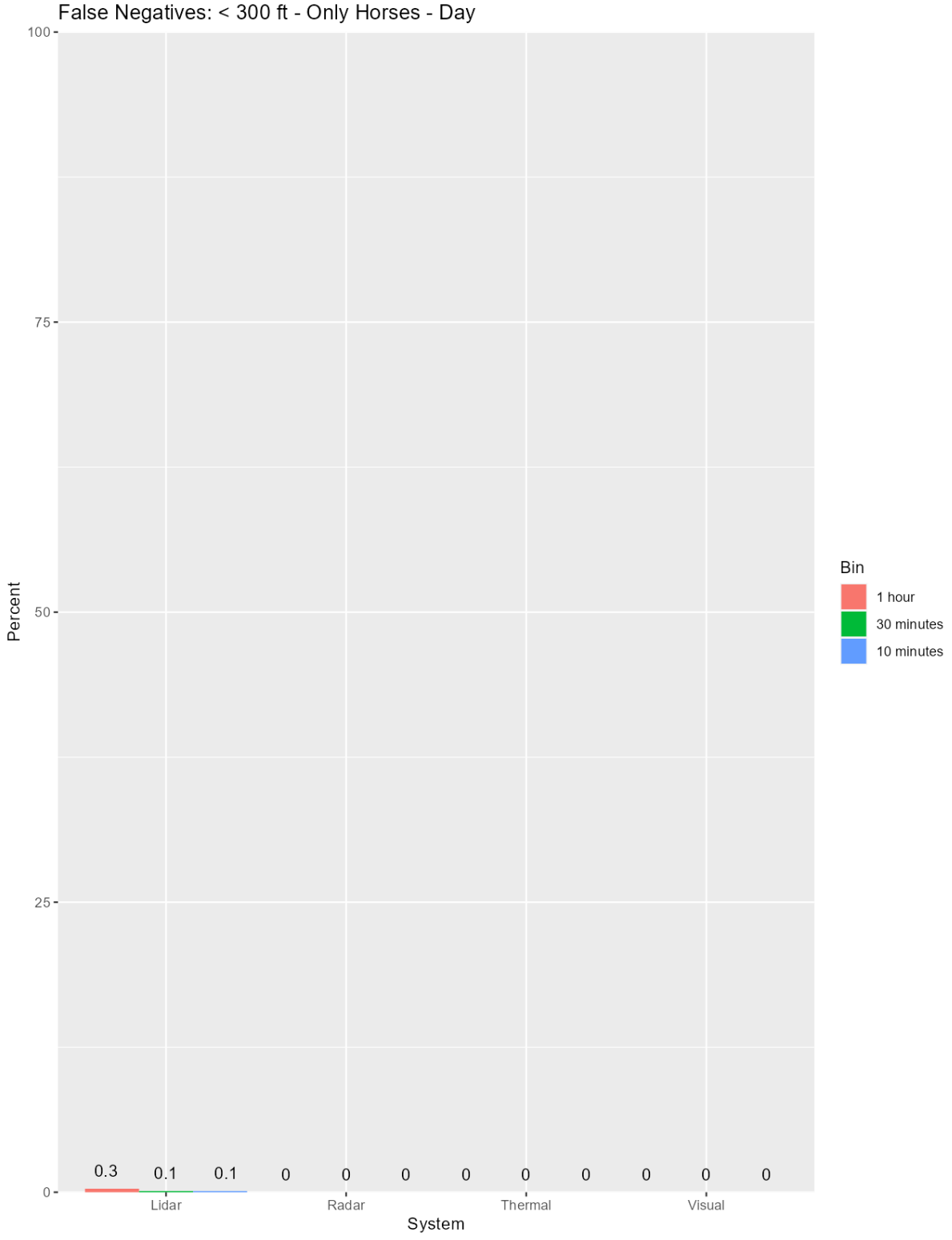
False Negatives:

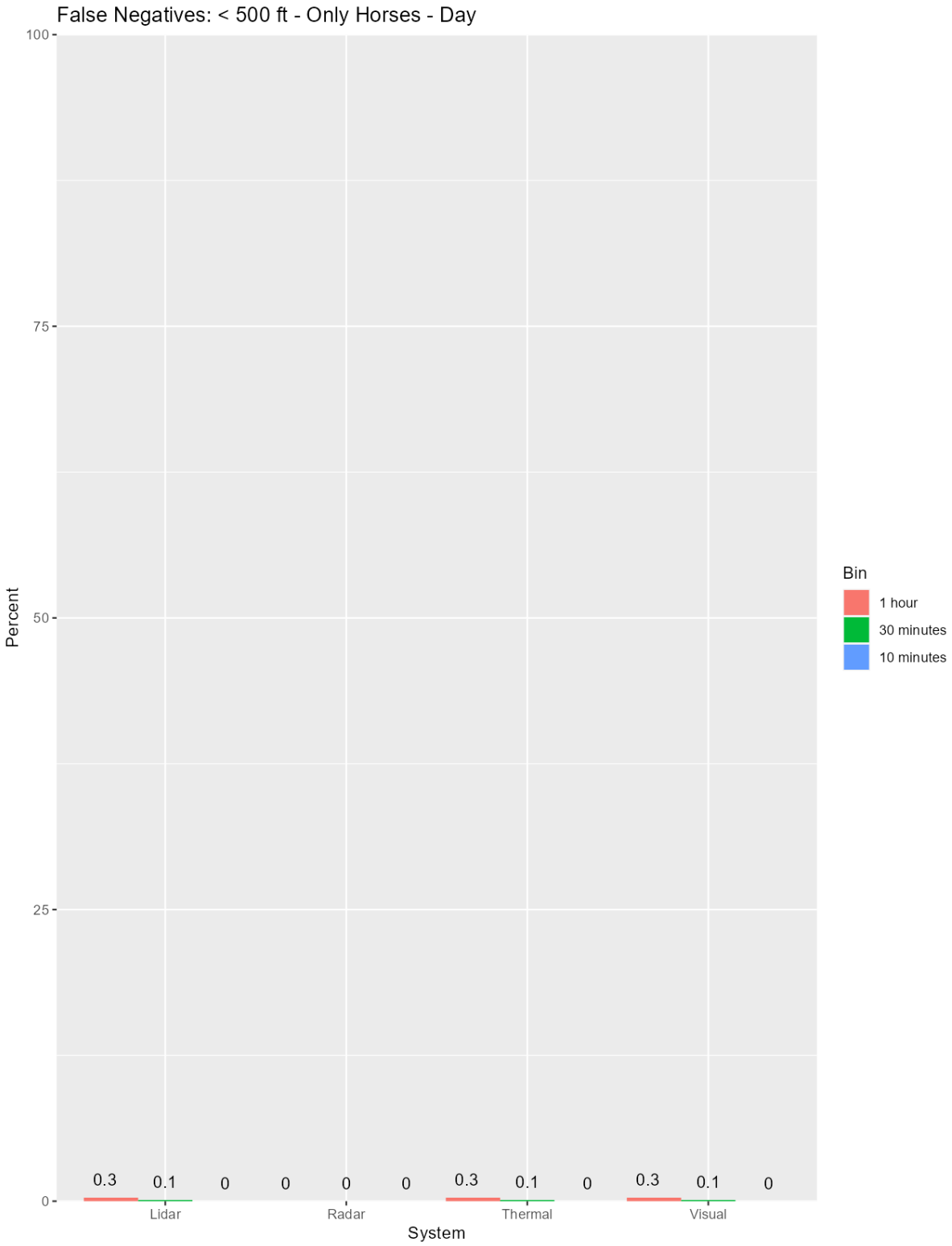
Cycle 3 - Day:

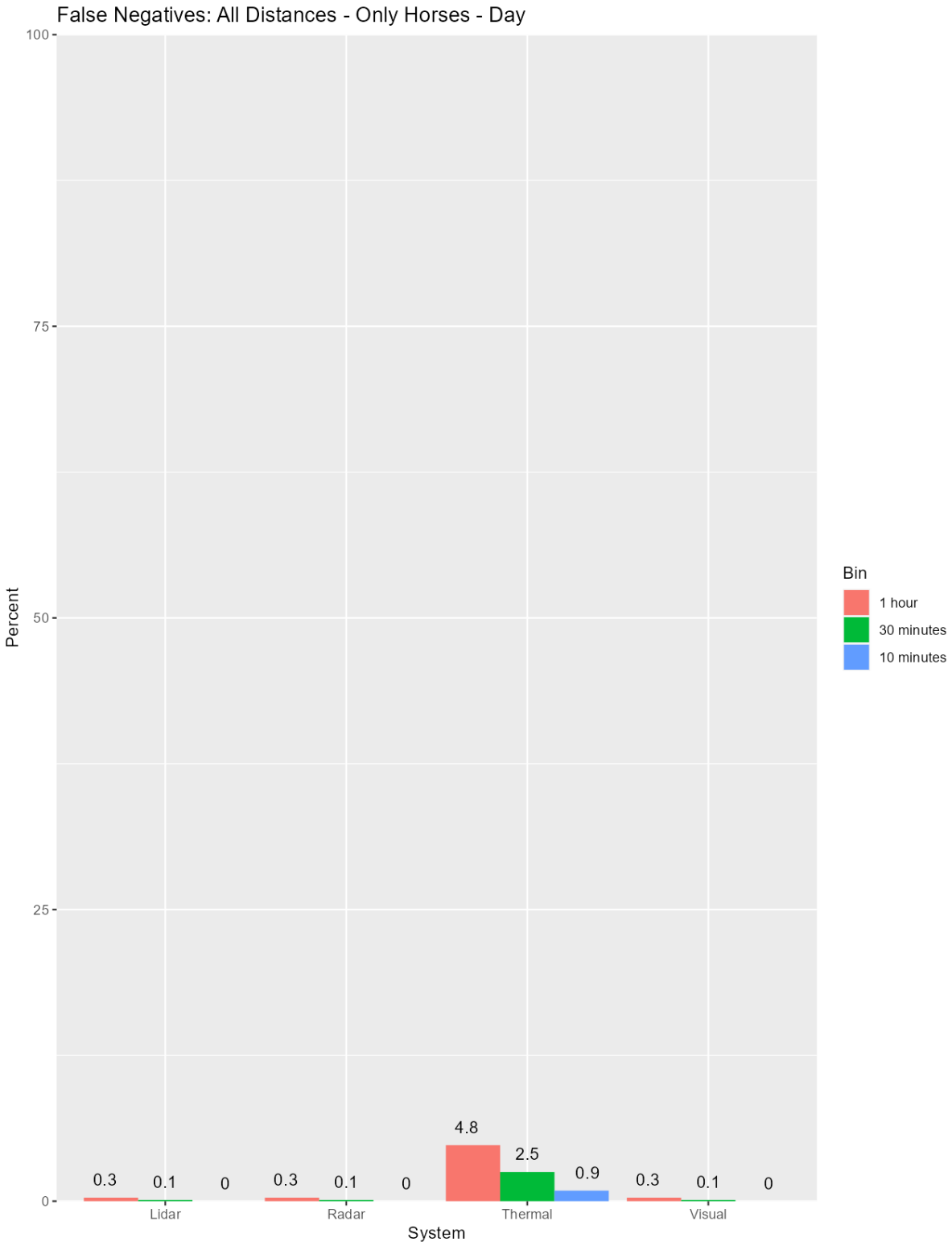


False Negative Time Bins:

Cycle 1 - Day:

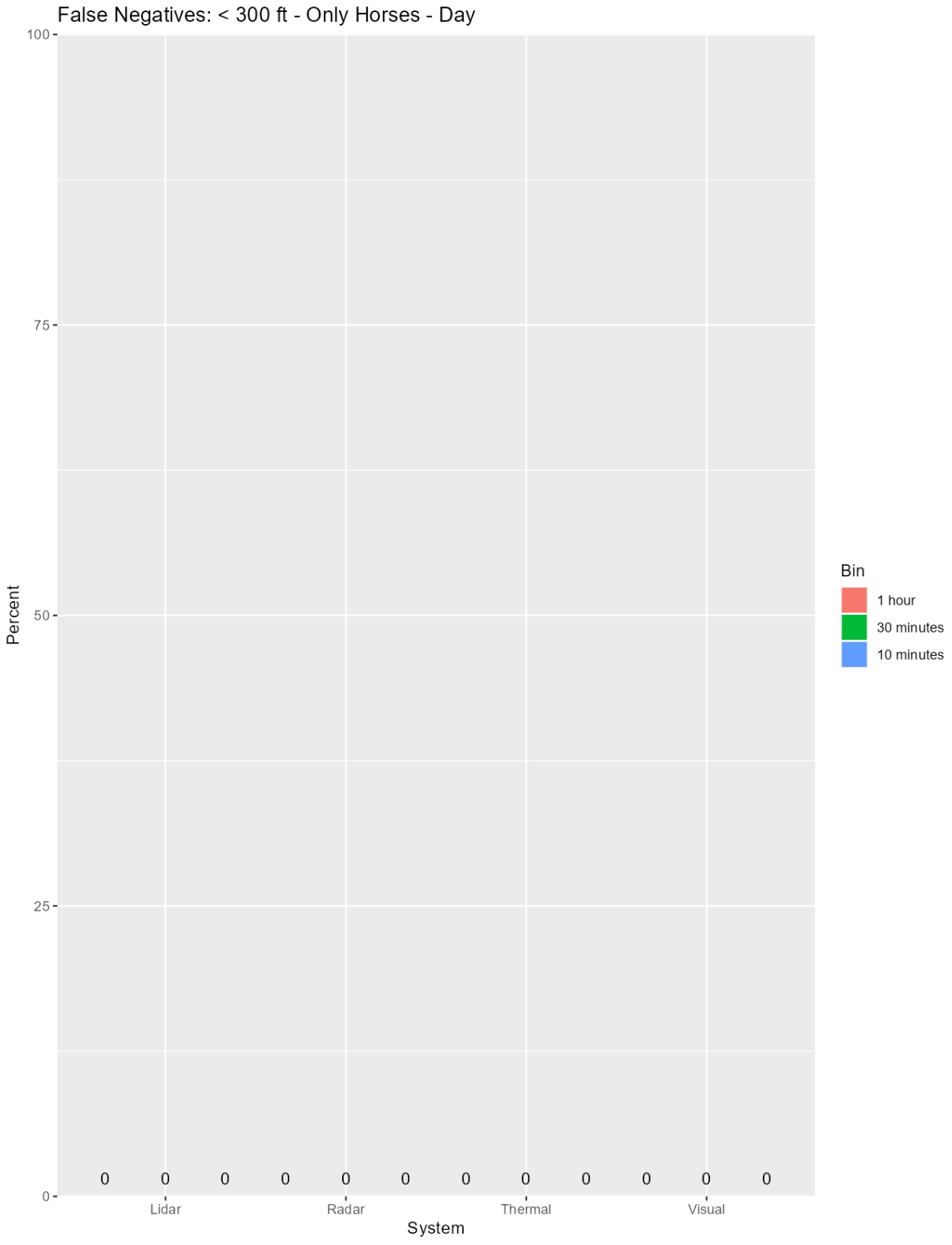


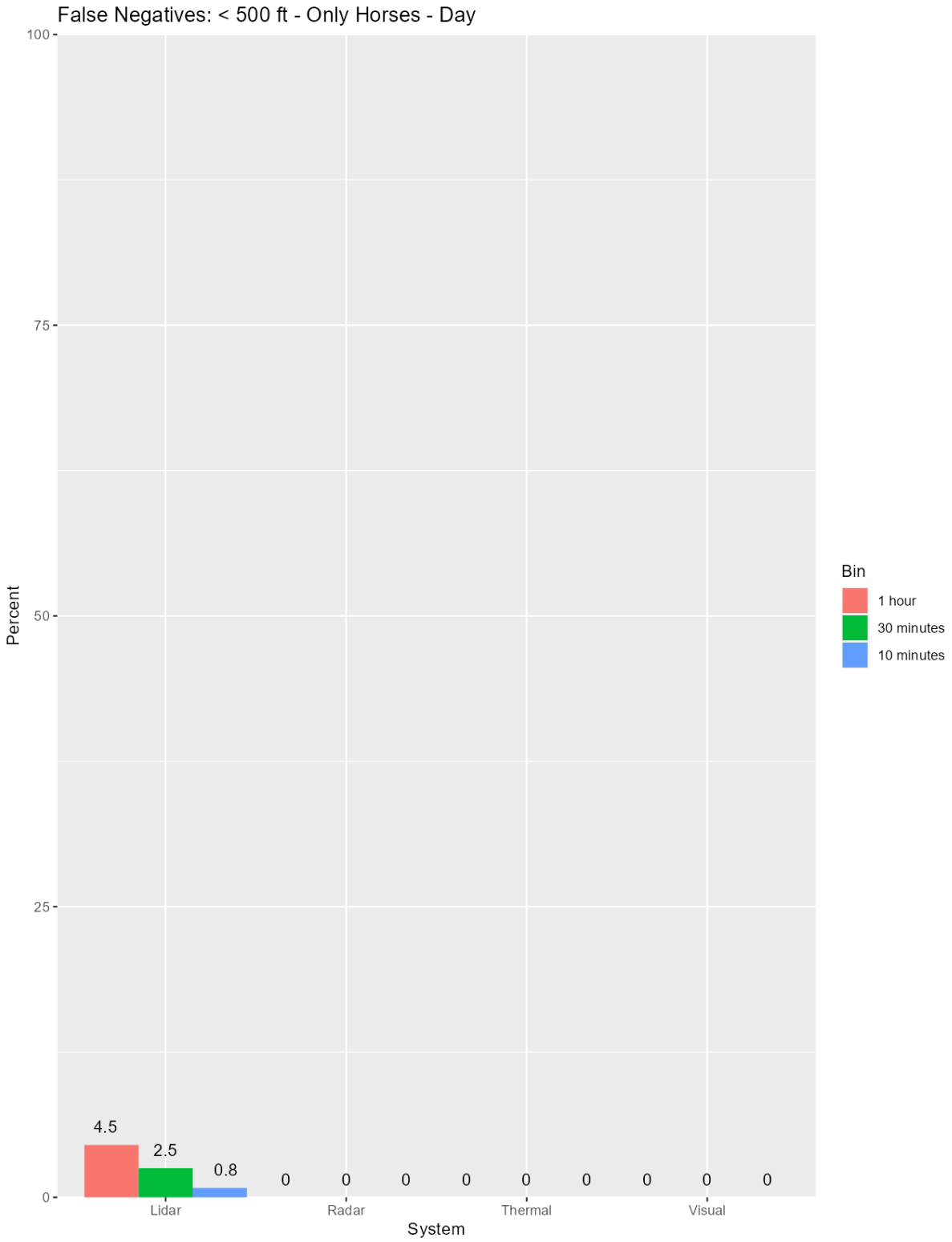

False Negatives: < 500 ft - Only Horses - Day
100
75
50
25
0
Percent
0.3
0.1
0
0
0
0
0.3
0.1
0
0.3
0.1
0
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

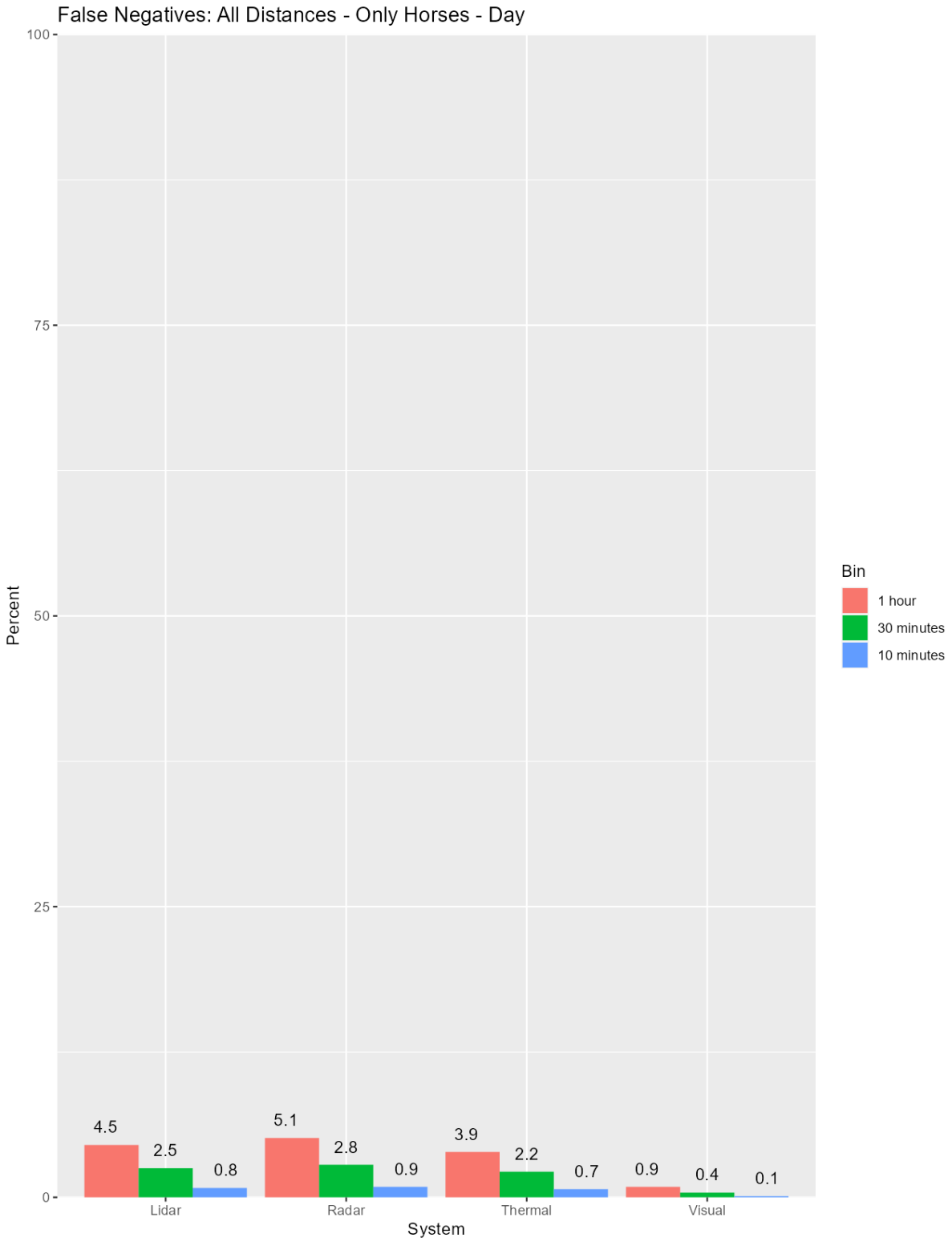

False Negatives: All Distances - Only Horses - Day
100
75
50
25
0
Percent
0.3
0.1
0
0.3
0.1
0
4.8
2.5
0.9
0.3
0.1
0
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

False Negative Time Bins:

Cycle 2 - Day:

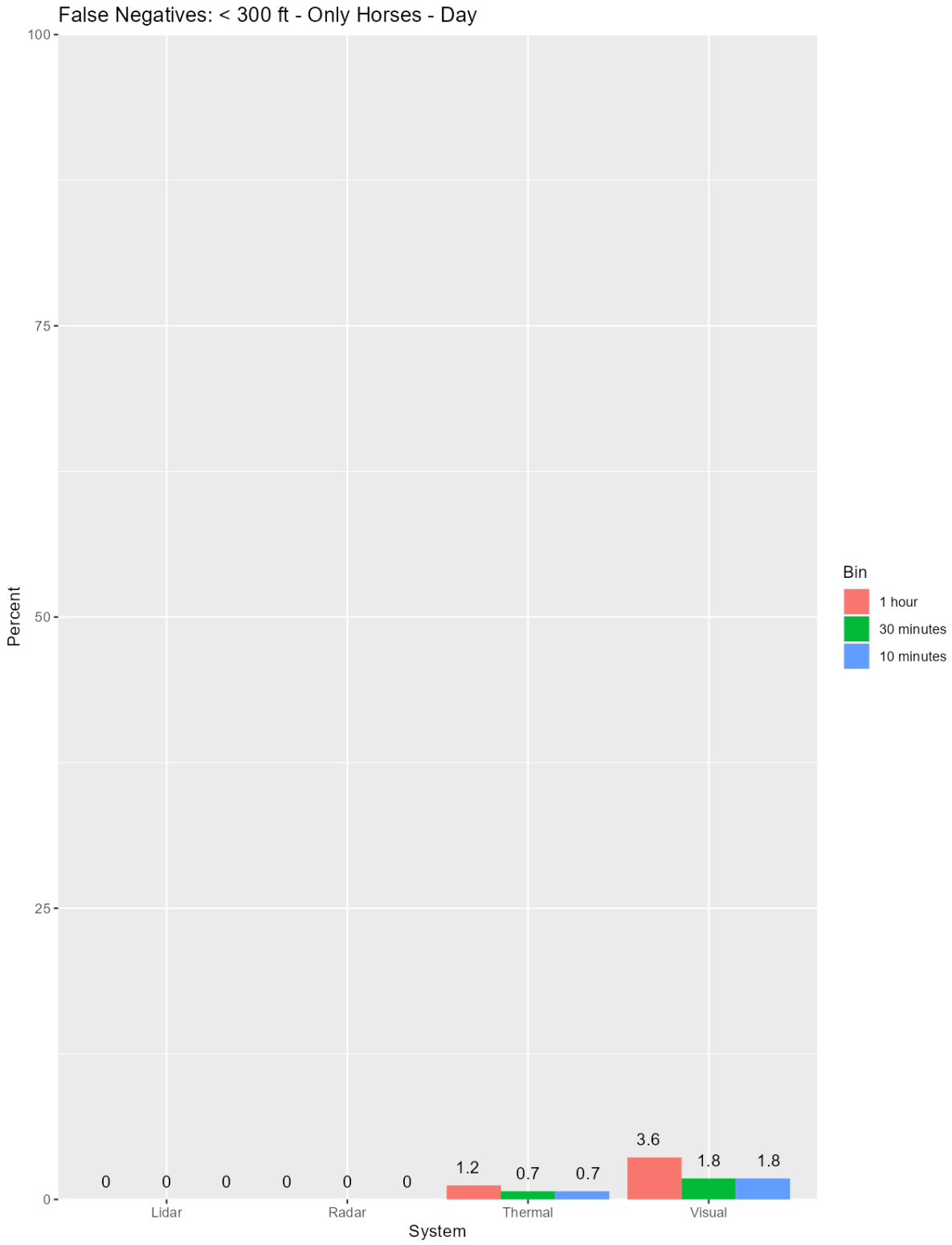


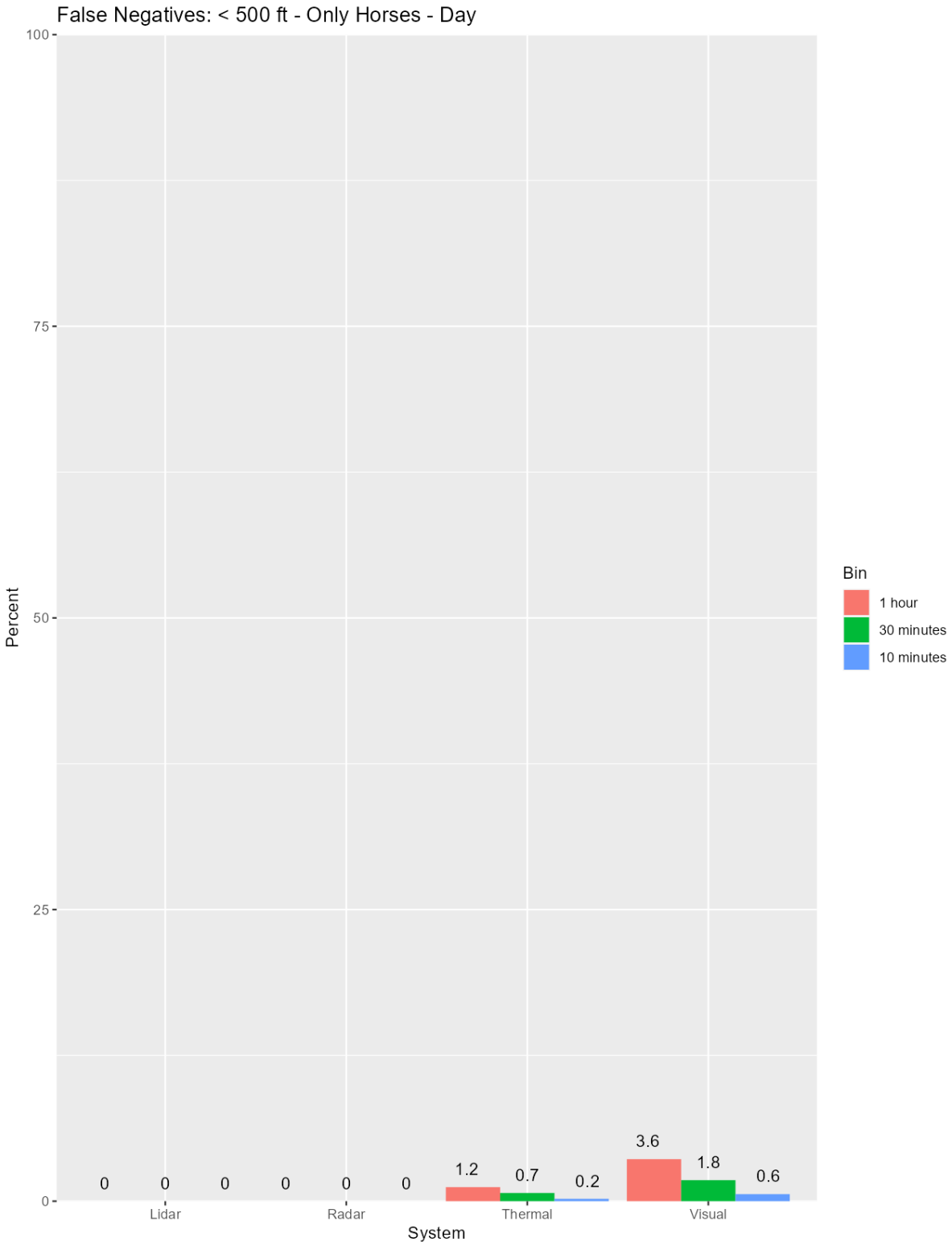

False Negatives: < 500 ft - Only Horses - Day
100
75
50
25
0
Percent
4.5
2.5
0.8
0
0
0
0
0
0
0
0
0
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

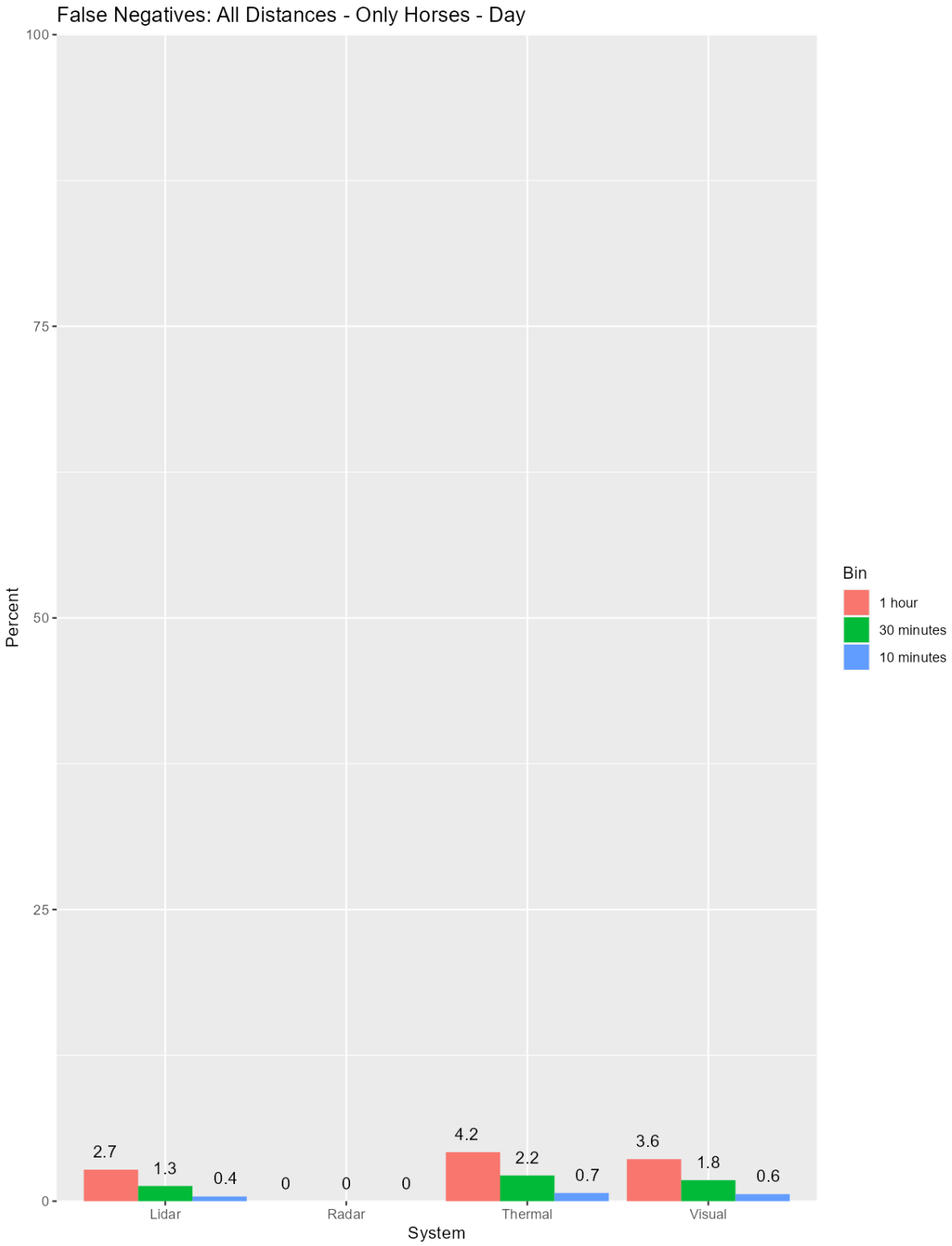

False Negatives: All Distances - Only Horses - Day
100
75
50
25
0
Percent
4.5
2.5
0.8
5.1
2.8
0.9
3.9
2.2
0.7
0.9
0.4
0.1
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

False Negative Time Bins:

Cycle 3 - Day:

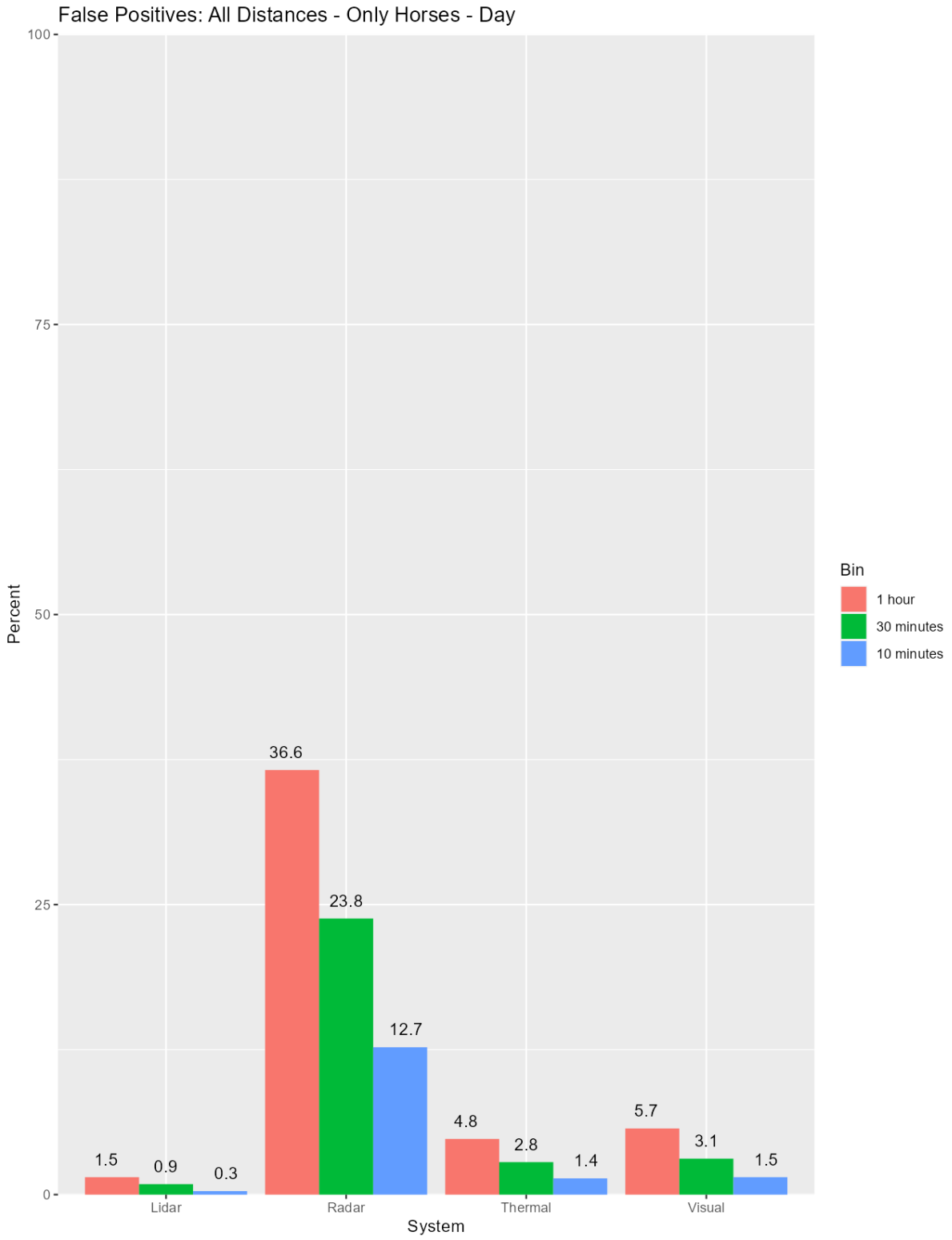


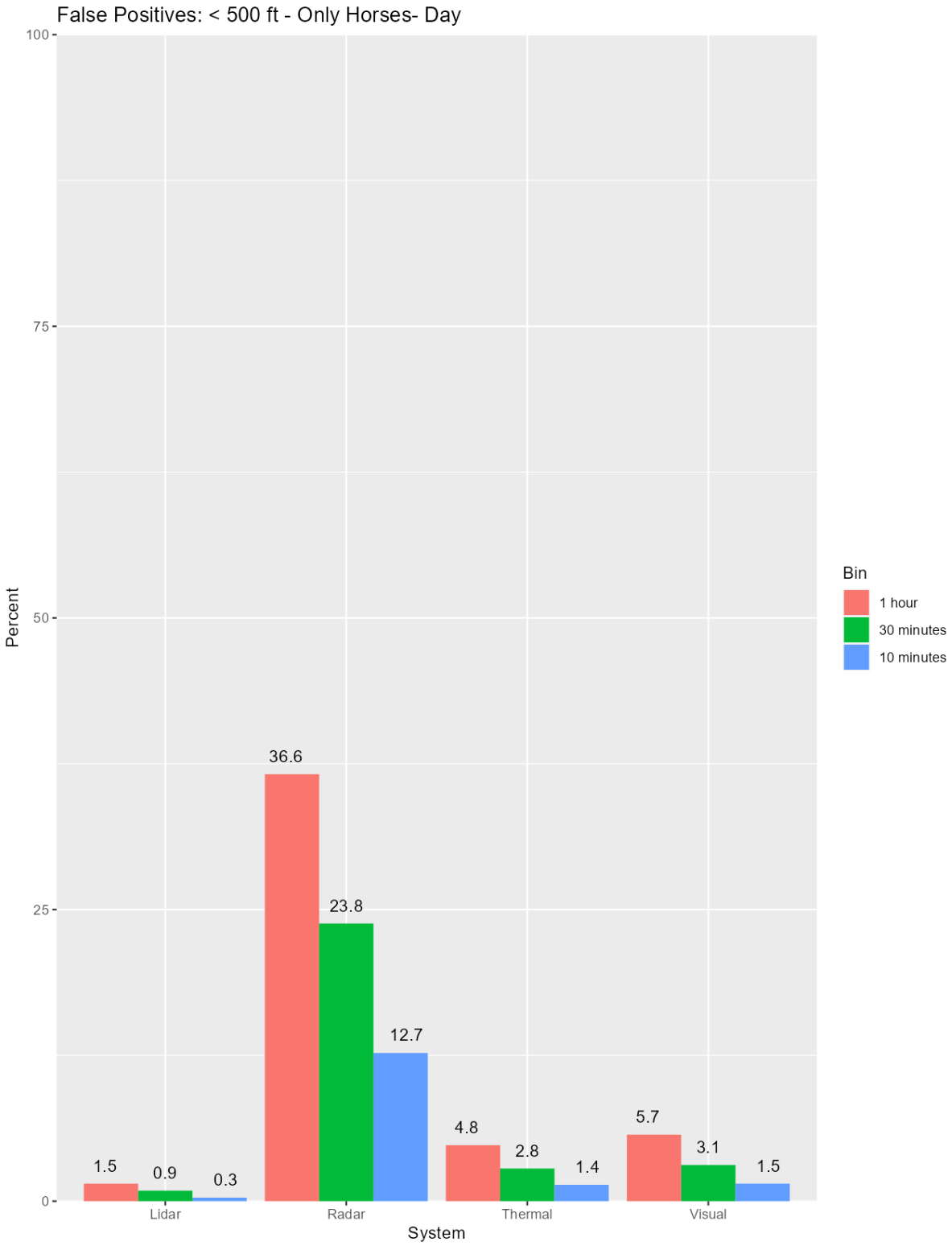

False Negatives: < 500 ft - Only Horses - Day
100
75
50
25
0
Percent
0
0
0
0
0
0
1.2
0.7
0.2
3.6
1.8
0.6
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

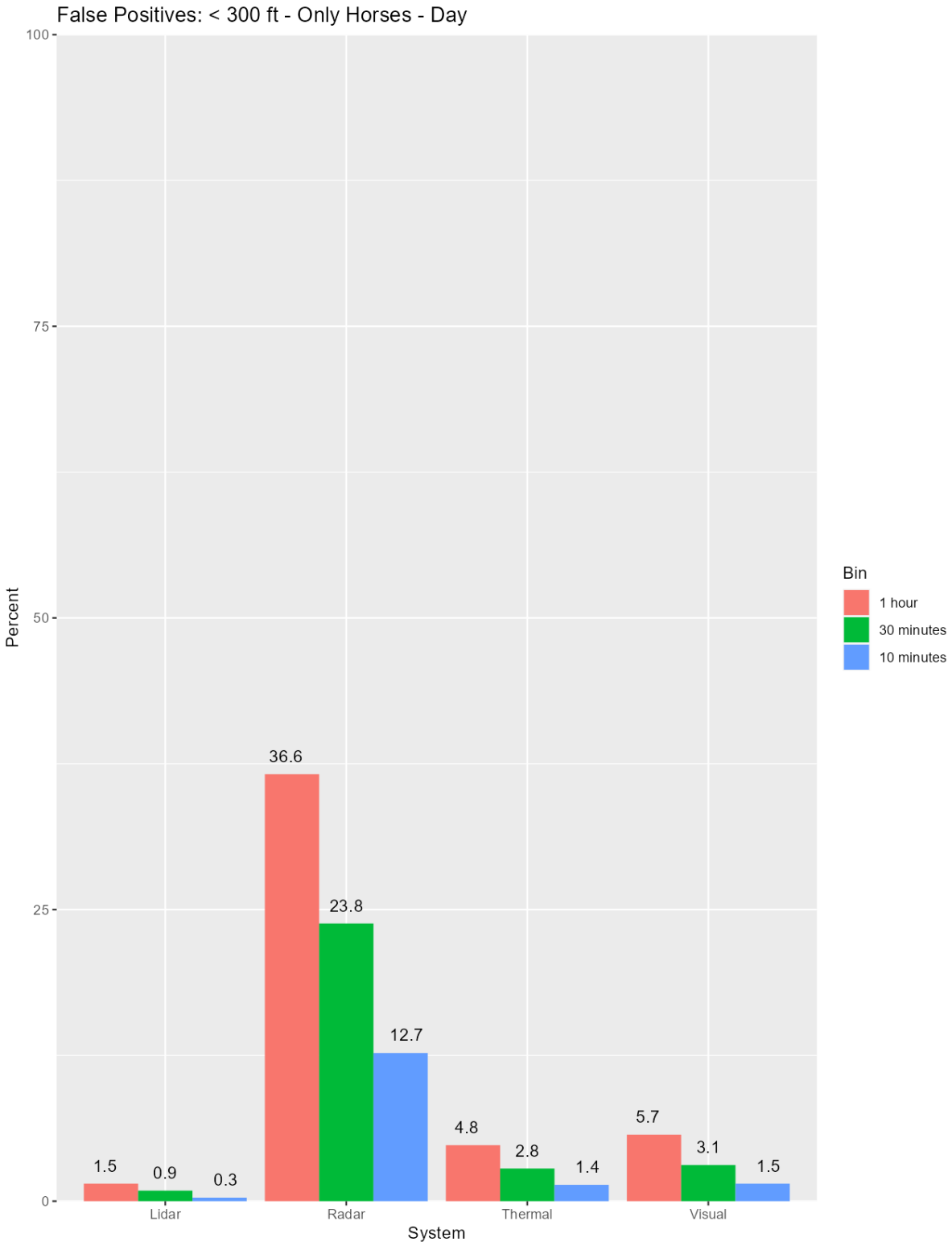

False Negatives: All Distances - Only Horses - Day
100
75
50
25
0
Percent
2.7
1.3
0.4
0
0
0
4.2
2.2
0.7
3.6
1.8
0.6
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

False Positive Time Bins:

Cycle 1 - Day:

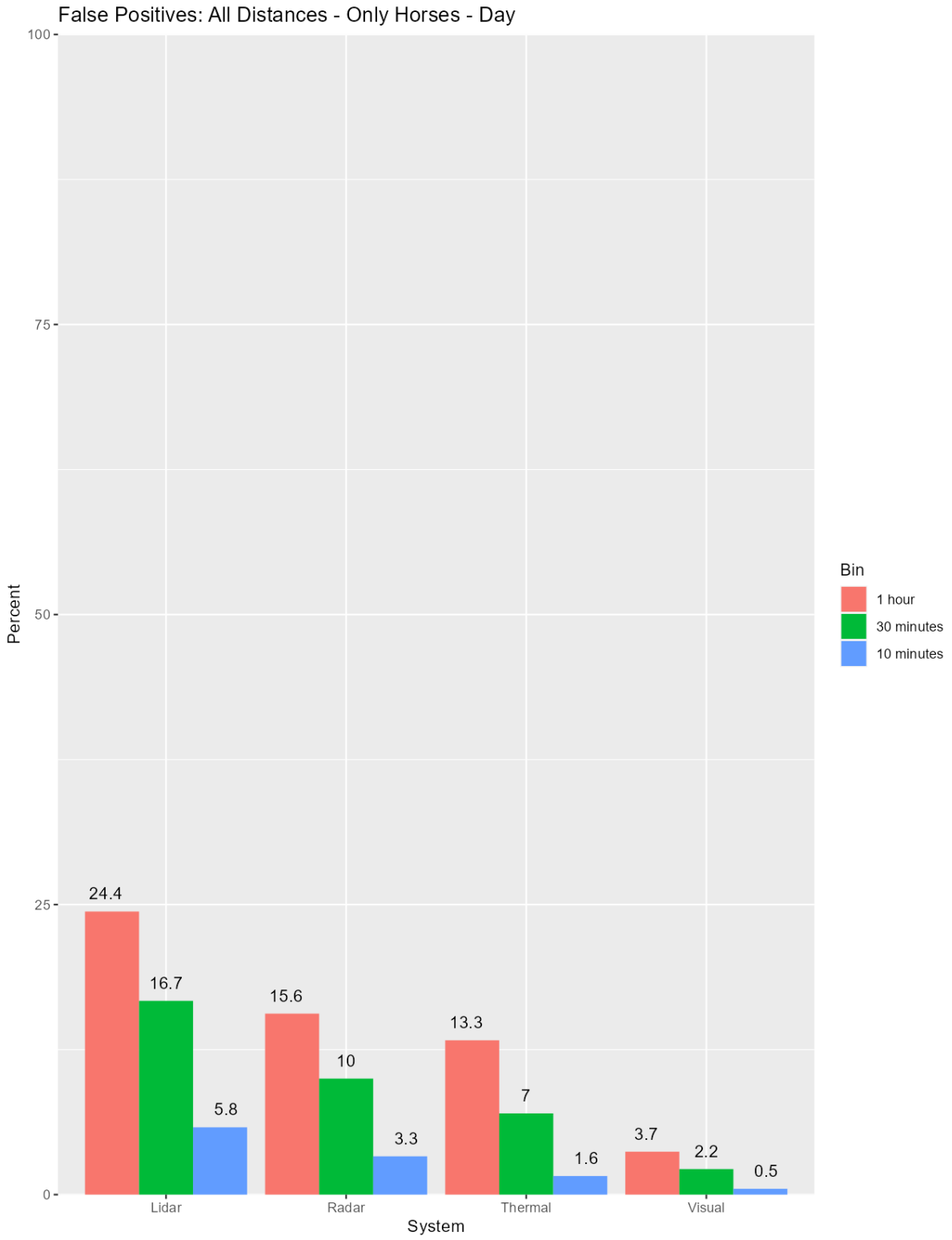


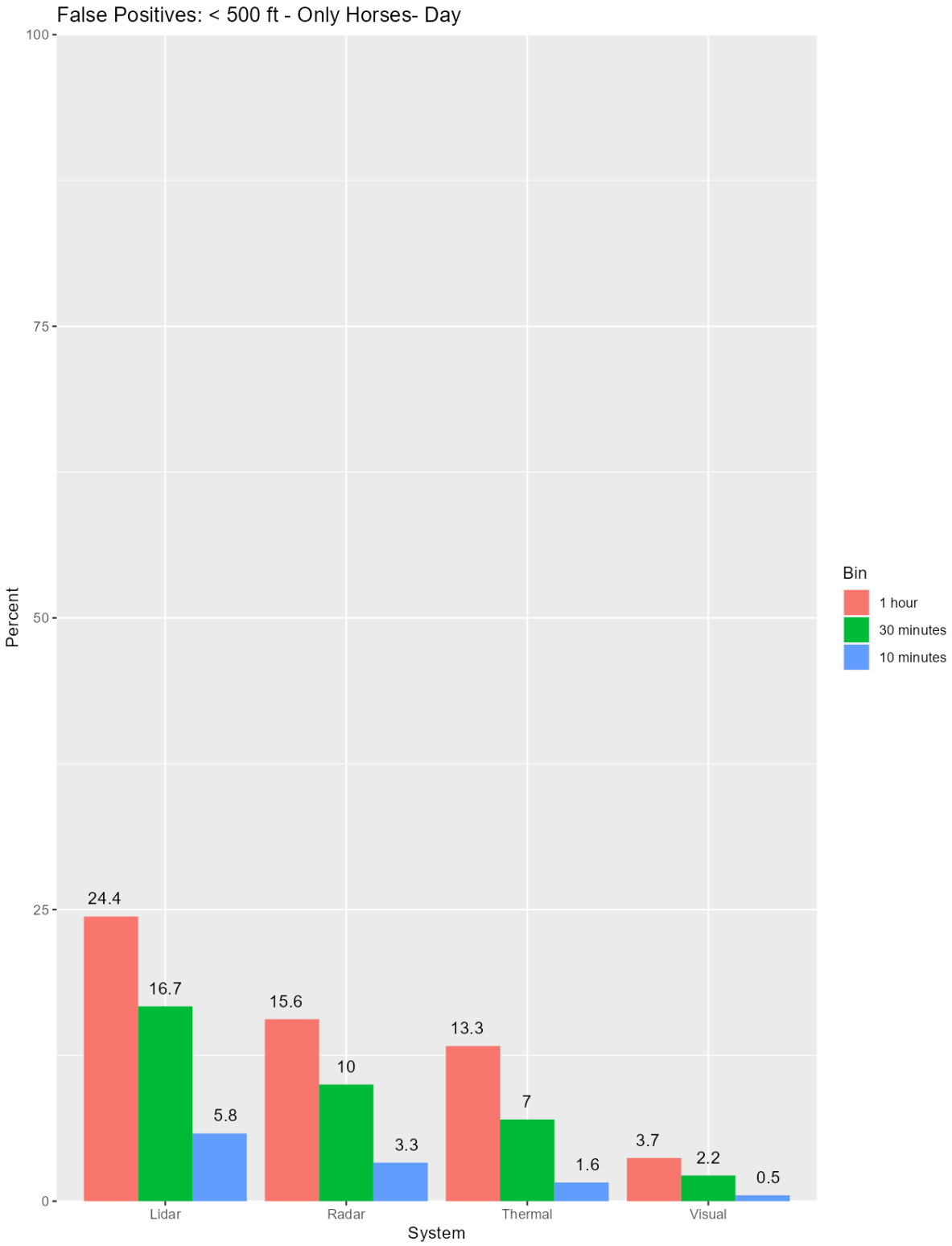

False Positives: < 500 ft - Only Horses- Day
100
75
50
25
0
Percent
1.5
0.9
0.3
36.6
23.8
12.7
4.8
2.8
1.4
5.7
3.1
1.5
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

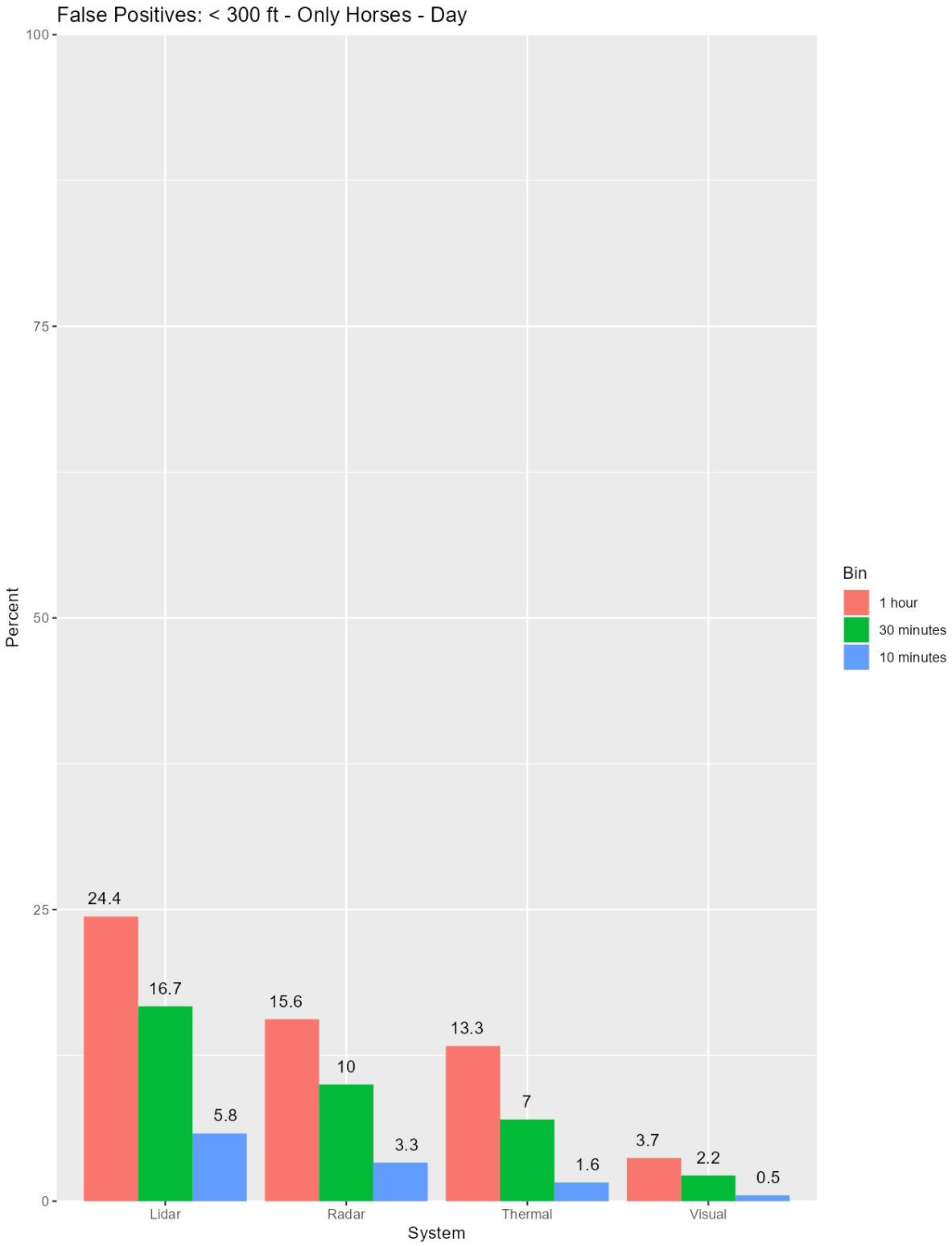

False Positives: < 300 ft - Only Horses - Day
100
75
50
25
0
Percent
1.5
0.9
0.3
36.6
23.8
12.7
4.8
2.8
1.4
5.7
3.1
1.5
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

False Positive Time Bins:

Cycle 2 - Day:

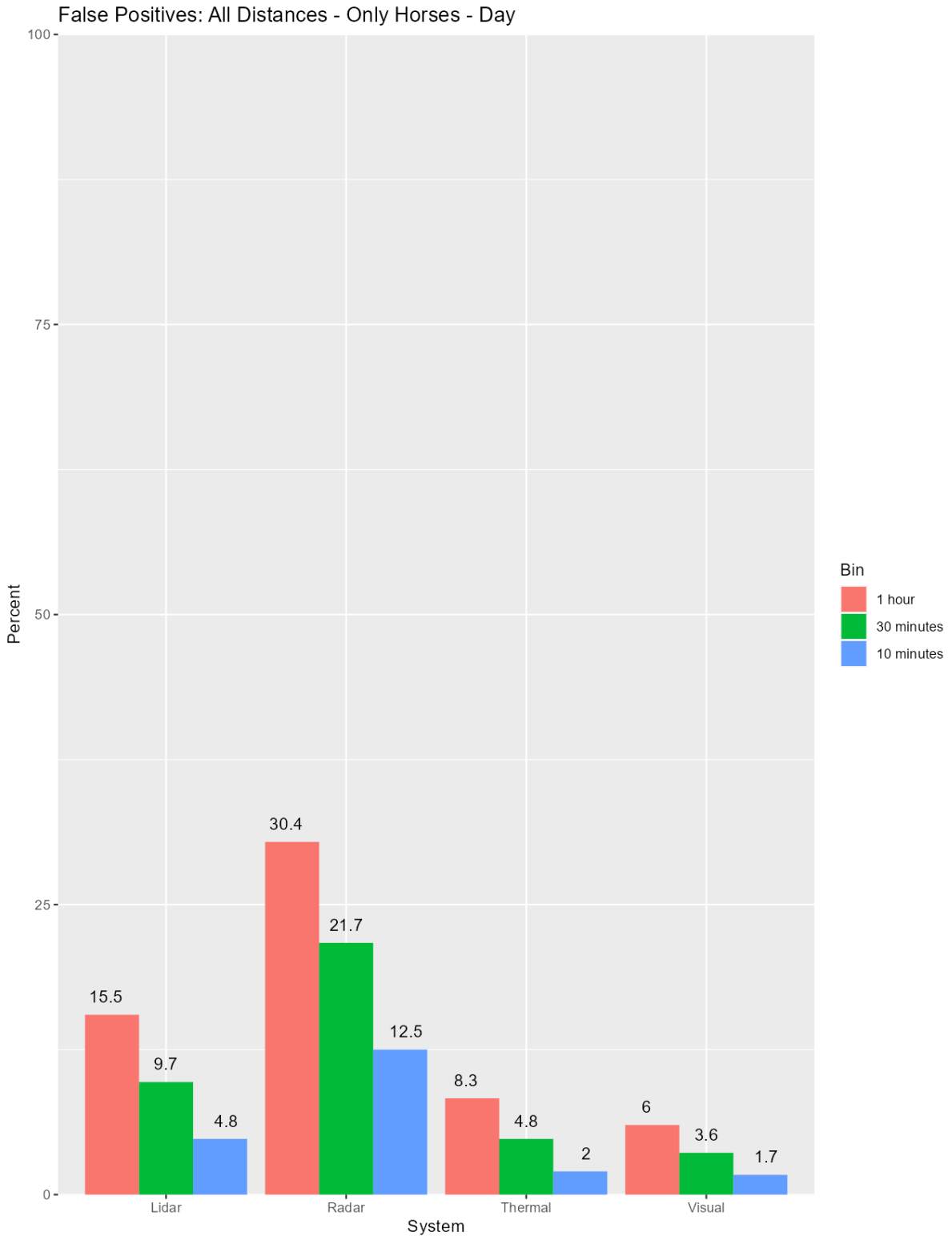


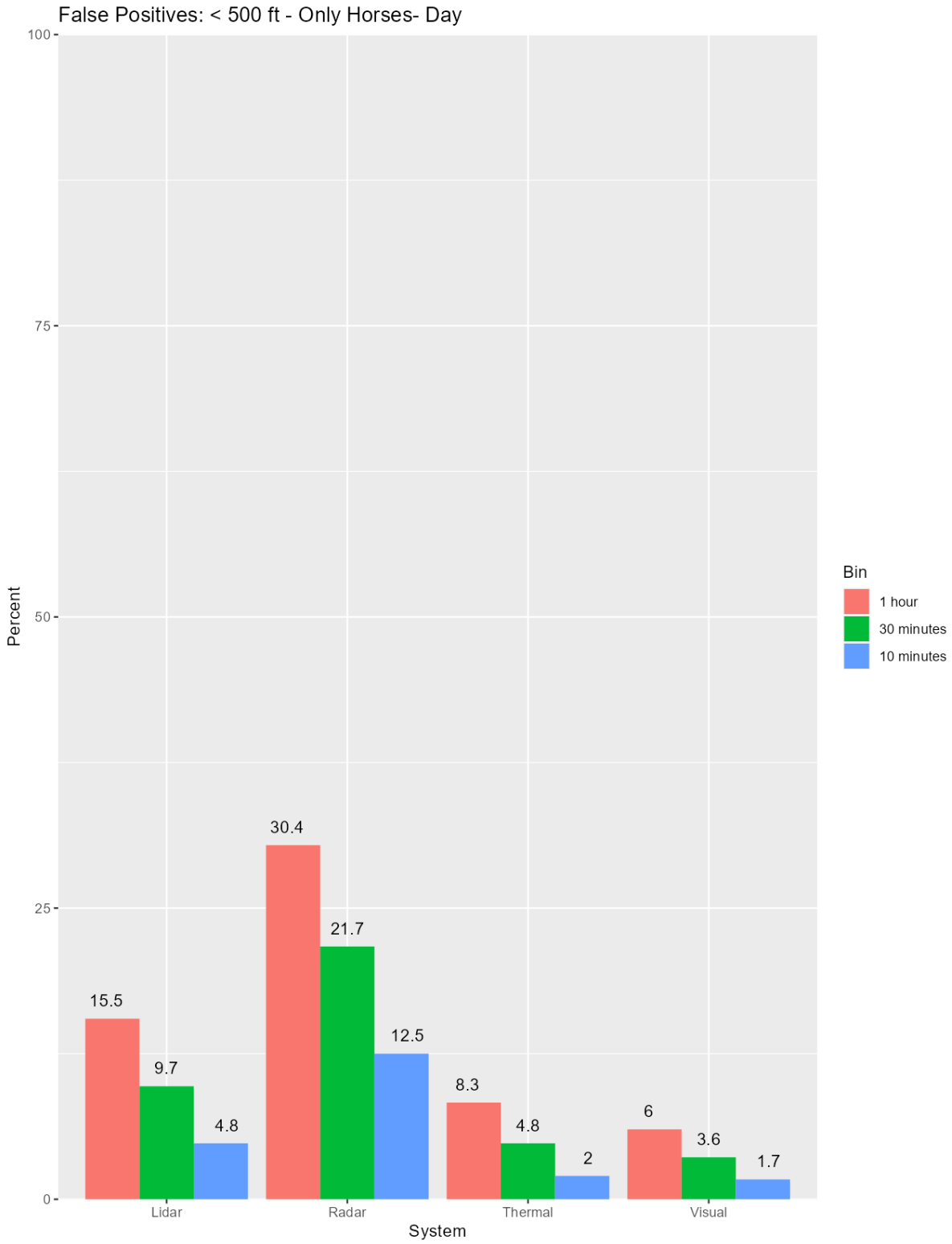

False Positives: < 500 ft - Only Horses- Day
100
75
50
25
0
Percent
24.4
16.7
5.8
15.6
10
3.3
13.3
7
1.6
3.7
2.2
0.5
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

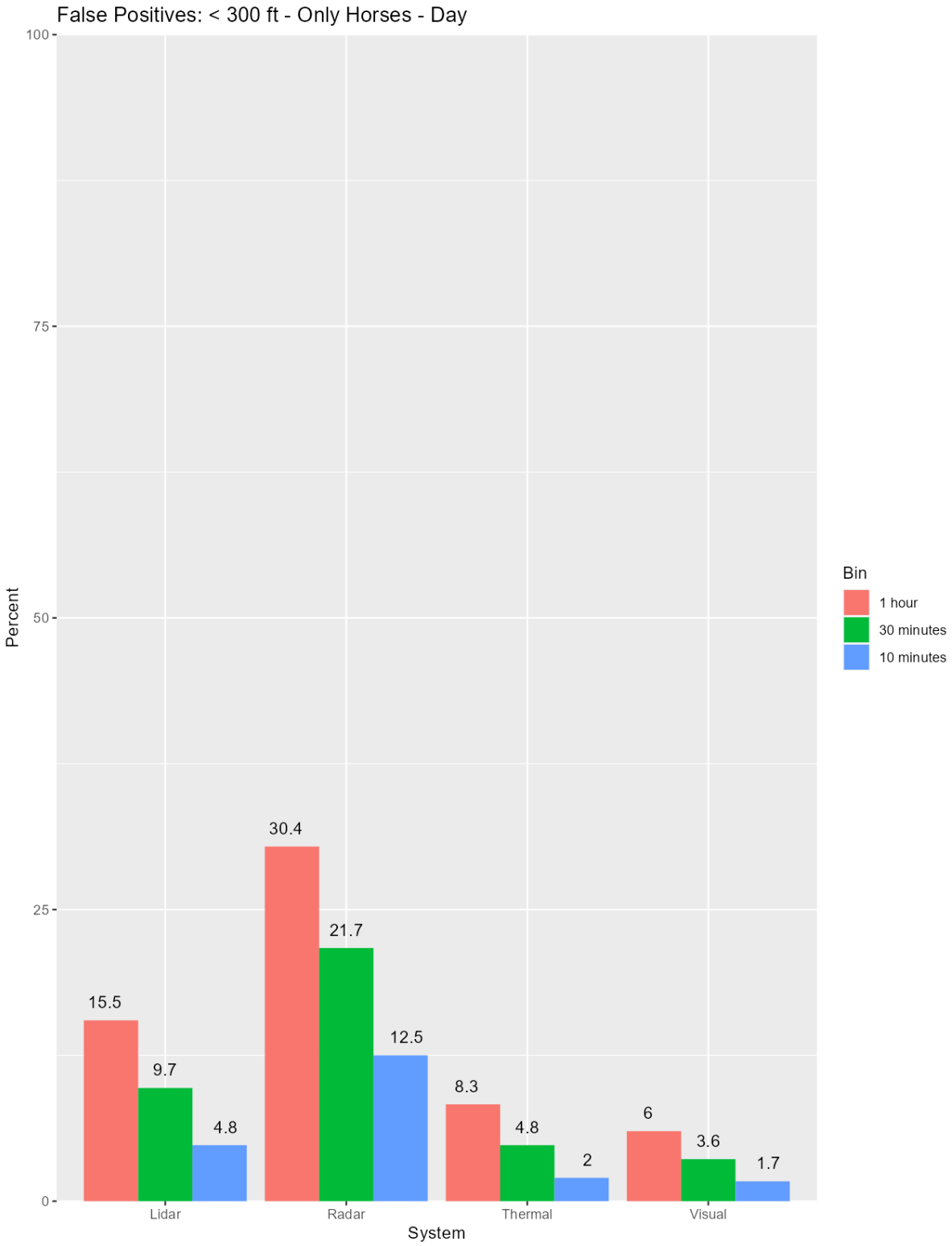

False Positives: < 300 ft - Only Horses - Day
100
75
50
25
0
Percent
24.4
16.7
5.8
15.6
10
3.3
13.3
7
1.6
3.7
2.2
0.5
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

False Positive Time Bins:

Cycle 3 - Day:

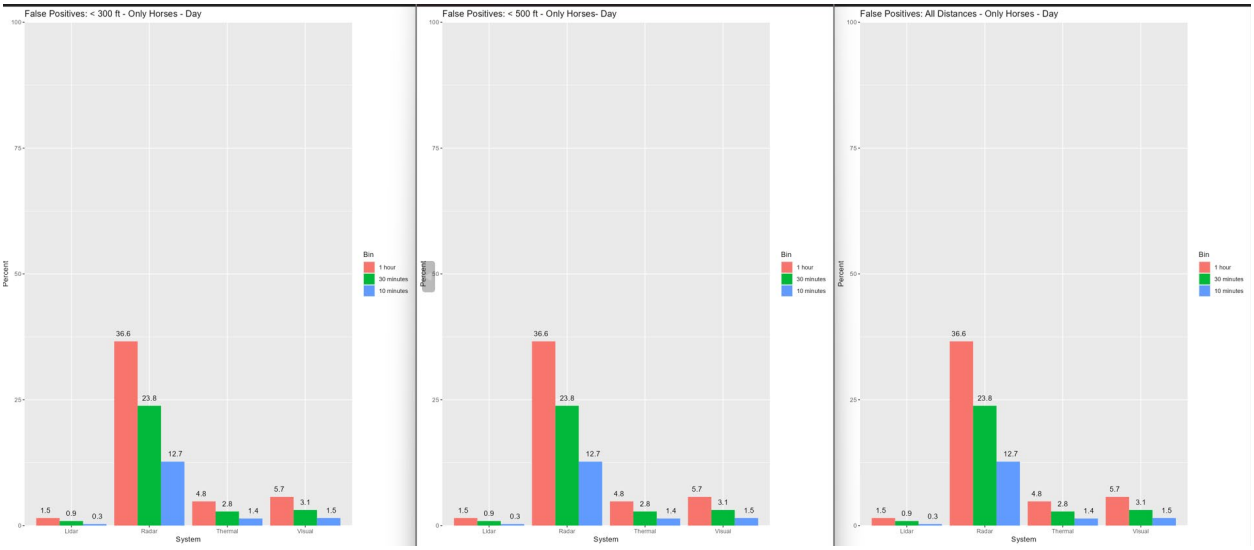



False Positives: < 500 ft - Only Horses- Day
100
75
50
25
0
Percent
15.5
9.7
4.8
30.4
21.7
12.5
8.3
4.8
2
6
3.6
1.7
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

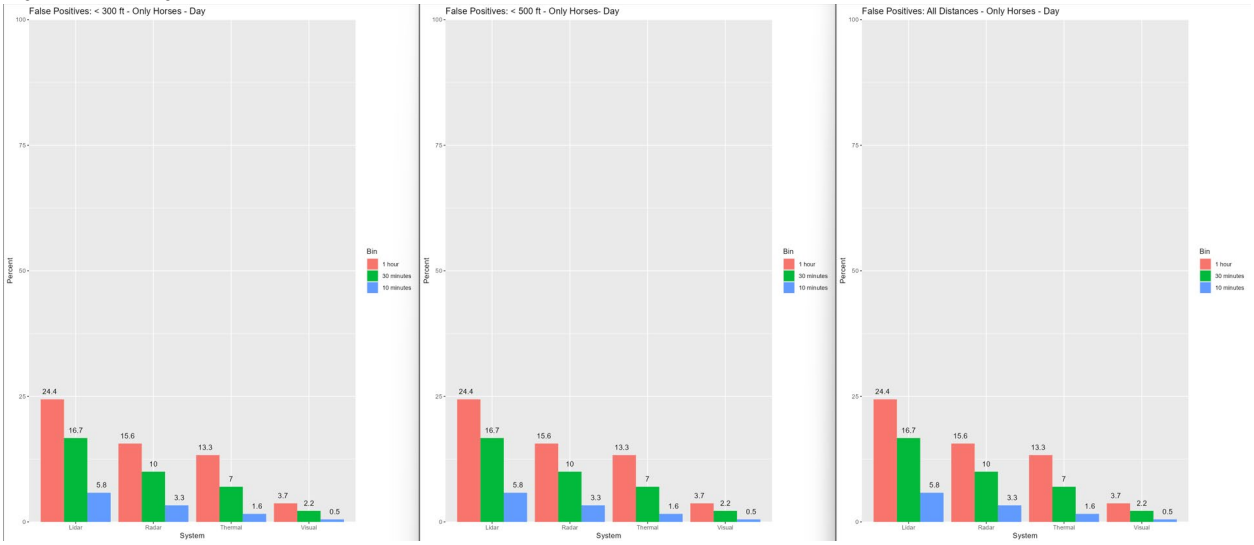

False Positives: < 300 ft - Only Horses - Day
100
75
50
25
0
Percent
15.5
9.7
4.8
30.4
21.7
12.5
8.3
4.8
2
6
3.6
1.7
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

False Positive Side-by-Side Results :

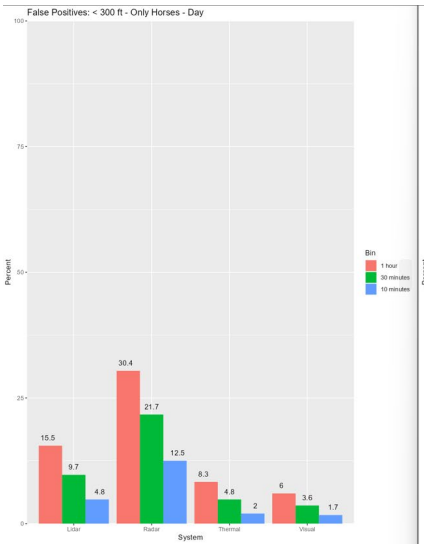
Cycle 1 - Day:

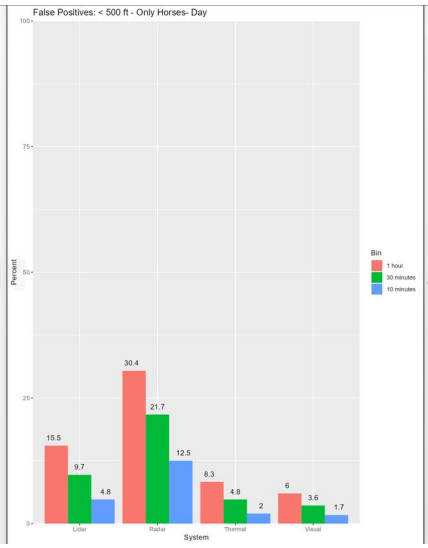


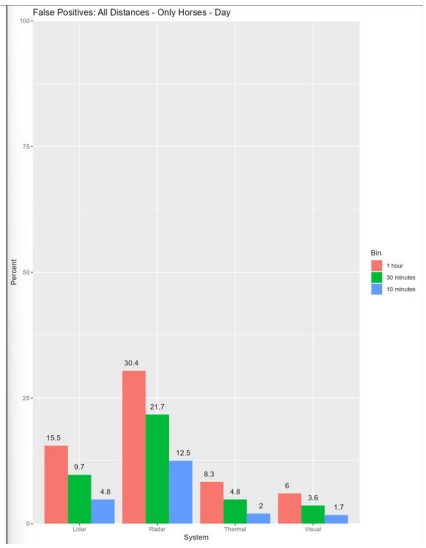
Cycle 2 - Day:



Cycle 3 - Day:

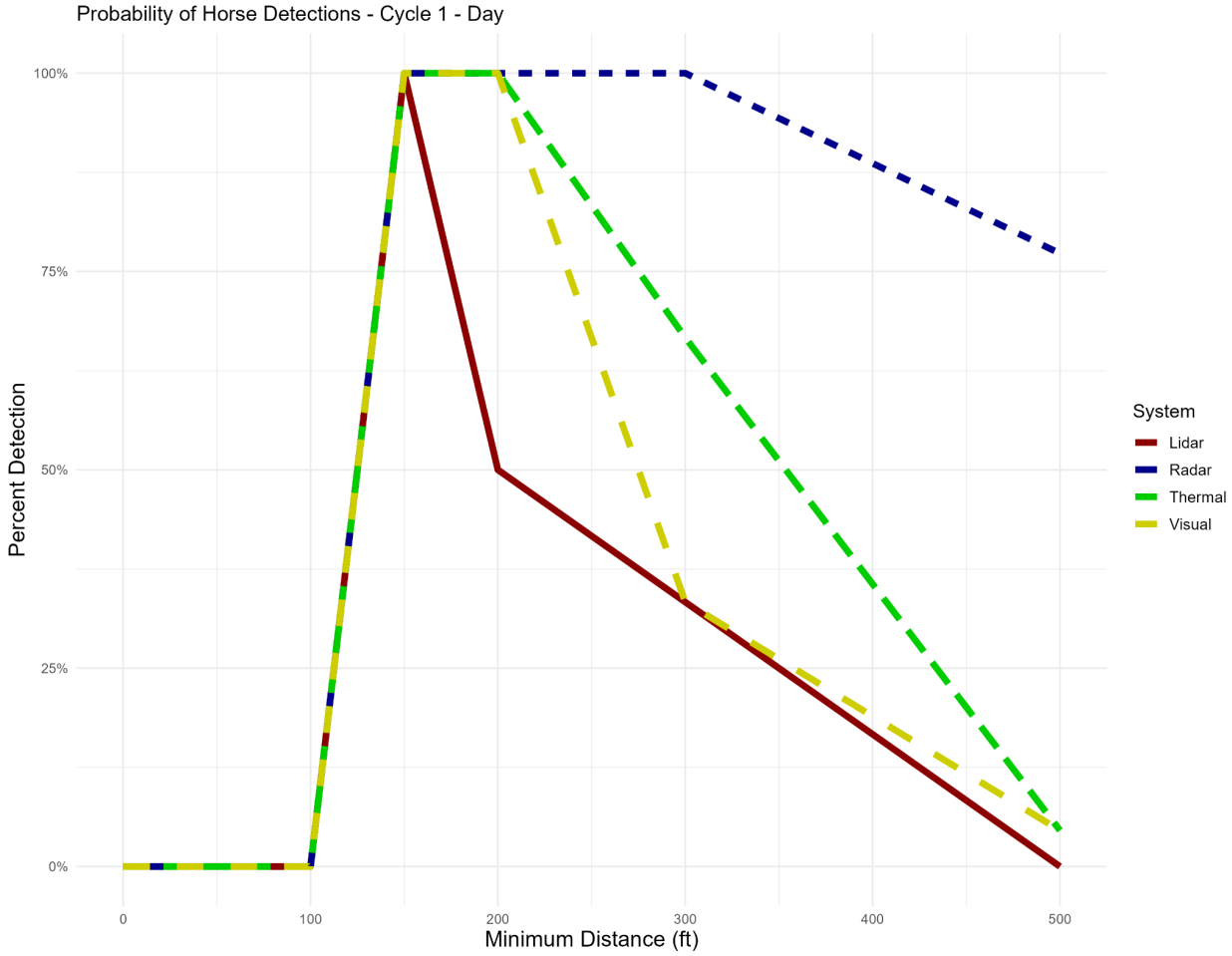

False Positives: < 300 ft - Only Horses - Day
Percent
System
Bin
1 hour
30 minutes
10 minutes
15.5
9.7
4.8
30.4
21.7
12.5
8.3
4.8
2
6
3.6
1.7
Lidar
Radar
Thermal
Visual


False Positives: < 500 ft - Only Horses- Day
Percent
System
Bin
1 hour
30 minutes
10 minutes
15.5
9.7
4.8
30.4
21.7
12.5
8.3
4.8
2
6
3.6
1.7
Lidar
Radar
Thermal
Visual


False Positives: All Distances - Only Horses - Day
Percent
System
Bin
1 hour
30 minutes
10 minutes
15.5
9.7
4.8
30.4
21.7
12.5
8.3
4.8
2
6
3.6
1.7
Lidar
Radar
Thermal
Visual

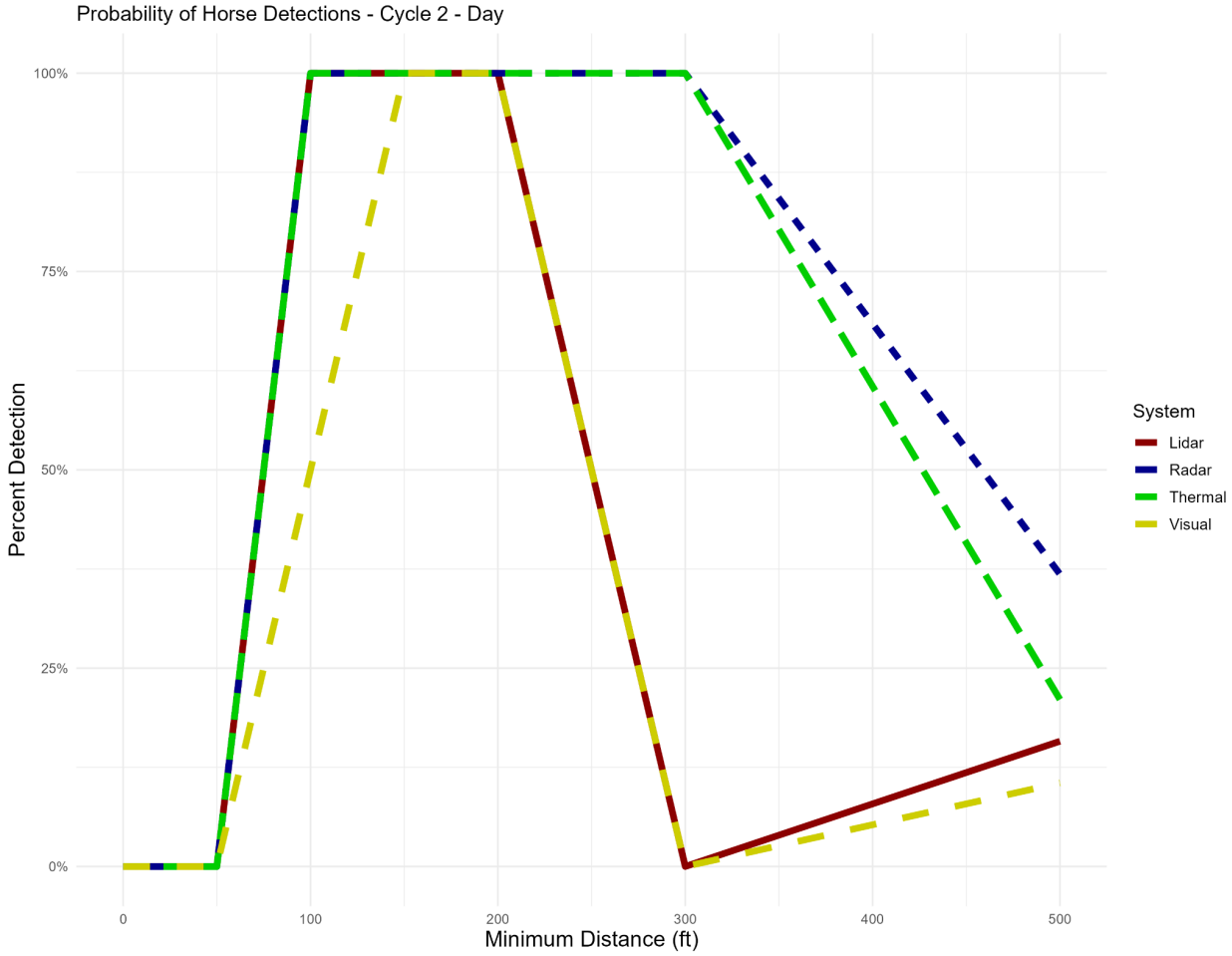
Probability of Detection - Minimum Distance Line Charts

Cycle 1 - Day:

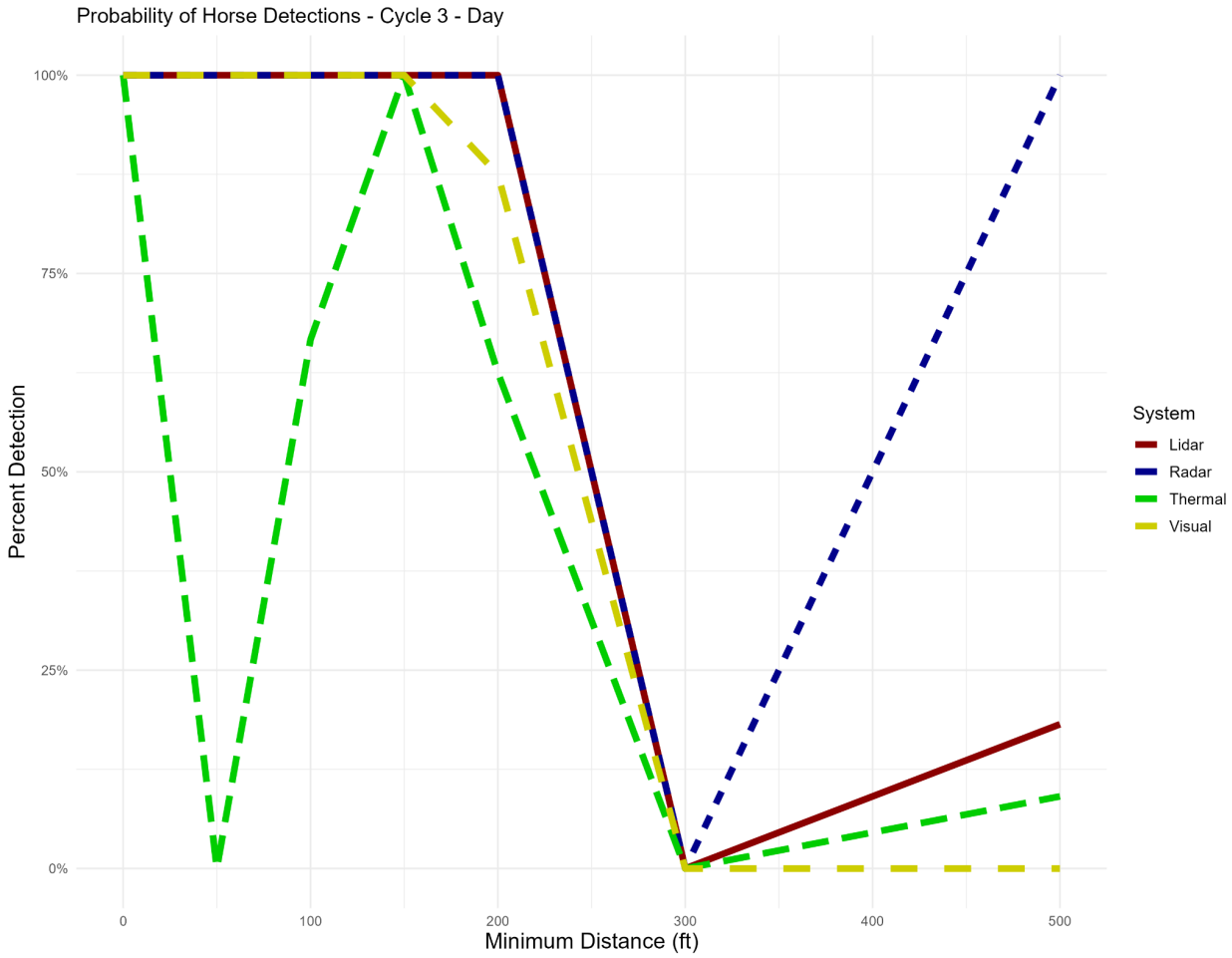


Probability of Detection - Minimum Distance Line Charts

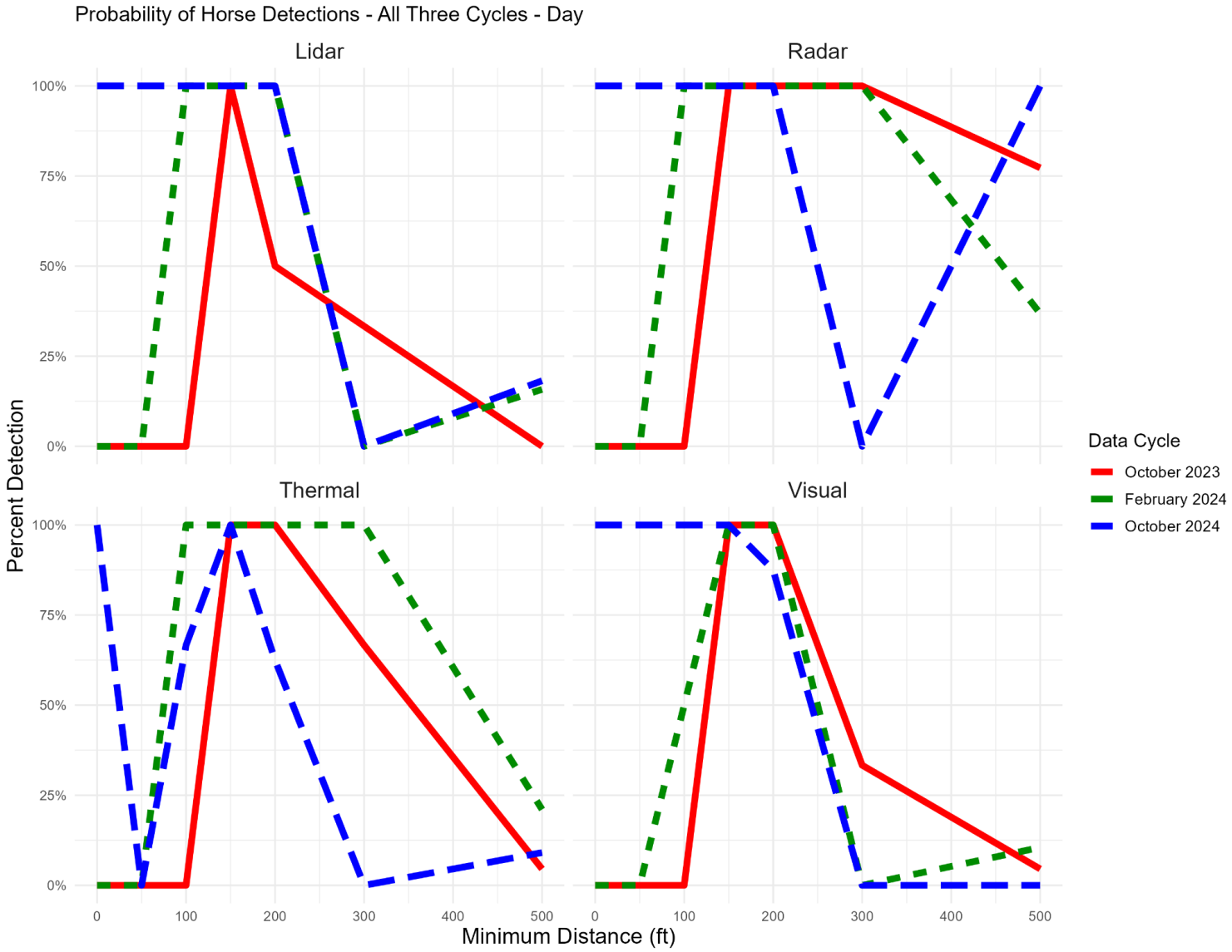
Cycle 2 - Day:



Probability of Detection - Minimum Distance Line Charts
Cycle 3 - Day:



Probability of Detection - Minimum Distance Line Charts
All Three Cycles - Day:



Results: Only Night

Baseline summary information for each data collection cycle

Cycle 1 - October 2023: October 13, 2023 at 00:00:00 – October 26 at 23:59:59
Count of baseline events of horses:
<300 ft: 13
<500 ft: 15
>500 ft: 43

Total loiter time of horse events: 30 hours, 02 minutes, and 47 seconds.

Cycle 2 - February 2024: February 1, 2024 at 00:00:00 – February 14, 2024 at 23:59:59
Count of baseline events of horses:
<300 ft: 6
<500 ft: 7
>500 ft: 27

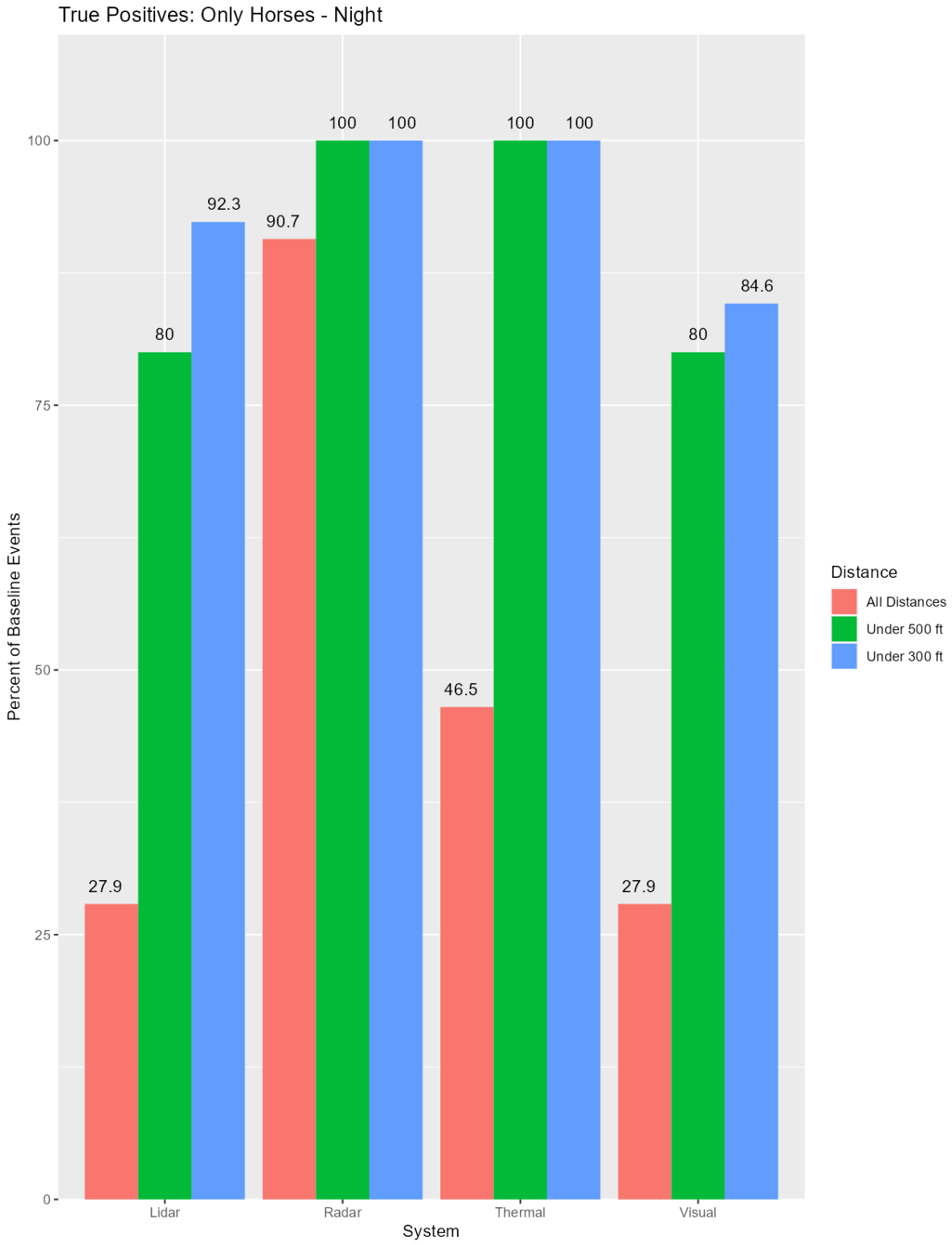
Total loiter time of horse events: 37 hours, 21 minutes, and 44 seconds.

Cycle 3 - October 2024: October 17, 2024 at 00:00:00 through October 30, 2024 at 23:59:59
Count of baseline events of horses:
<300 ft: 6
<500 ft: 8
>500 ft: 36

Total loiter time of horse events: 23 hours, 42 minutes, and 18 seconds.

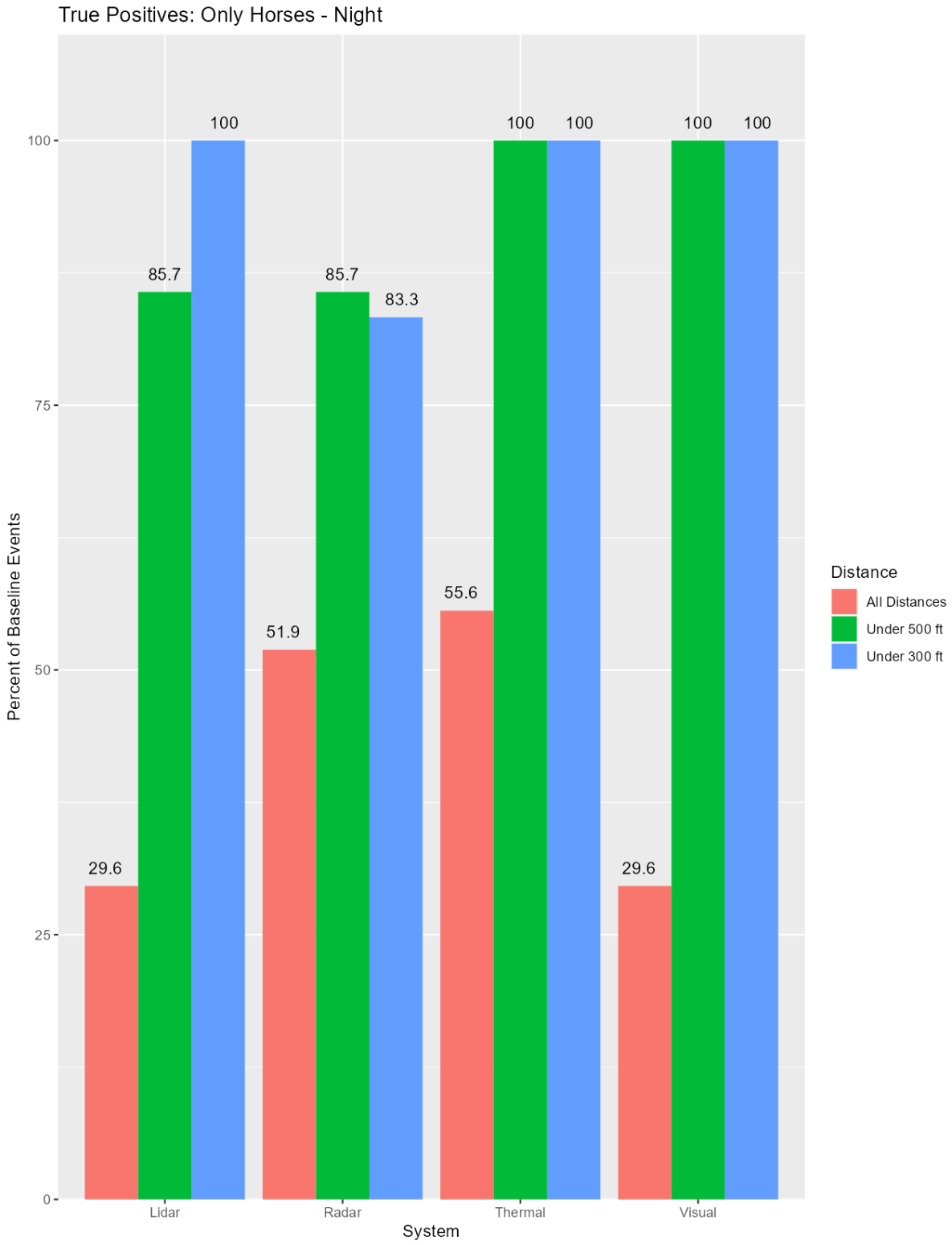
True Positives:

Cycle 1 - Night:



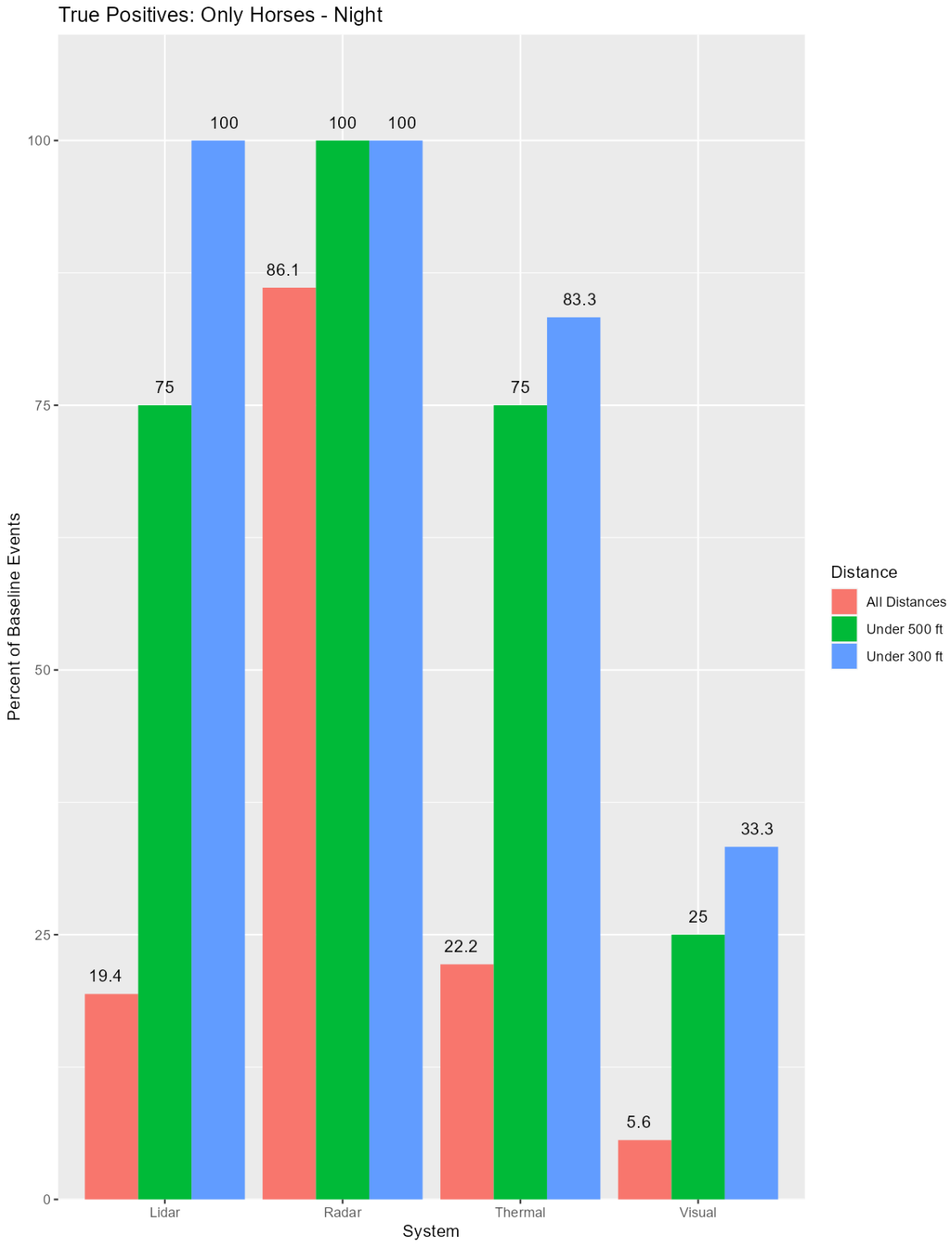
True Positives:

Cycle 2 - Night:



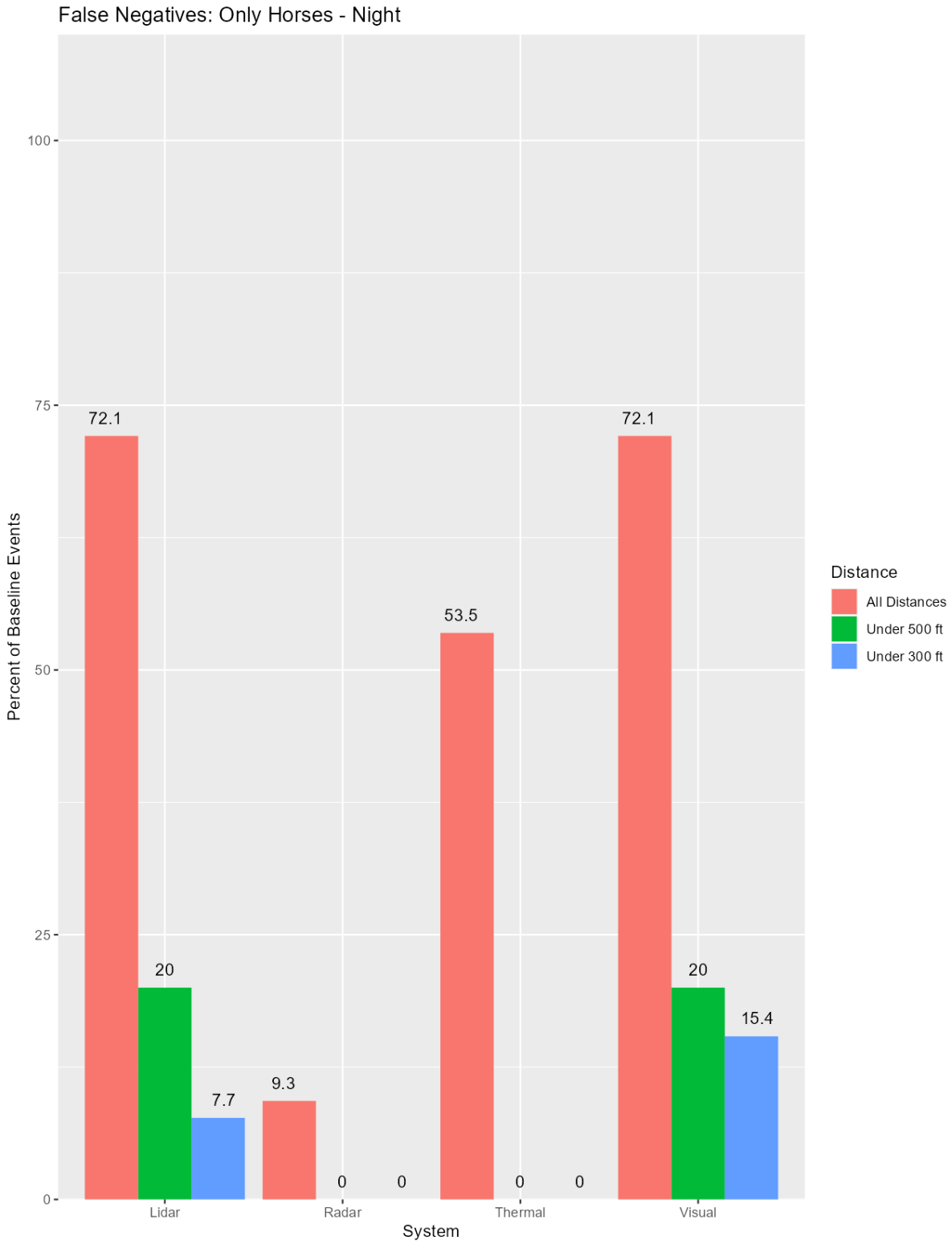
True Positives:

Cycle 3 - Night:



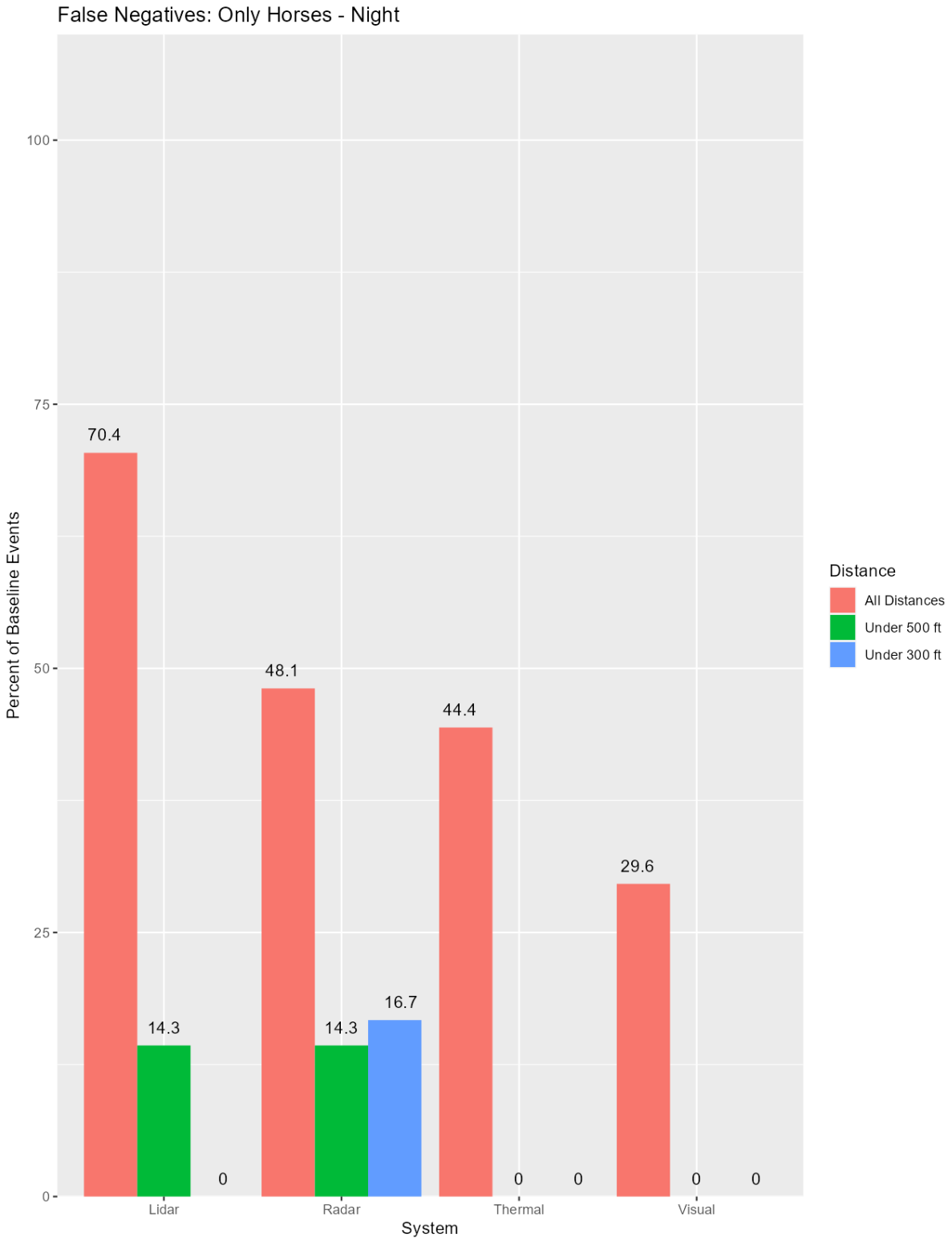
False Negatives:

Cycle 1 - Night:



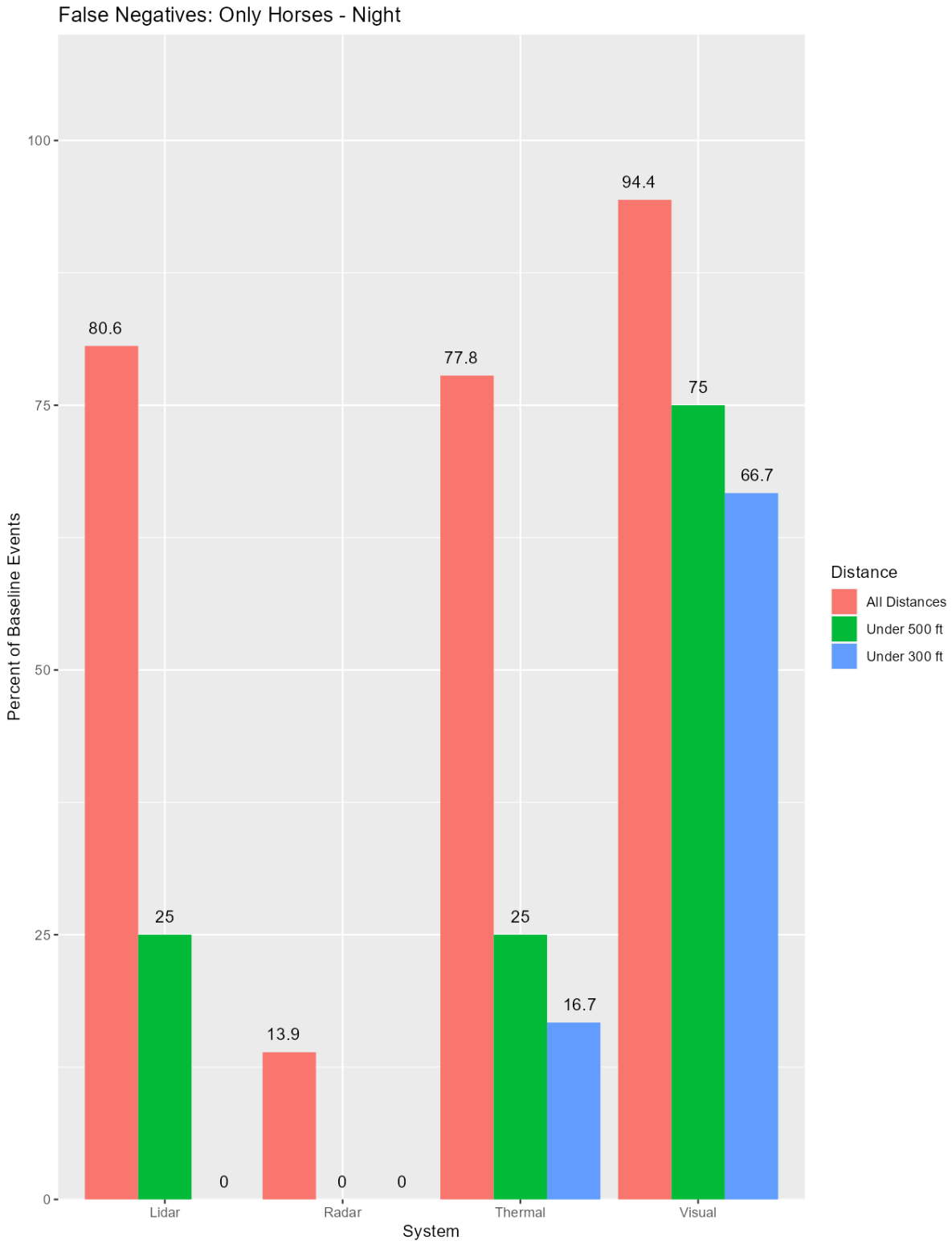
False Negatives:

Cycle 2 - Night:



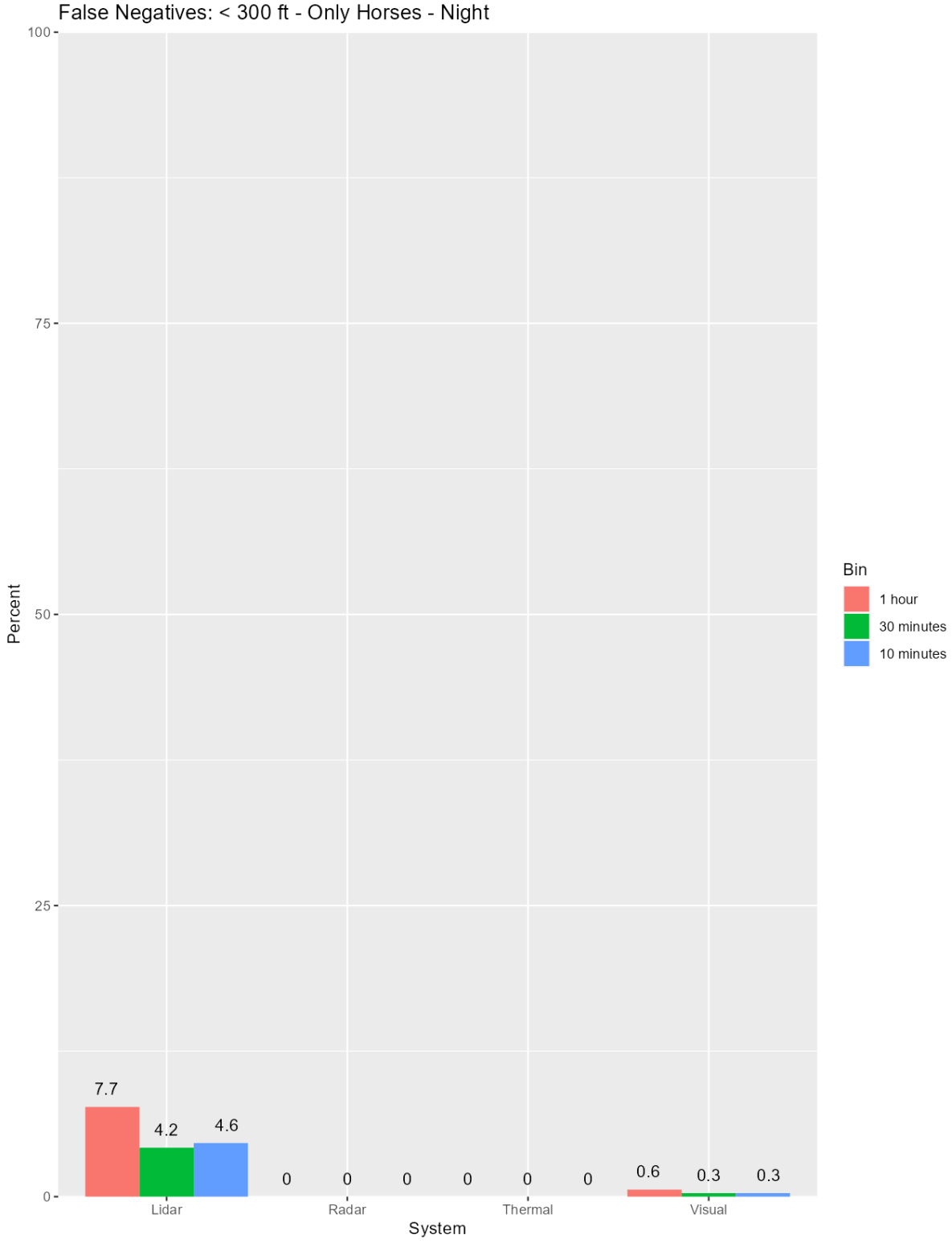
False Negatives:

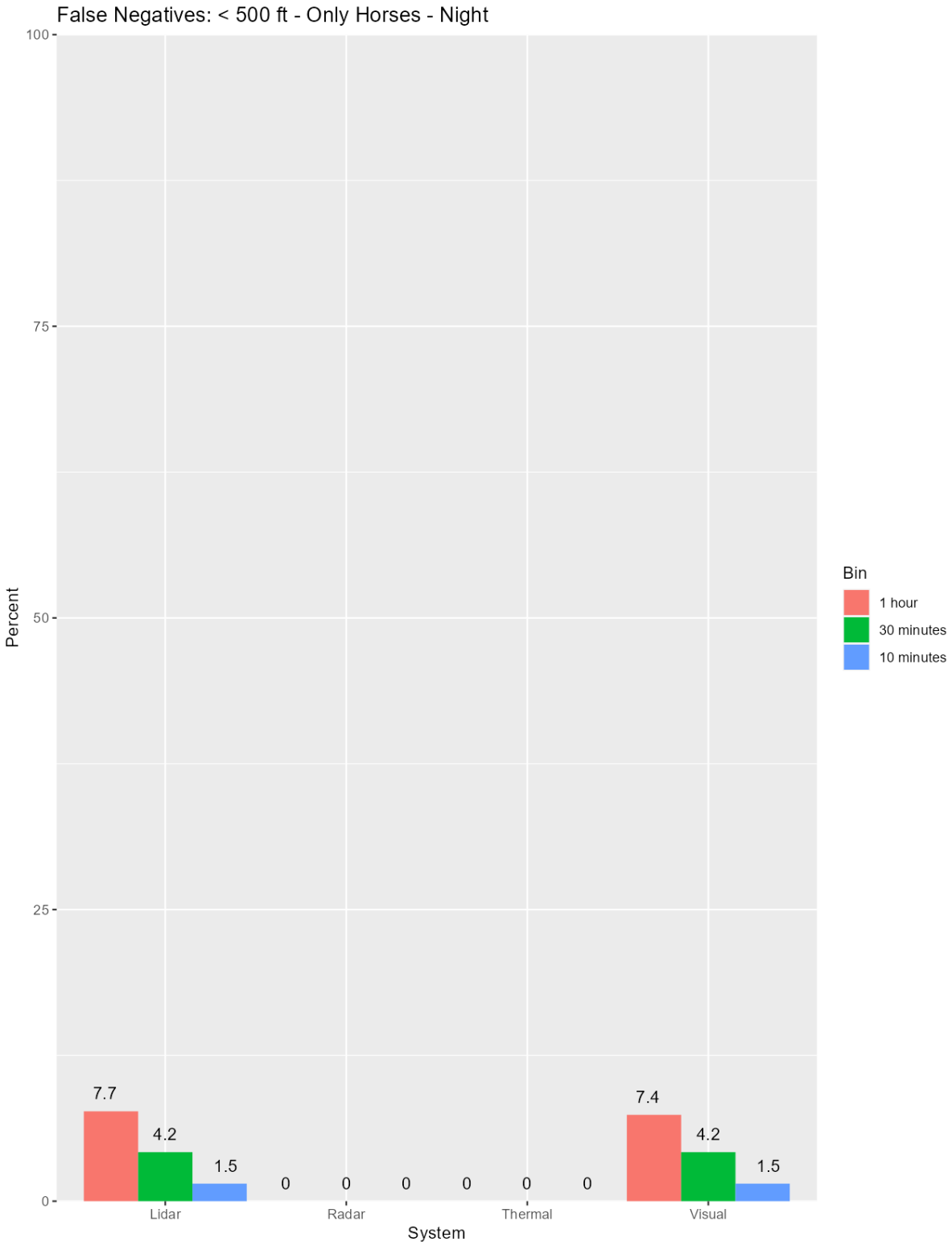
Cycle 3 - Night:

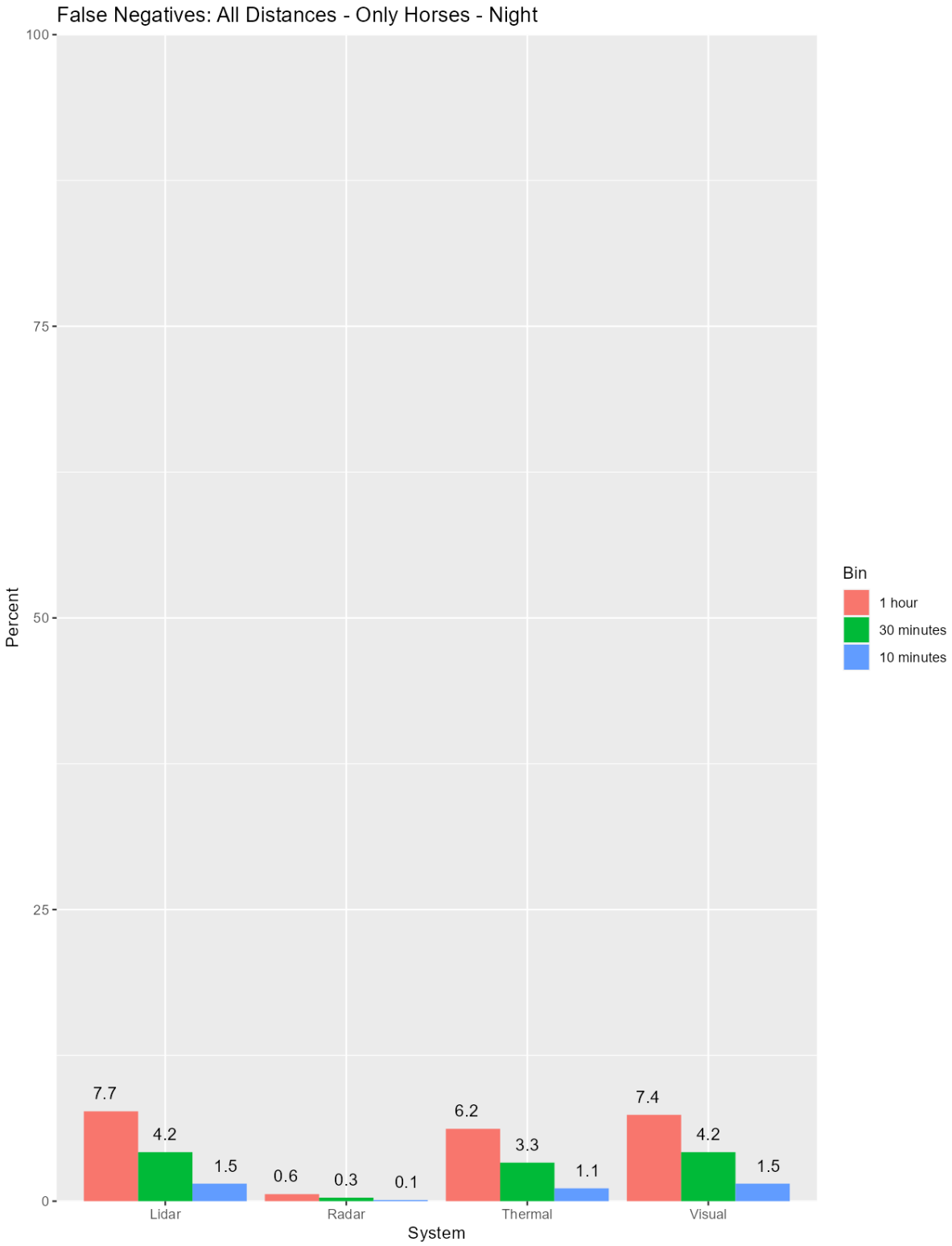


False Negative Time Bins:

Cycle 1 - Night:

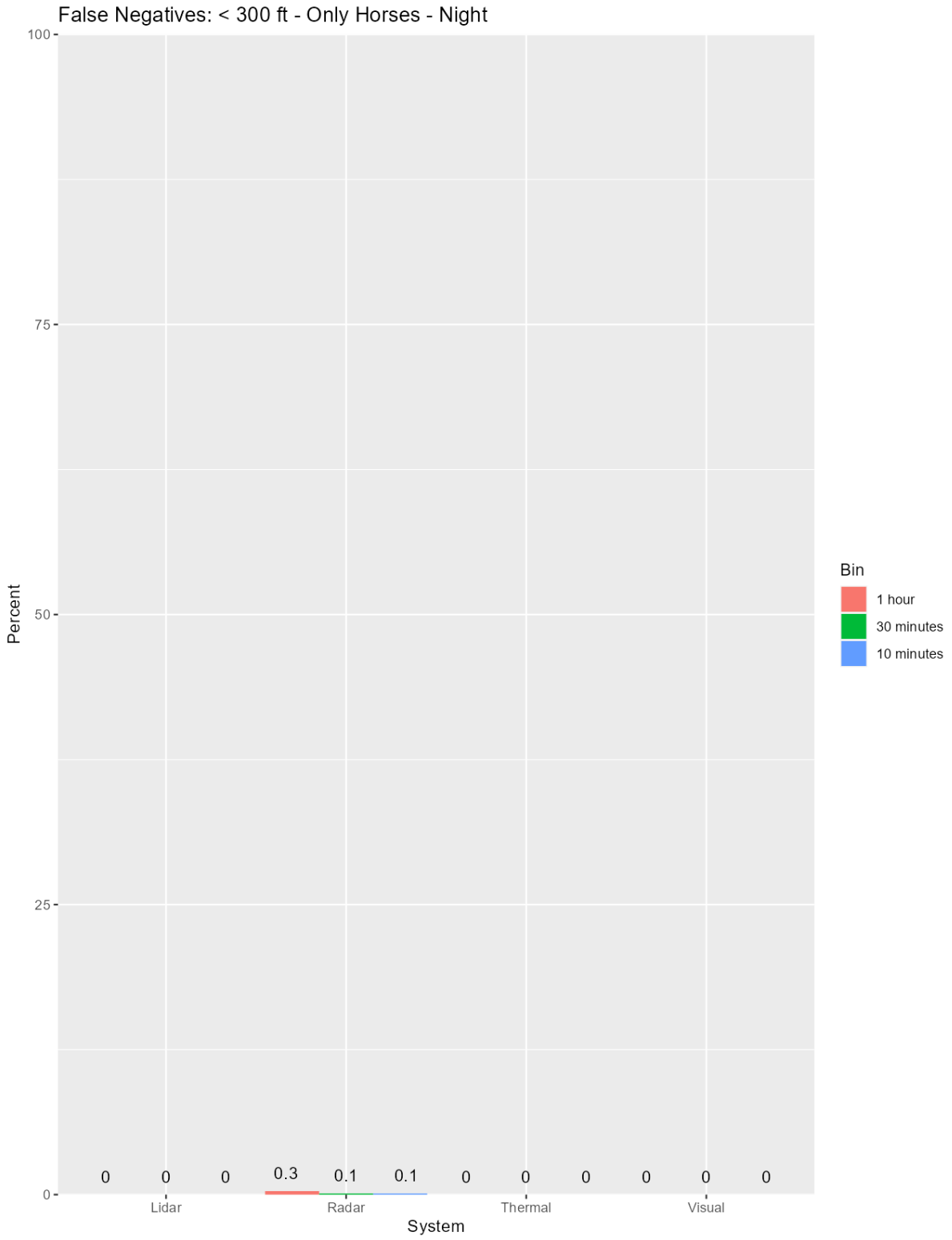


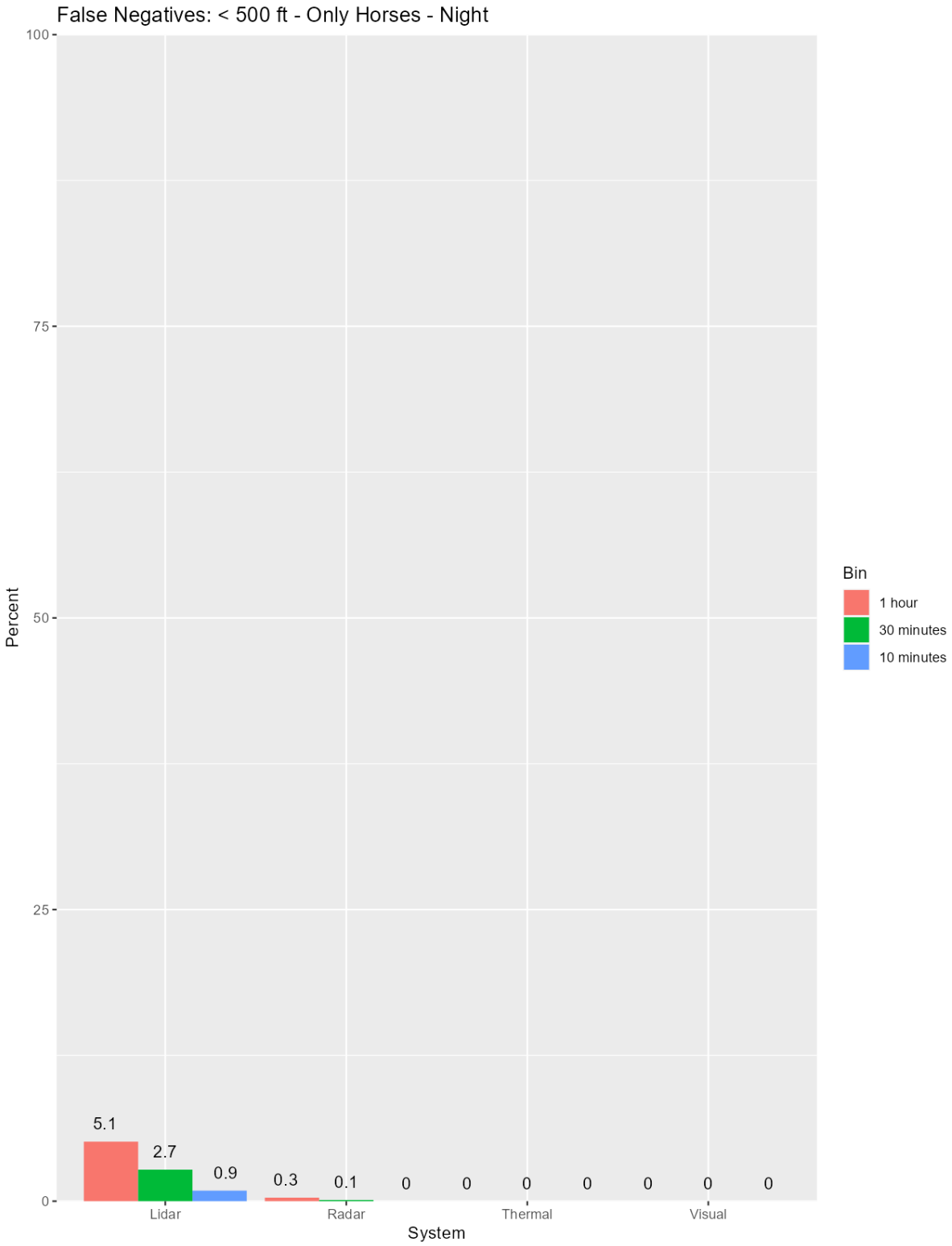

False Negatives: < 500 ft - Only Horses - Night
100
75
50
25
0
Percent
7.7
4.2
1.5
0
0
0
0
0
0
7.4
4.2
1.5
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

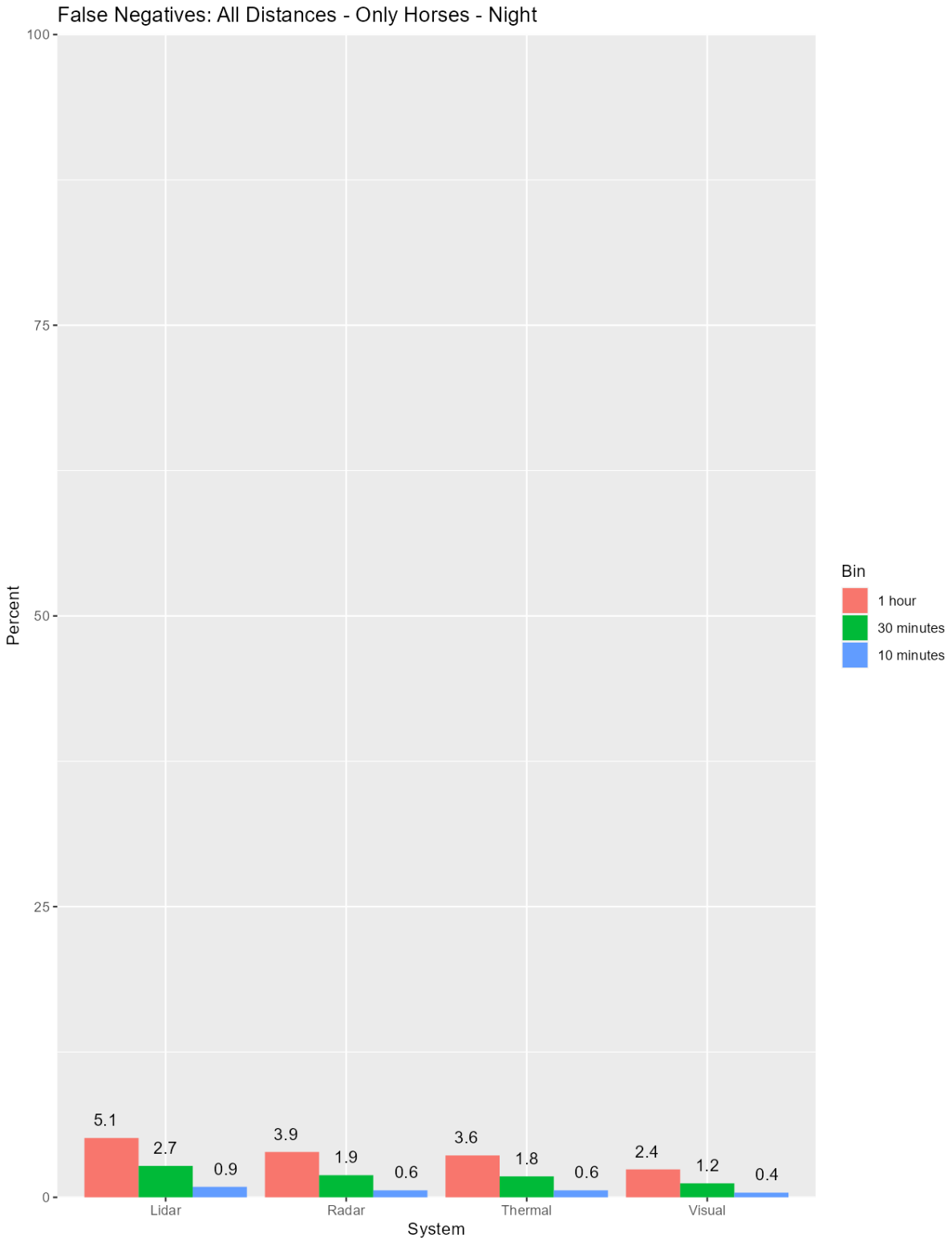

False Negatives: All Distances - Only Horses - Night
100
75
50
25
0
Percent
7.7
4.2
1.5
0.6
0.3
0.1
6.2
3.3
1.1
7.4
4.2
1.5
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

False Negative Time Bins:

Cycle 2 - Night:

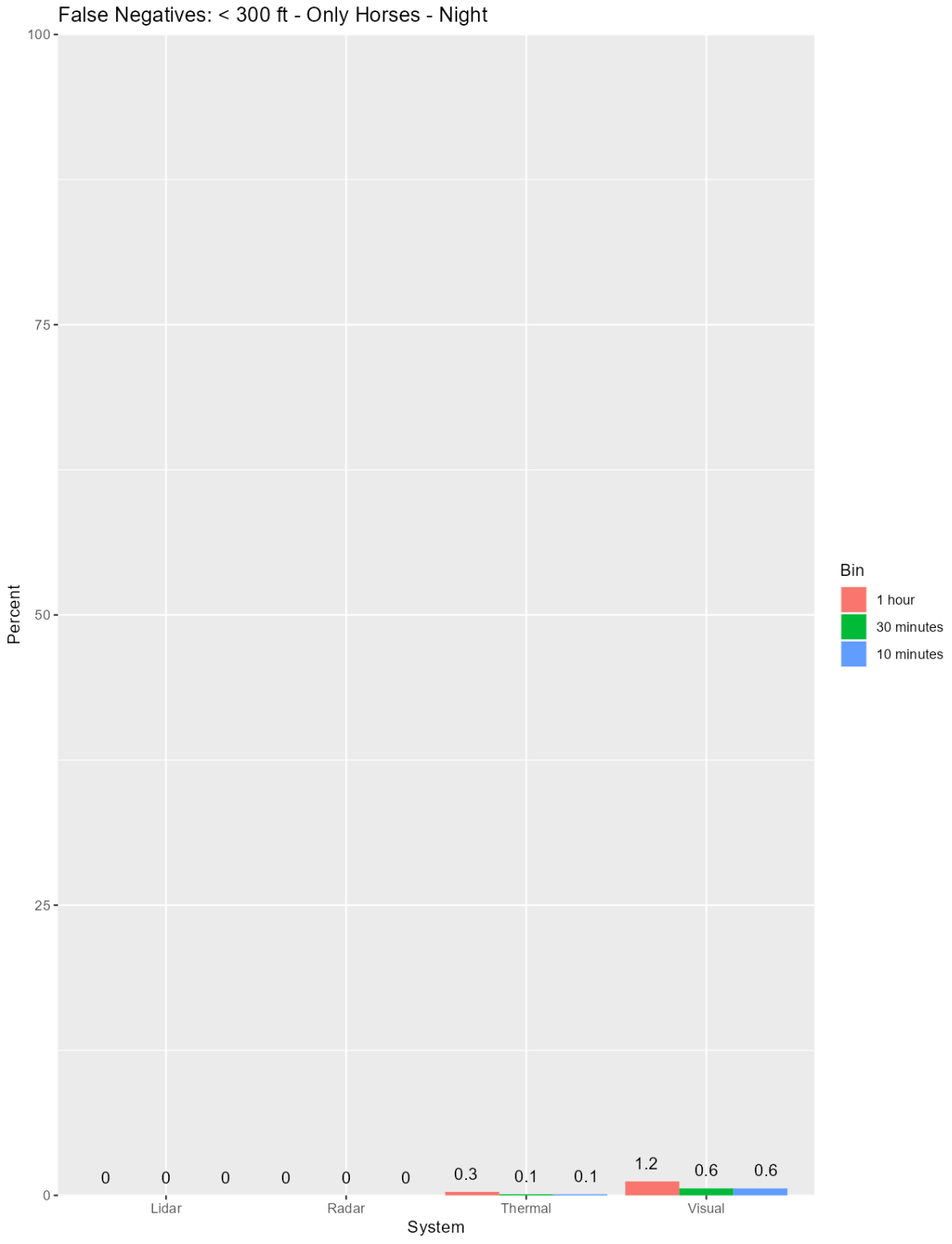


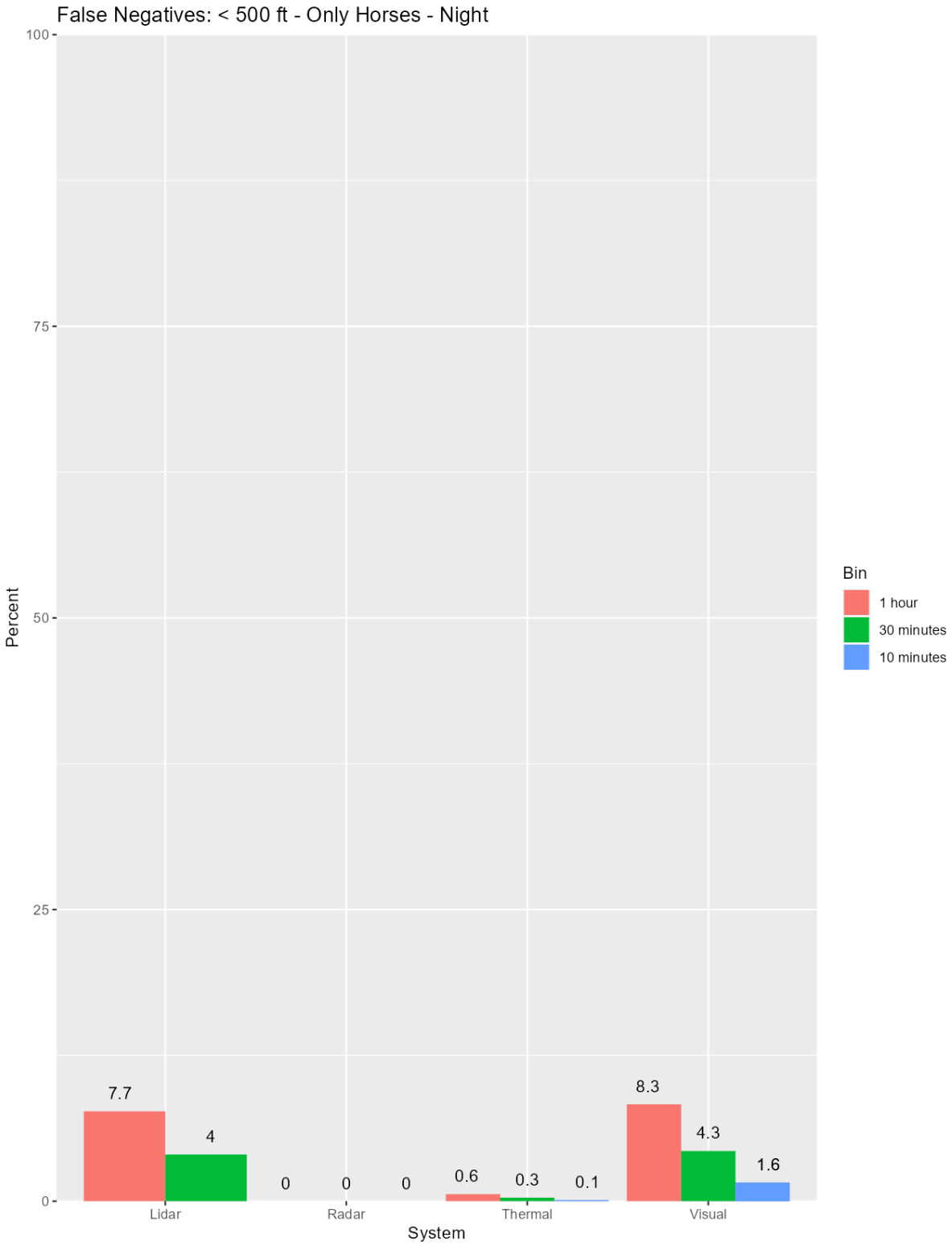

False Negatives: < 500 ft - Only Horses - Night
100
75
50
25
0
Percent
5.1
2.7
0.9
0.3
0.1
0
0
0
0
0
0
0
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

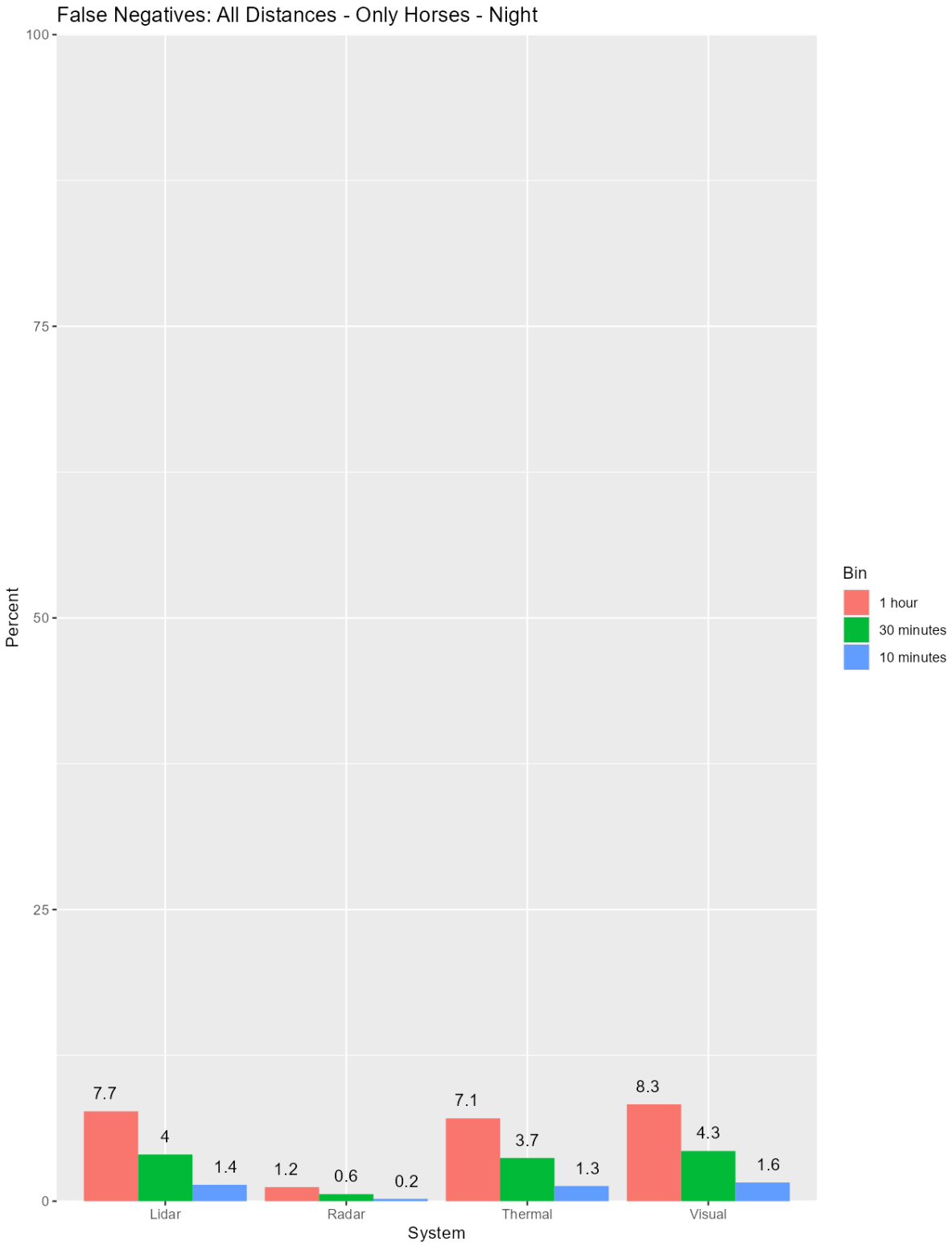

False Negatives: All Distances - Only Horses - Night
100
75
50
25
0
Percent
5.1
2.7
0.9
3.9
1.9
0.6
3.6
1.8
0.6
2.4
1.2
0.4
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

False Negative Time Bins:

Cycle 3 - Night:

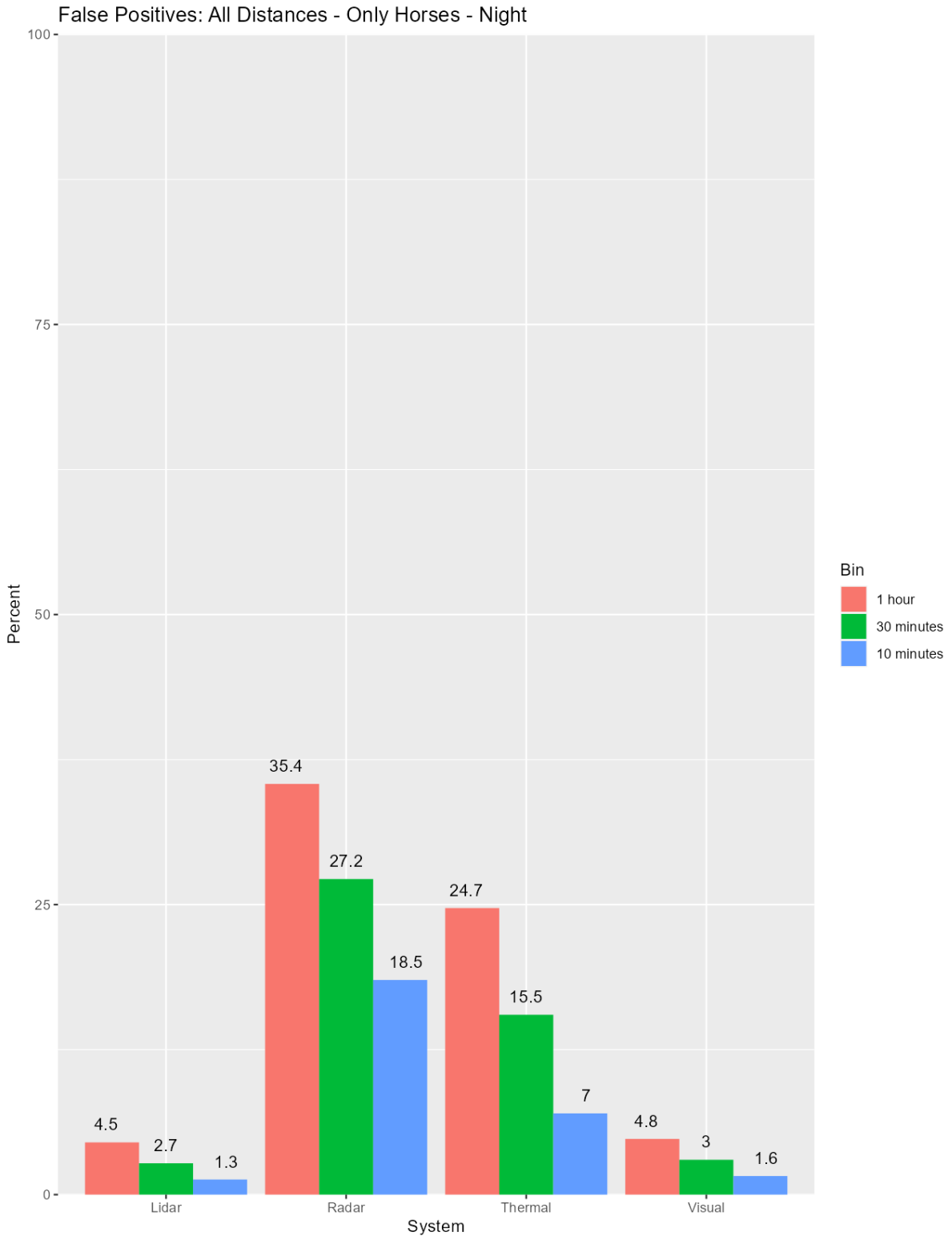


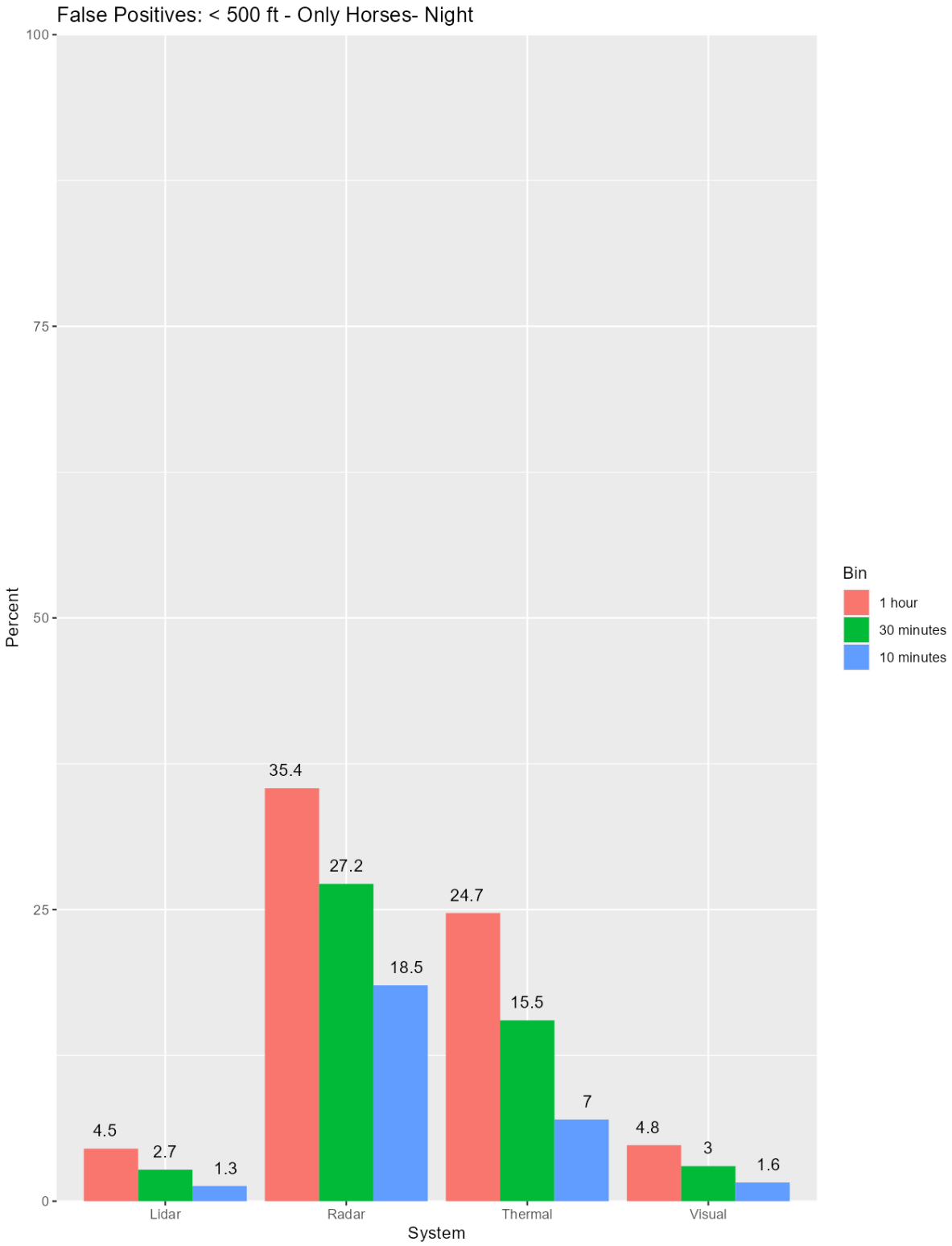

False Negatives: < 500 ft - Only Horses - Night
100
75
50
25
0
Percent
7.7
4
0
0
0
0.6
0.3
0.1
8.3
4.3
1.6
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

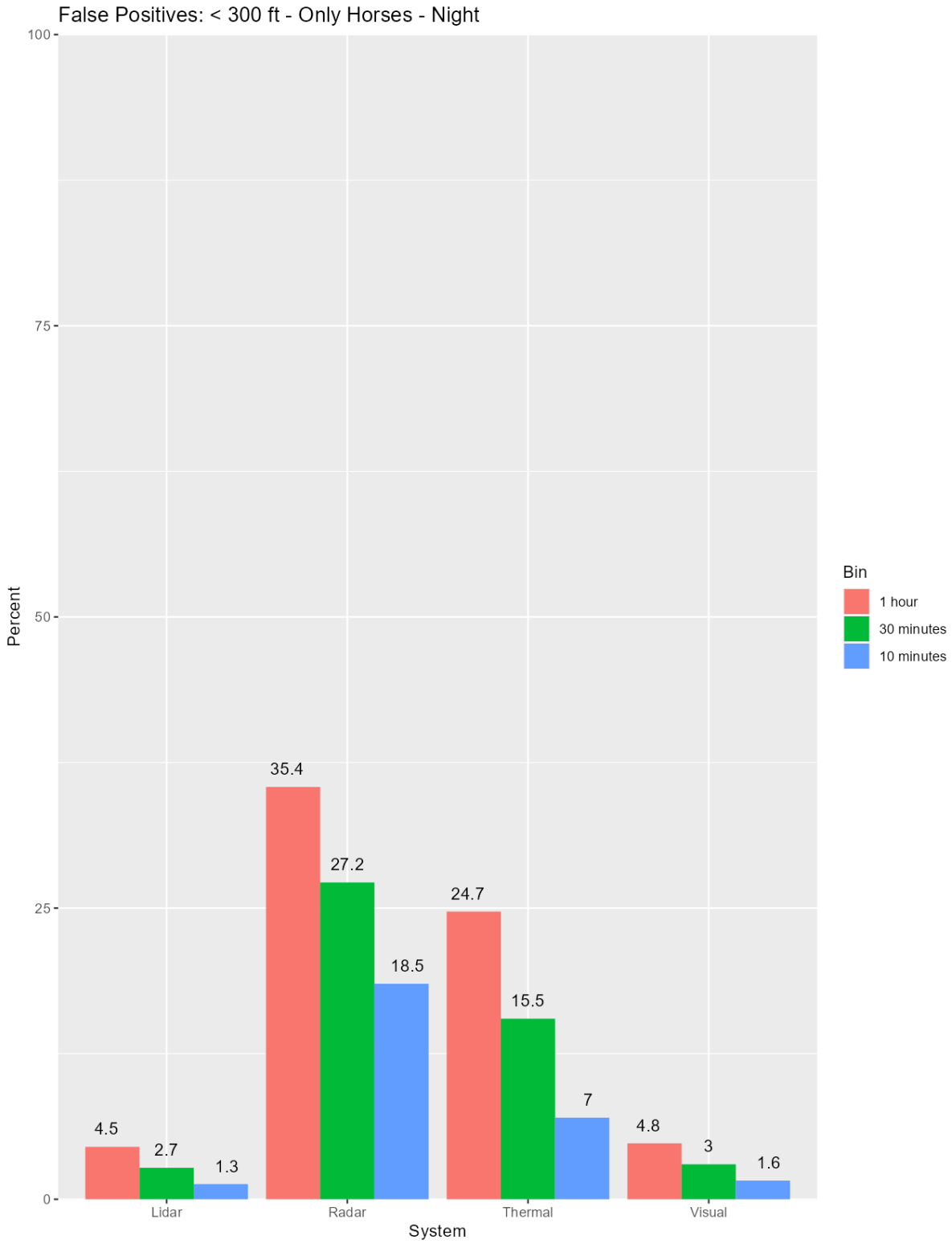

False Negatives: All Distances - Only Horses - Night
100
75
50
25
0
Percent
7.7
4
1.4
1.2
0.6
0.2
7.1
3.7
1.3
8.3
4.3
1.6
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

False Positive Time Bins:

Cycle 1 - Night:

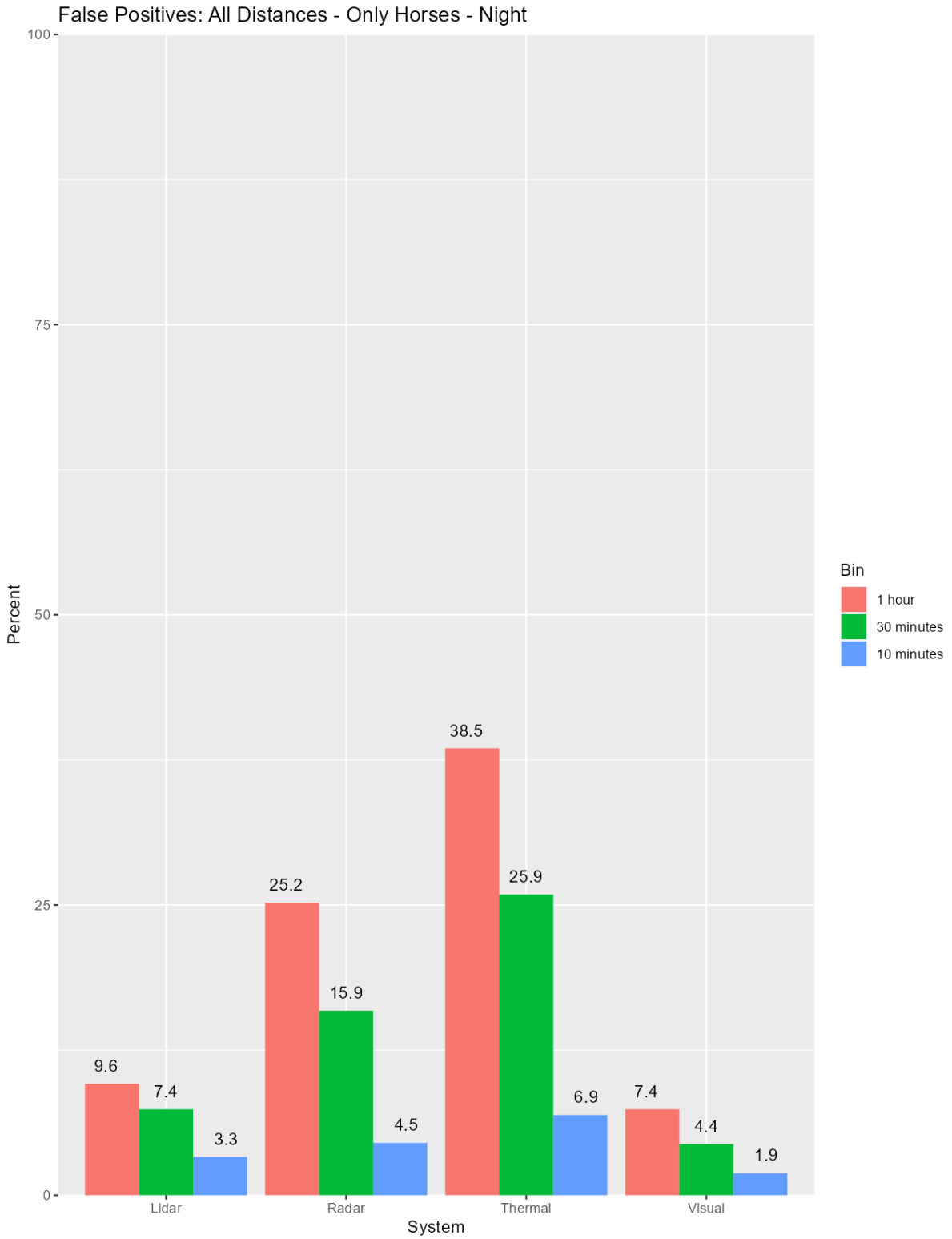


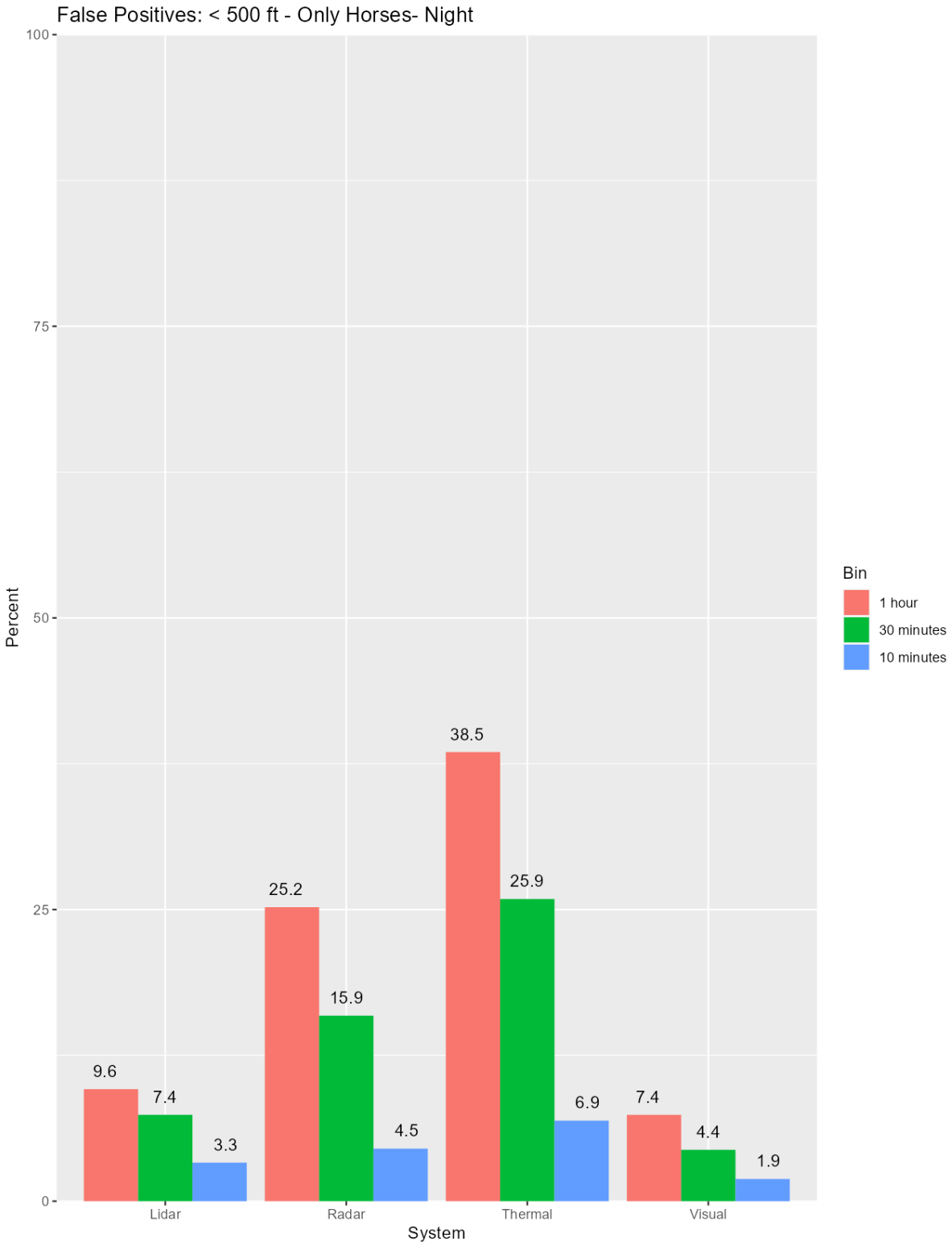

False Positives: < 500 ft - Only Horses- Night
100
75
50
25
0
Percent
4.5
2.7
1.3
35.4
27.2
18.5
24.7
15.5
7
4.8
3
1.6
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

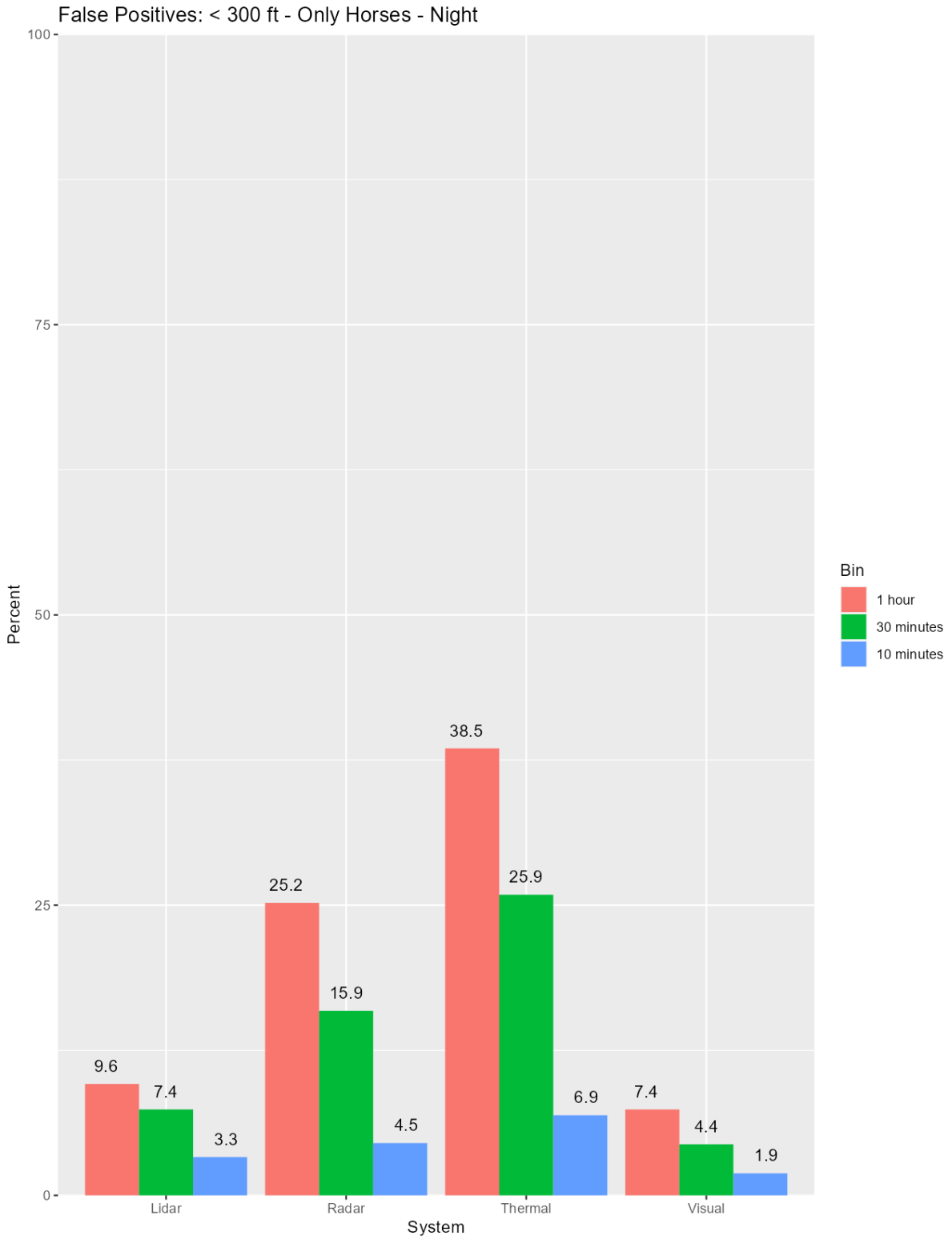

False Positives: < 300 ft - Only Horses - Night
100
75
50
25
0
Percent
4.5
2.7
1.3
35.4
27.2
18.5
24.7
15.5
7
4.8
3
1.6
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

False Positive Time Bins:

Cycle 2 - Night:

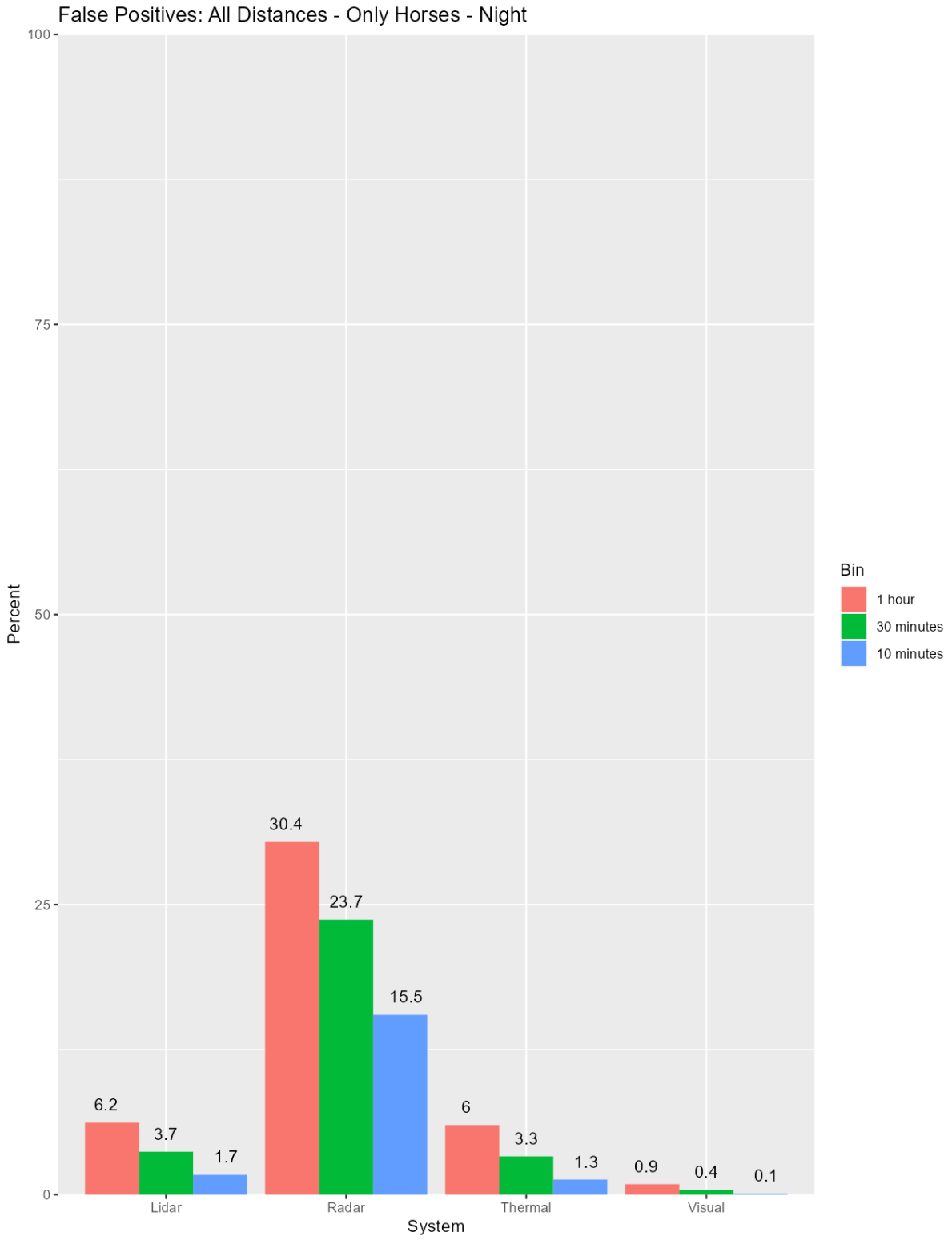


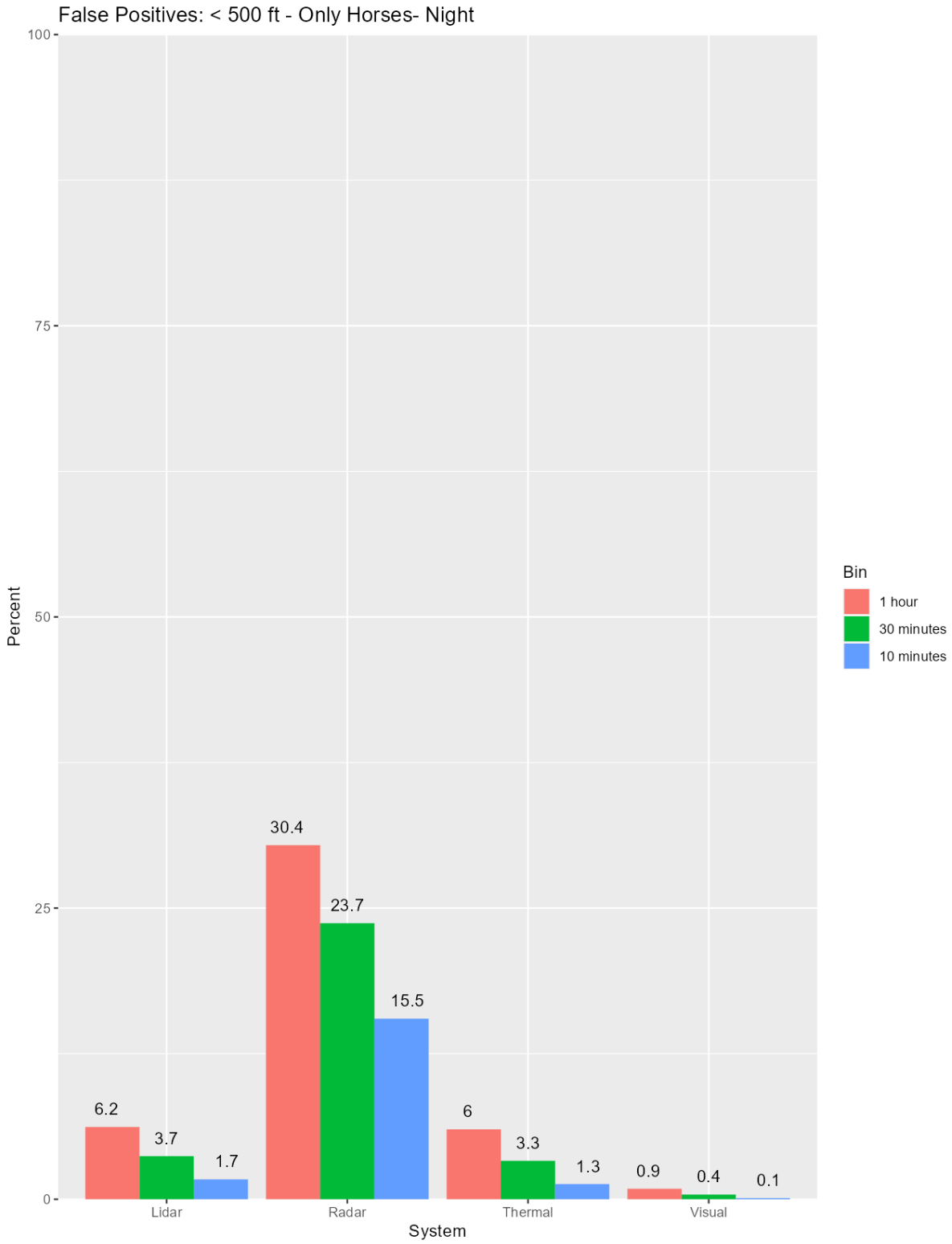

False Positives: < 500 ft - Only Horses- Night
Percent
100
75
50
25
0
9.6
7.4
3.3
25.2
15.9
4.5
38.5
25.9
6.9
7.4
4.4
1.9
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

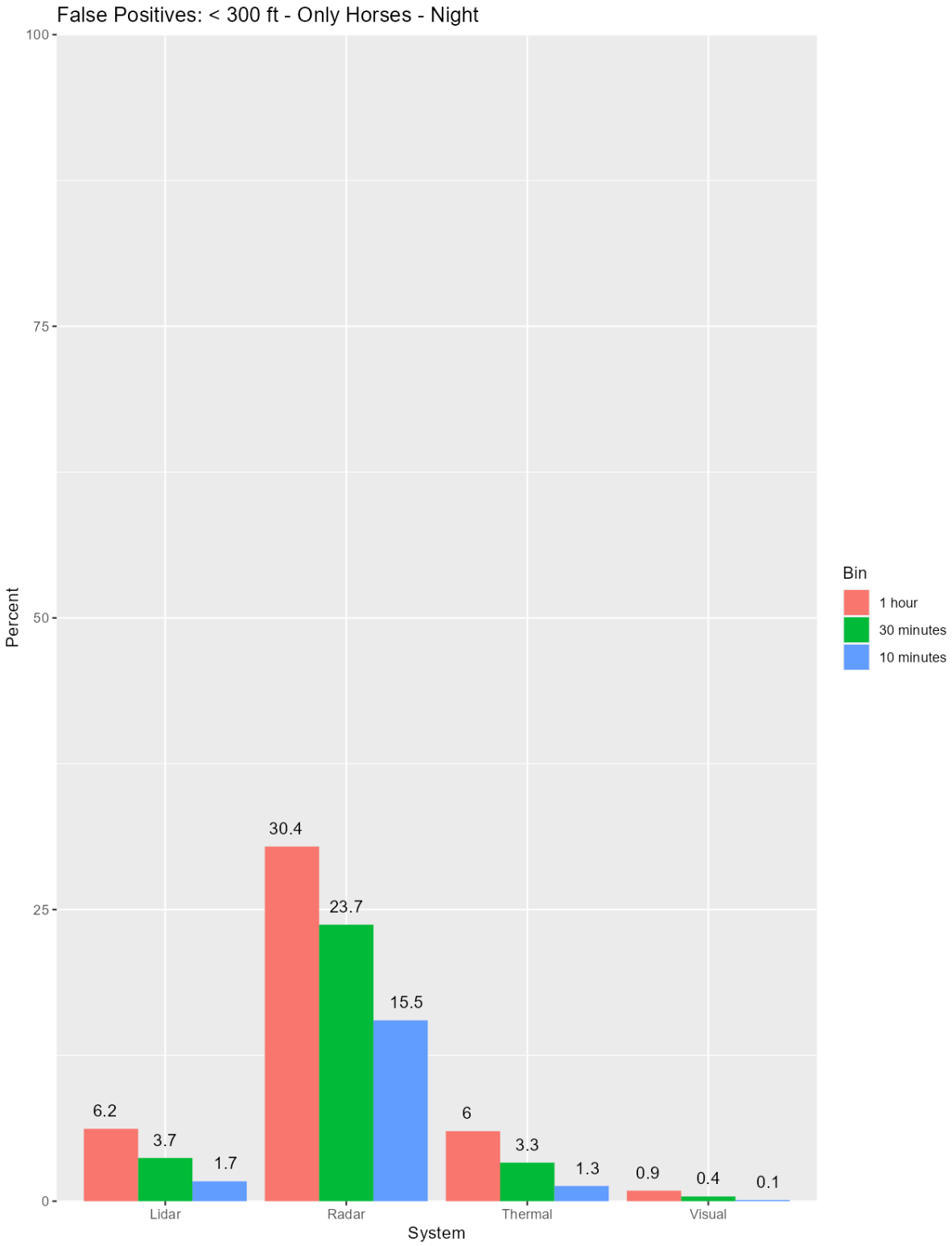

False Positives: < 300 ft - Only Horses - Night
100
75
50
25
0
Percent
9.6
7.4
3.3
25.2
15.9
4.5
38.5
25.9
6.9
7.4
4.4
1.9
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

False Positive Time Bins:

Cycle 3 - Night:

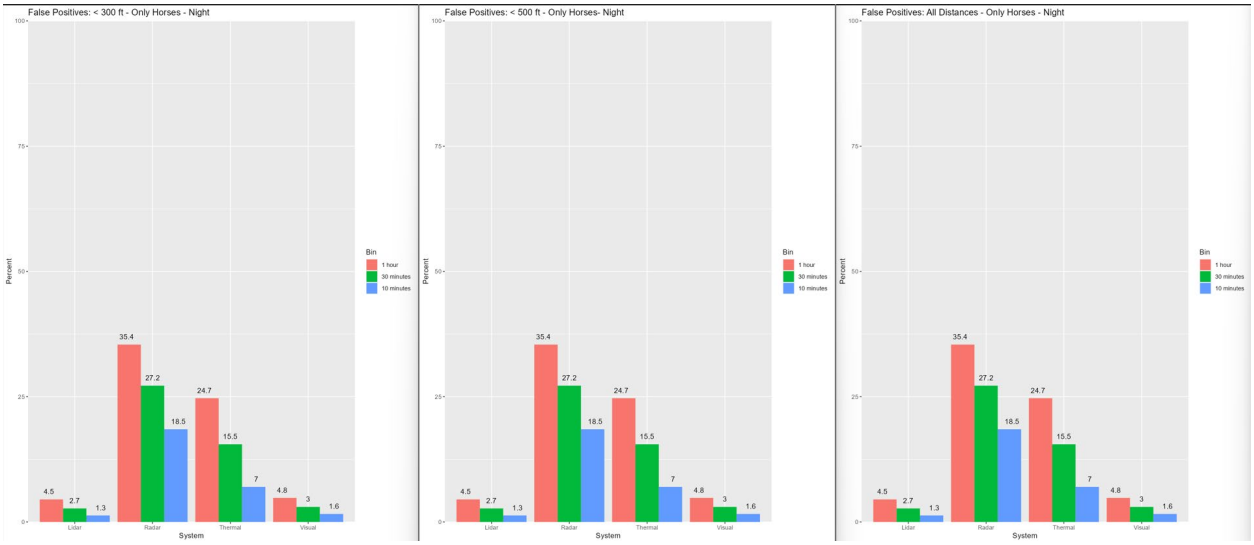



False Positives: < 500 ft - Only Horses- Night
Percent
100
75
50
25
0
6.2
3.7
1.7
30.4
23.7
15.5
6
3.3
1.3
0.9
0.4
0.1
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

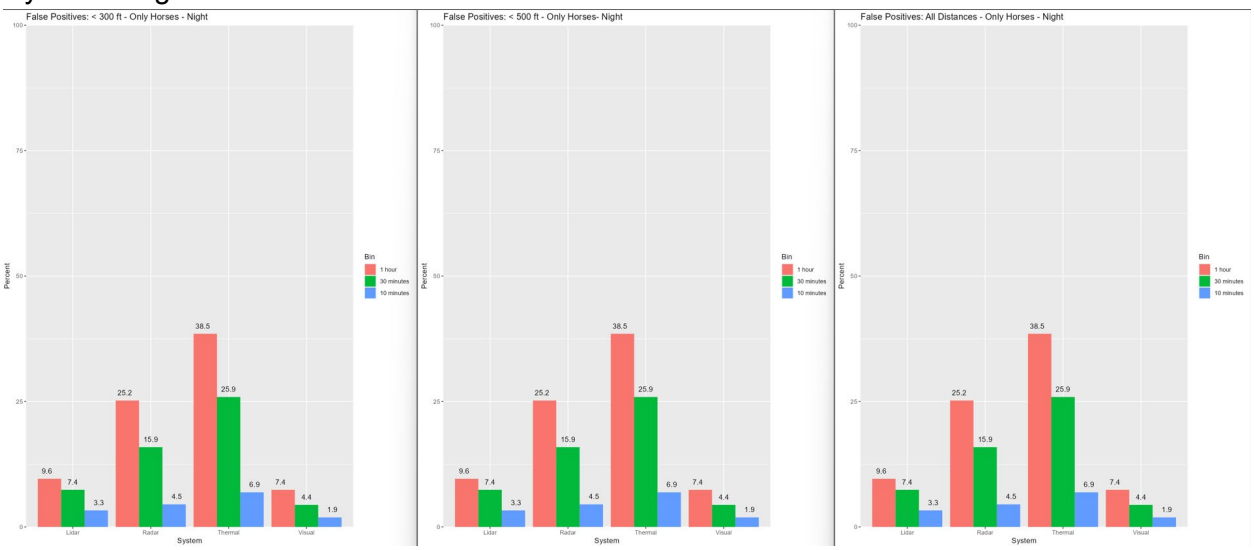

False Positives: < 300 ft - Only Horses - Night
100
75
50
25
0
Percent
6.2
3.7
1.7
30.4
23.7
15.5
6
3.3
1.3
0.9
0.4
0.1
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

False Positive Side-by-Side Results :

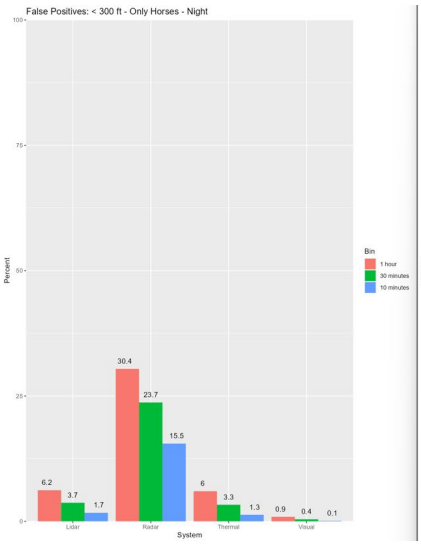
Cycle 1 - Night:

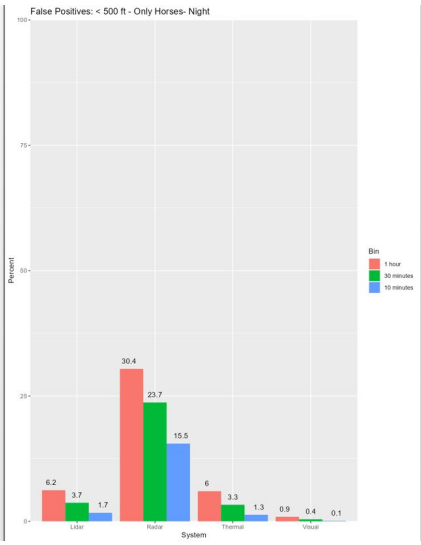


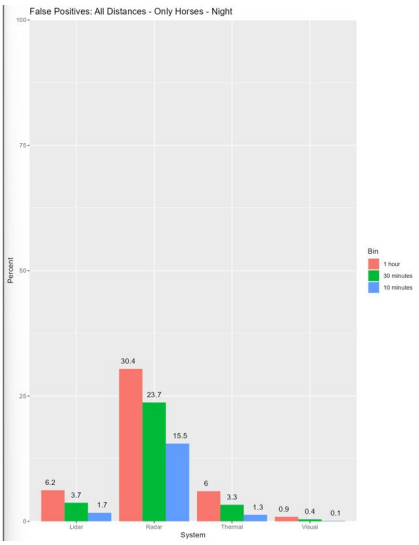
Cycle 2 - Night:



Cycle 3 - Night:

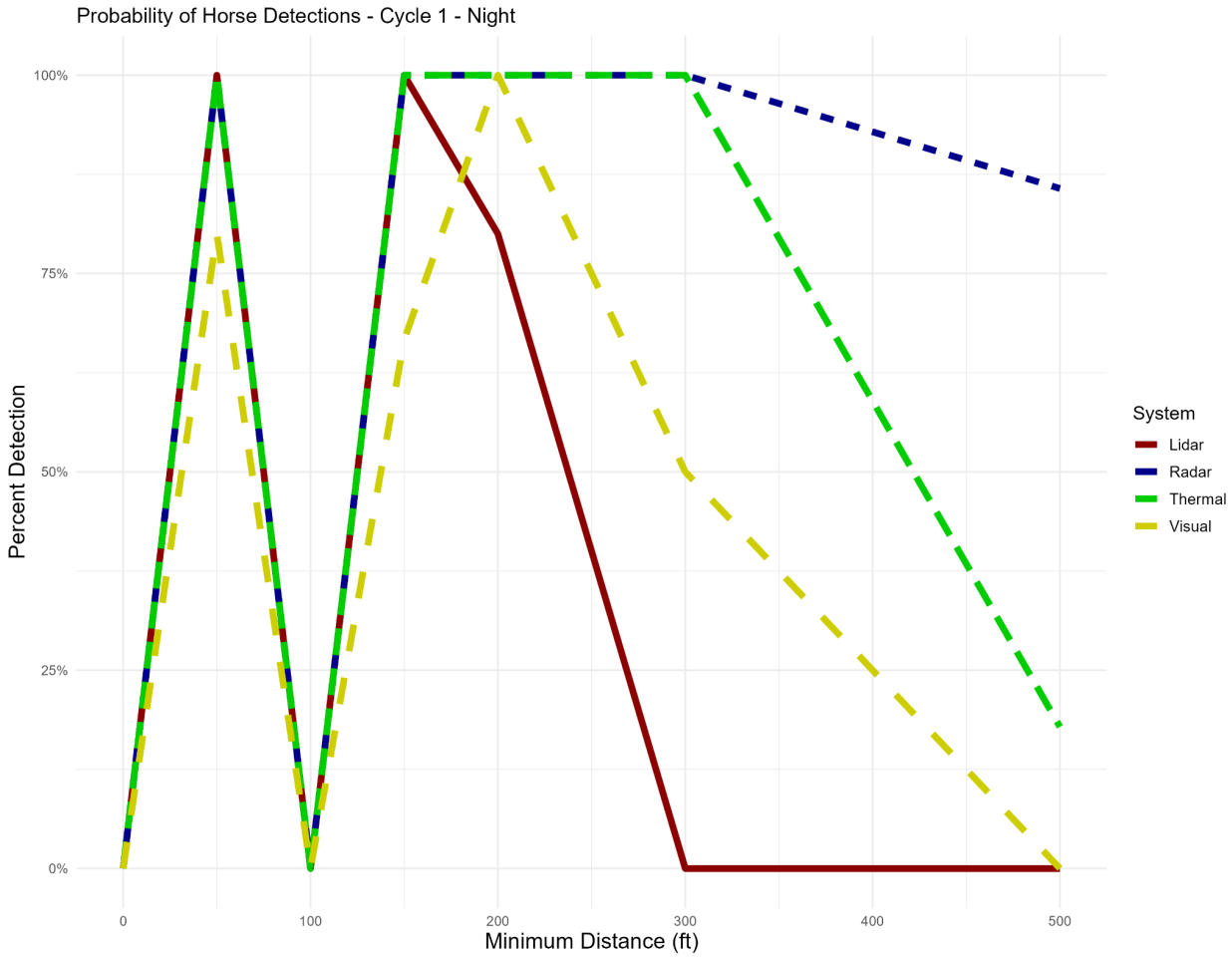

False Positives: < 300 ft - Only Horses - Night
Percent
100
75
50
25
0
6.2
3.7
1.7
30.4
23.7
15.5
6
3.3
1.3
0.9
0.4
0.1
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes


False Positives: < 500 ft - Only Horses- Night
Percent
100
75
50
25
0
6.2
3.7
1.7
30.4
23.7
15.5
6
3.3
1.3
0.9
0.4
0.1
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

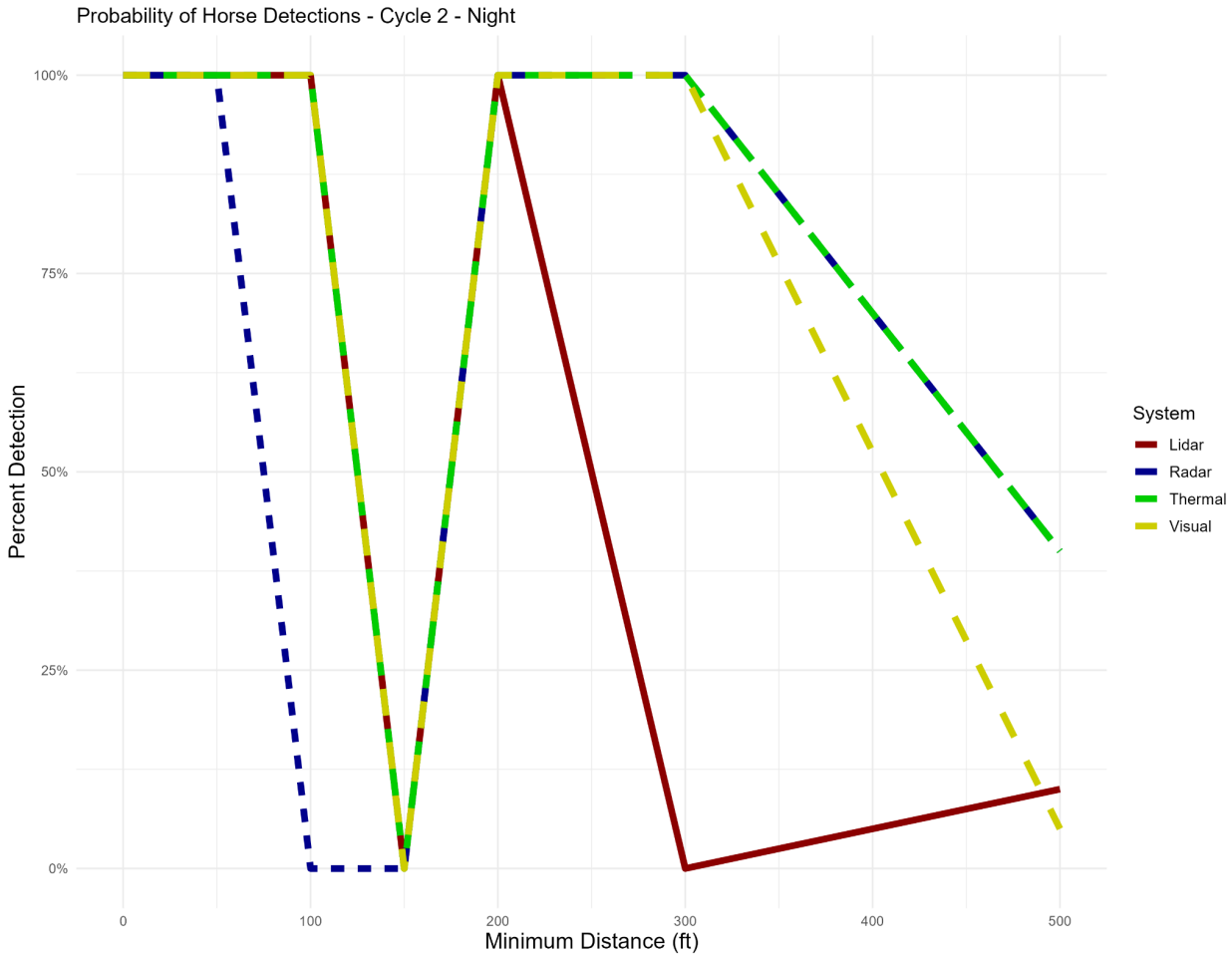

False Positives: All Distances - Only Horses - Night
Percent
100
75
50
25
0
6.2
3.7
1.7
30.4
23.7
15.5
6
3.3
1.3
0.9
0.4
0.1
Lidar
Radar
Thermal
Visual
System
Bin
1 hour
30 minutes
10 minutes

Probability of Detection - Minimum Distance Line Charts

Cycle 1 - Night:

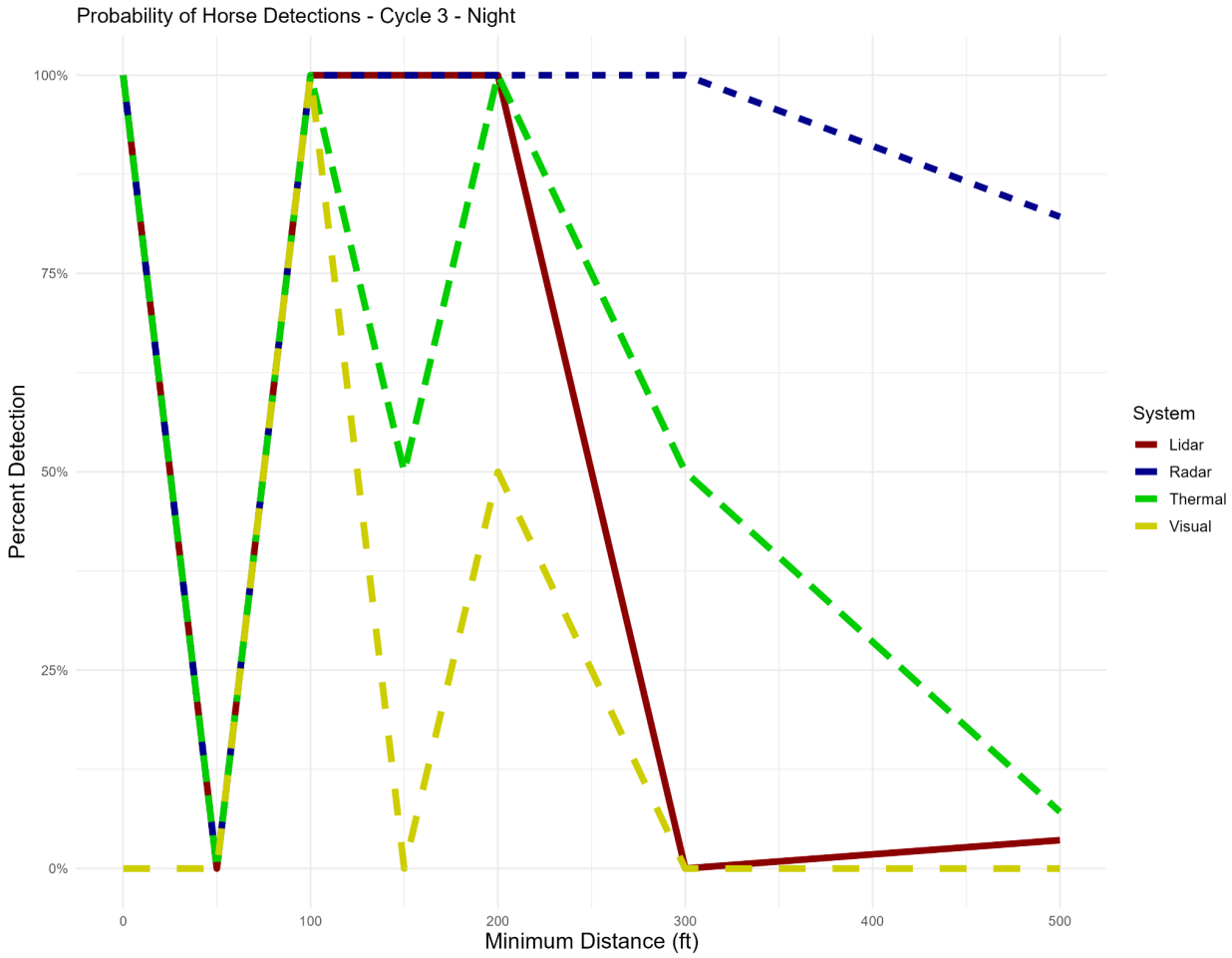


Probability of Detection - Minimum Distance Line Charts
Cycle 2 - Night:



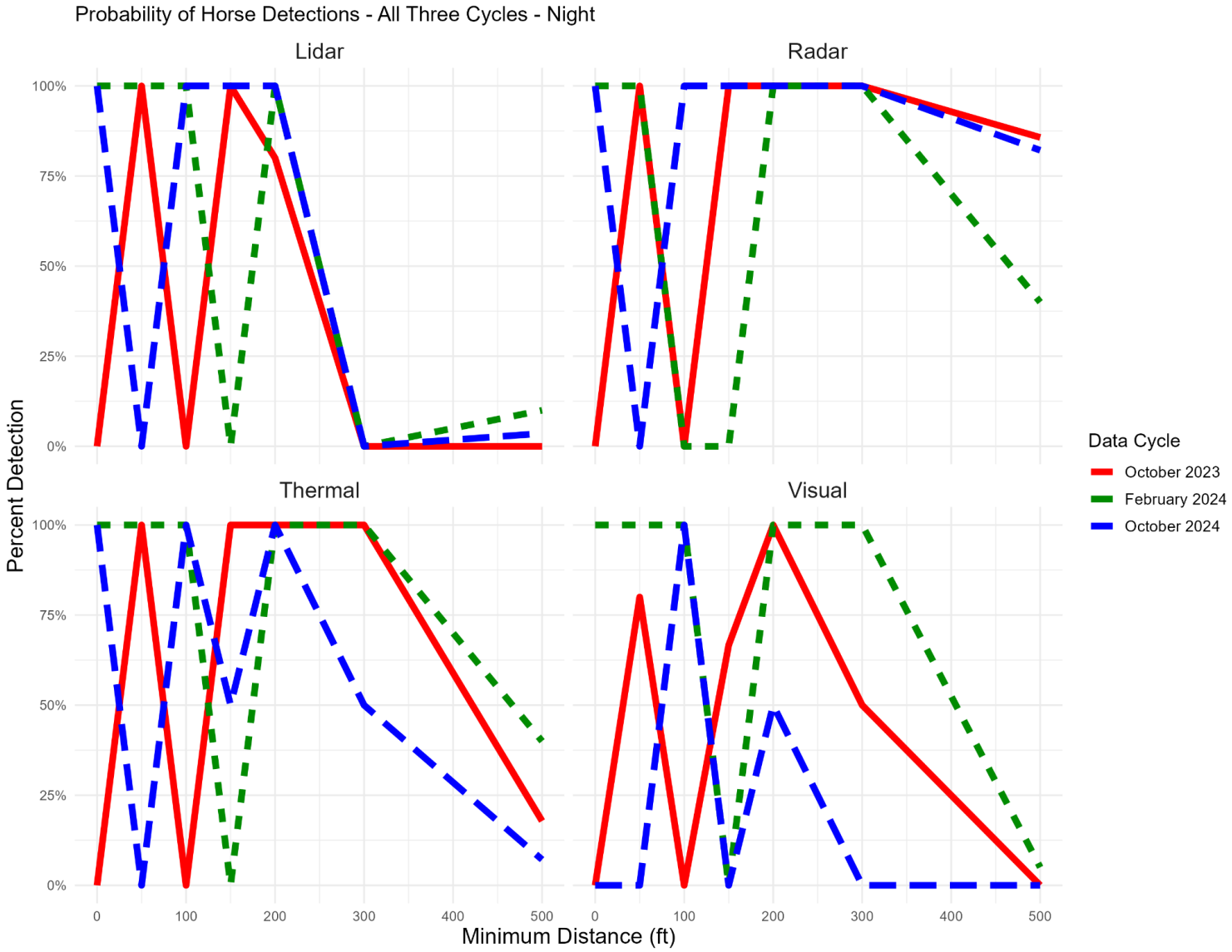
Probability of Detection - Minimum Distance Line Charts

Cycle 3 - Night:



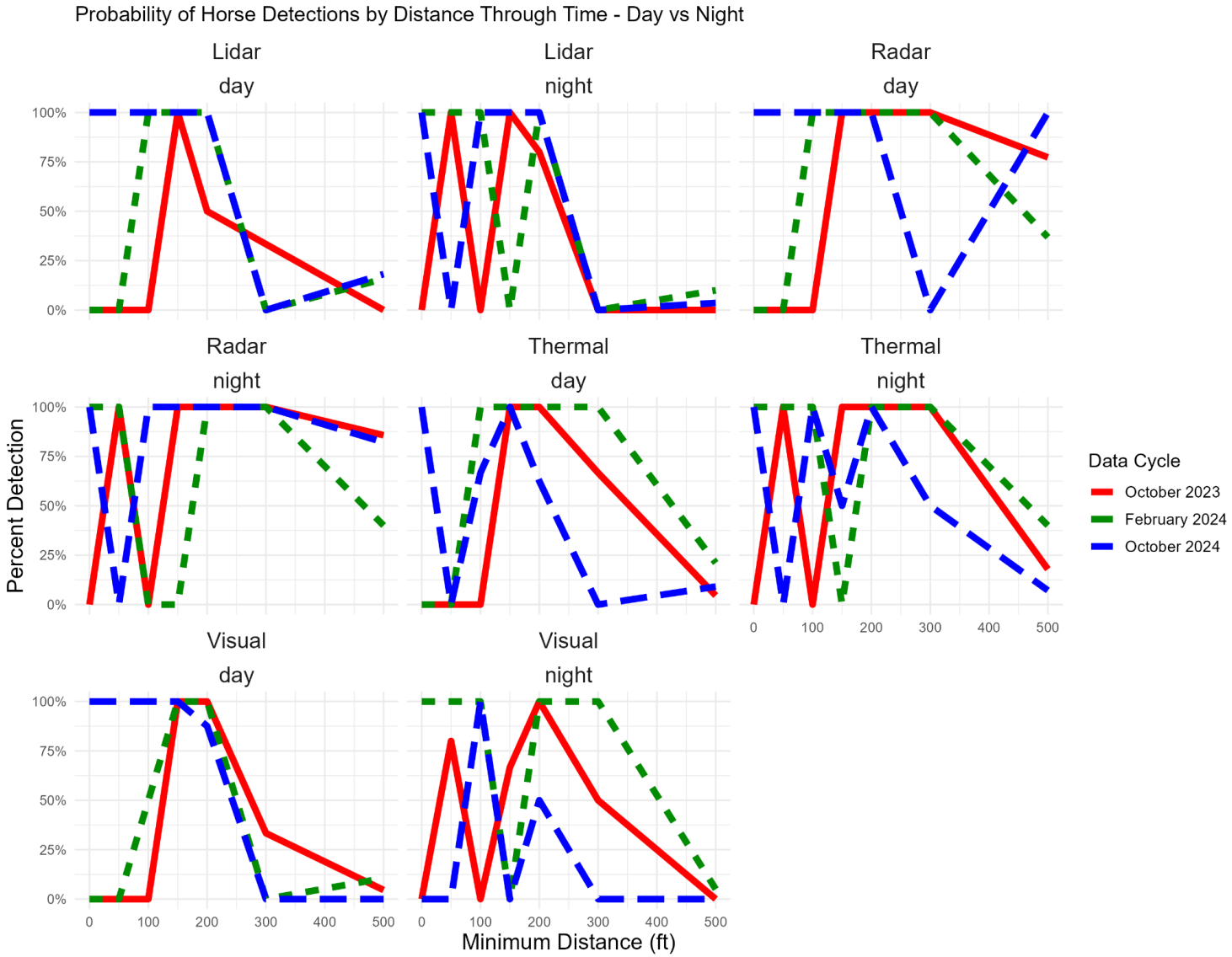
Probability of Detection - Minimum Distance Line Charts

All Three Cycles - Night:



Probability of Detection - Minimum Distance Line Charts

All Three Cycles - Day vs Night:





Nevada Department of Transportation

Tracy Larkin-Thomason, P.E. Director

Lucy Koury, Research Division Chief

(775) 888-7223

lkoury@dot.nv.gov

1263 South Stewart Street

Carson City, Nevada 89712