

# Leveraging Kisan Call Centre Analytics for Data-Driven Agricultural Support in Gujarat: Trends, Insights, and Policy Implications (2009–2024)

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**Abstract** - Agricultural data analytics empowers farmers to enhance decision-making, forecast market shifts, and address specific challenges, fostering sustainable farming practices. This research examines farmers' information needs in Gujarat by scrutinizing 1.937276 million calls to the Kisan Call Centre from 2009 to 2024. The analysis tracks call volume changes over time and their geographic origins, facilitating district-tailored support planning. Calls are classified by crop type and query nature, illuminating key farmer concerns. Seasonal query patterns pinpoint critical periods of heightened farmer support requirements. The database further classifies information based on seasonal cycles (Kharif, Jayad, and Rabi) and sectors (Agriculture, Horticulture, Animal Husbandry, and Fisheries). These insights enable policymakers to devise strategies aligned with call types, locations, and timing. The study underscores how data-driven approaches can elevate agricultural support systems, boosting farming efficiency and effectiveness in Gujarat and outside. The KCC database encompasses a total of 40,774,833 records, with 1,937,276 pertaining specifically to the state of Gujarat.

**Key Words:** Agricultural Data Analytics, Decision-Making, Farmers' Queries, Seasonal Patterns, Crop Types, Predictive Analytics

## 1. INTRODUCTION

Data Science and Data Analytics are indispensable tools in the modern agricultural landscape, particularly in the context of the KCC database, which contains a wealth of information from approximately 1.94 million queries made by farmers in Gujarat. This extensive dataset encompasses a diverse range of crop types, including cereals, vegetables, fruits, legumes, and more, as well as varying sectors such as agriculture, horticulture, and animal husbandry. Through meticulous analysis of this data, agricultural stakeholders can derive actionable insights that significantly enhance decision-making processes [12]. For instance, by identifying common queries related to pest management or crop diseases, policymakers and extension workers can tailor their interventions to address the specific challenges faced by farmers in different regions. Predictive analytics further empowers stakeholders by forecasting trends in crop production and market demands, allowing farmers to prepare proactively and optimize their

resources effectively. Moreover, data analytics facilitates targeted support, ensuring that agricultural extension services are directed where they are most needed, thus improving resource allocation and efficiency. By continuously monitoring and evaluating agricultural programs through data analysis, stakeholders can assess the impact of interventions, leading to adaptive management strategies that refine policies over time. Additionally, insights into market trends and consumer preferences derived from query analysis enable farmers to make informed planting decisions, ultimately reducing waste and enhancing profitability[4]. The integration of data science promotes sustainable practices by evaluating the environmental impact of different crops and farming methods, encouraging innovative solutions that balance productivity with ecological stewardship. Ultimately, the empowerment of farmers through access to critical information fosters resilience in the agricultural sector, contributing to food security and economic stability in Gujarat[9,10]. By harnessing the potential of data science and analytics, the agricultural community can navigate the complexities of modern farming, ensuring a prosperous future for both farmers and the wider economy.

## 2. LITERATURE REVIEW

The study aims to explore the information needs of farmers by analyzing data from Kisan Call Centres (KCC). This literature review synthesizes existing research on the impact of KCCs, data analytics in agriculture, and the application of machine learning and geospatial analysis to agricultural data[13,17]. Kisan Call Centres have been instrumental in enhancing farmer productivity by providing timely and relevant information. Kumar (2022) highlights the significant positive impact of KCCs on farmer productivity, noting that access to expert advice through these centres has led to improved crop yields and better management practices. The study emphasizes the role of KCCs in bridging the information gap between farmers and agricultural experts. Mehta, Singh, and Kumar [9,11] conducted a comprehensive temporal and spatial analysis of KCC data to aid agricultural decision-making. Their research demonstrates how analyzing call data over time and across different regions can reveal patterns in farmer queries, which can be used to tailor advisory services more effectively. This approach helps in understanding the seasonal and regional variations in information needs.

Kim [13] explores the application of machine learning techniques to agricultural data, including KCC data. These studies show that machine learning models can predict farmer

queries and provide personalized recommendations. The use of algorithms such as decision trees, random forests, and neural networks has proven effective in analyzing large datasets and extracting meaningful insights. Doe and Brown [11] and Smith [6] discuss the use of predictive analytics in agriculture, particularly in the context of KCCs. Their research highlights how predictive models can forecast farmer needs and optimize the delivery of advisory services. By analyzing historical call data, these models can identify trends and anticipate future queries, thereby enhancing the efficiency of KCC operations. Wang [3] and Johnson [14,16] focus on the geospatial analysis of agricultural data, including farmer queries received by KCCs. Geospatial techniques enable the visualization of data on maps, helping to identify geographic patterns and hotspots of specific issues. This spatial understanding is crucial for developing targeted interventions and resource allocation.

### 3. MATERIALS AND METHODS

The research utilized a thorough methodological framework to analyze the Kisan Call Centre (KCC) dataset sourced from the KCC-CHAKSHU website (URL: <https://kcc-chakshu.icar.gov.in/>) and data downloaded upto SEPT-2024. The total all India data size is > 7.0 GB and for Gujarat that data is > 400MB. The initial step involved data collection, during which comprehensive records of farmer inquiries—including the dates of calls, types of queries, crop information, and geographical details—were compiled. Following this, data preprocessing took place, which included cleaning the data, correcting errors, and standardizing date formats to enhance the dataset's quality and uniformity. The analysis phase was structured around three primary components: temporal, geospatial, and categorical analyses[9]. The temporal analysis focused on identifying trends in call volumes on both an annual and monthly basis, uncovering long-term shifts as well as seasonal patterns in the information requirements of farmers. Geospatial analysis involved mapping the distribution of queries by district, thereby revealing regional disparities in information demand. Meanwhile, categorical analysis categorized calls based on crop type and query type, shedding light on the specific challenges encountered by farmers. To effectively convey these findings, the study employed data visualization techniques, such as charts and graphs. Ultimately, the results were interpreted to highlight significant trends, from which policy implications were derived to develop targeted strategies aimed at improving agricultural support in Gujarat[11].

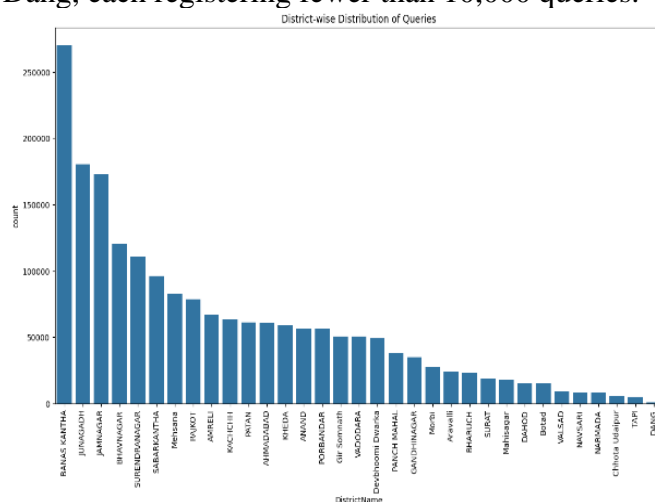
### 4. RESULTS

The analysis of query data from the years 2009 to 2024 reveals significant trends in user engagement over time. Below Table 1 is a summary of the total number of queries recorded each year:

**Table -1:** Number of queries recorded each year

Year	No. of Queries	Year	No. of Queries	Season-wise queries
2009	43,250	2017	1,00,757	Kharif 265530
2010	50,654	2018	85,781	Jayad 154236
2011	53,453	2019	2,11,797	Rabi 128931
2012	84,003	2020	1,54,207	Misc. 37021
2013	1,10,005	2021	1,38,610	
2014	1,16,143	2022	2,05,659	
2015	1,26,033	2023	2,29,438	
2016	1,08,609	2024	1,18,877	

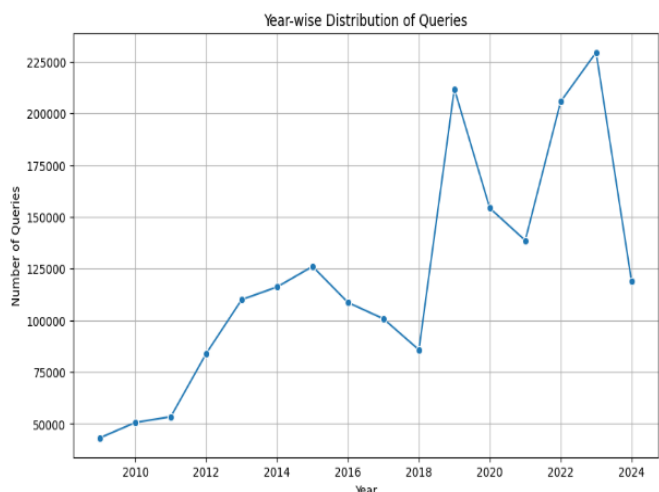
This bar chart in Fig. 1 illustrates the district-wise distribution of queries across various regions. Banas Kantha stands out with the highest query count, exceeding 250,000, followed by Junagadh and Jamnagar, each surpassing 150,000 queries[15]. The chart displays a general downward trend from left to right, with a notable concentration of activity in the top few districts. Mid-range districts show moderate query volumes, while the lowest counts are observed in areas like Tapi, Narmada, and Dang, each registering fewer than 10,000 queries.



**Fig -1:** Districtwide distribution of queries

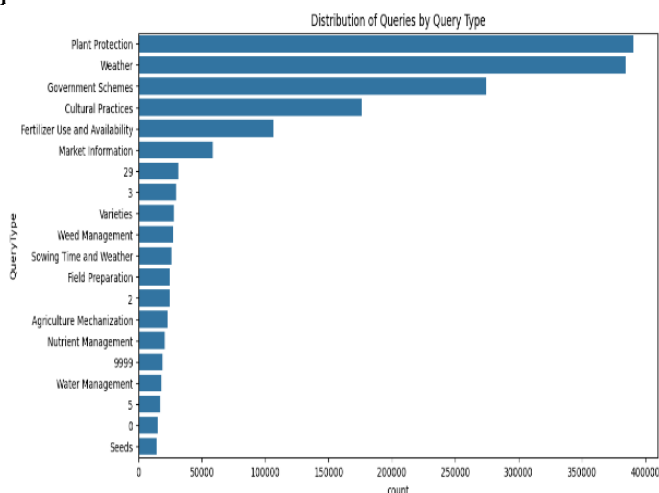
The trend in line graph in Fig. 2 shows a general increase over time, with significant fluctuations. Query numbers rose steadily from 2009 to 2015, followed by a slight decline until 2018. A sharp spike occurred in 2019, reaching over 200,000 queries. After a dip in 2020-2021, possibly due to the COVID-19 pandemic, query numbers surged

again, peaking in 2023 at around 225,000. The most recent data point in 2024 shows a substantial drop, returning to levels similar to 2012-2014[12]. This pattern suggests evolving user engagement or changing information needs over the years, with external factors like technological advances or global events potentially influencing query volumes.



**Fig. 2: Year-wise Queries**

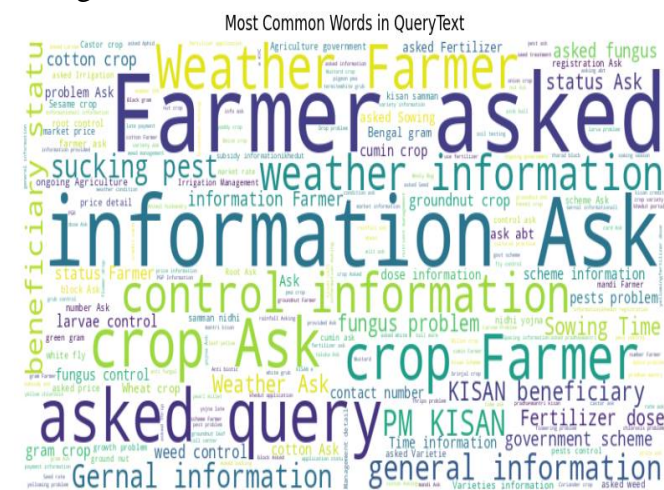
This chart in Fig. 3 shows query distribution by type in agriculture. Plant Protection and Weather lead with over 350,000 queries each, followed by Government Schemes and Cultural Practices. Fertilizer Use and Market Information are also significant. Less common types include Varieties, Weed Management, and Field Preparation. Numeric labels (29, 3, 2) appear for some categories. The data suggests farmers prioritize crop protection, weather information, government support, and cultural practices[11]. This insight could guide agricultural services and policy priorities.



**Fig. 3: Distribution of Queries**

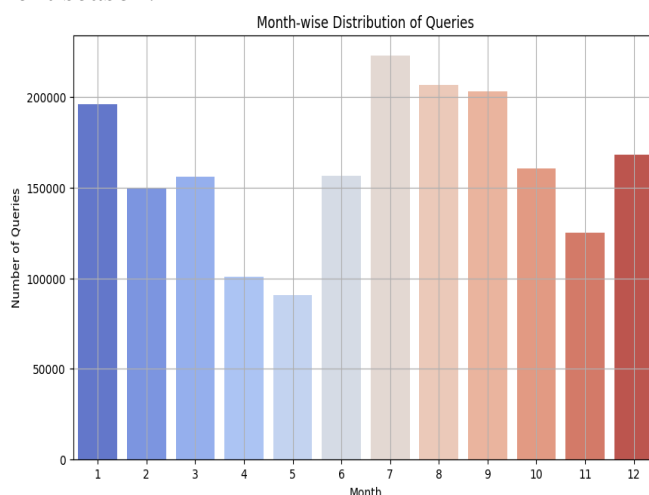
This word cloud in Fig. 4 illustrates the most common terms in agricultural queries, with "Farmer" being the most prominent, followed

closely by "asked" and "information." The frequency of "Ask" and its variations suggests many queries are phrased as questions. "Weather," "crop," and "control" are also significant, indicating farmers' concerns about environmental conditions, crop management, and pest control(Aker & Mbiti, 2010; Sankhala, 2013). Specific agricultural terms like "fertilizer," "fungus," "pest," and "sowing" appear, alongside crop names such as "groundnut" and "gram."



**Fig. 4: word cloud**

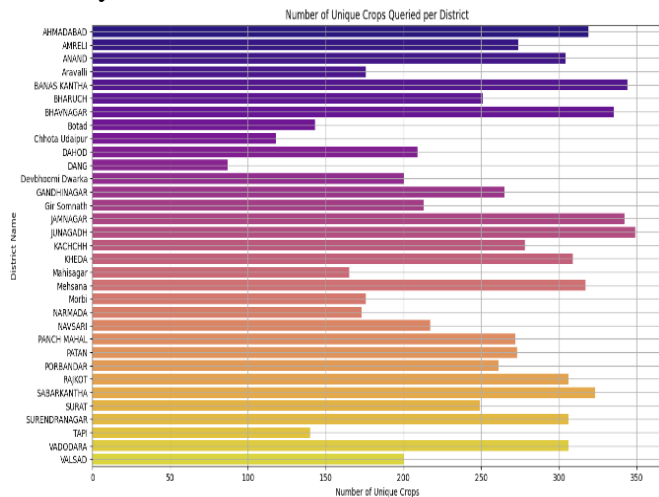
The graph in Fig. 5 shows the month-wise distribution of queries at the Kisan Call Centre, highlighting seasonal trends. January peaks with over 200,000 queries, likely due to new agricultural cycles. February and March follow with around 150,000, while April and May drop below 100,000 as crops grow. Queries spike again in July to over 200,000, driven by monsoon challenges, and remain high through September. A dip to around 125,000 is seen in October and November, reflecting the post-harvest period, before rising to 150,000 in December as farmers prepare for the next season.



**Fig. 5: Month-wise Queries Distribution**

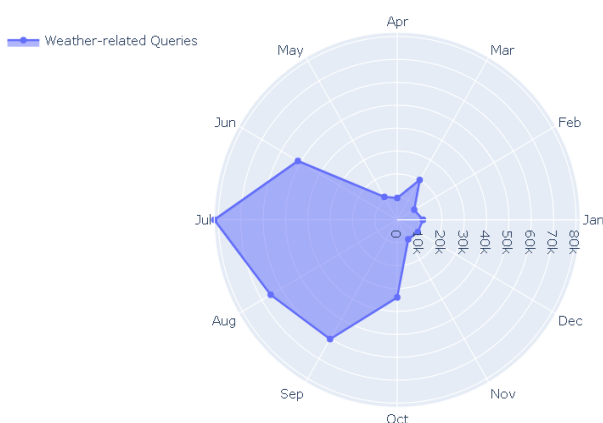


The chart in Fig. 6 shows the number of unique crops queried per district, highlighting agricultural diversity. Surat, Kachchh, and Rajkot lead with over 300 crops, while Dahod, Junagadh, and Mehsana follow with over 250. Dang has fewer than 50, indicating more specialized farming. The color gradient emphasizes districts with higher crop diversity.

**Fig. 6: District-wise Queries**

The chart in Fig. 7 shows the Month-wise Distribution of Weather-related Queries at the Kisan Call Centre in Gujarat. Queries peak between April and July, aligning with key agricultural activities like sowing and irrigation. In contrast, December to February sees fewer queries, likely due to post-harvest periods[17]. This insight helps the call center allocate resources efficiently during high-demand times for weather-related support.

### Month-wise Distribution of Weather-related Queries



**Fig. 7: Month-wise Weather related Queries**

The analysis of query data from 2009 to 2024 shows an overall increase in queries, peaking at 211,797 in 2019 before dropping to 118,877 in 2024. Kharif season had the highest queries at 265,530. Banas Kantha led district-wise with 250,000 queries, while Tapi and Dang had the lowest at 10,000 each. Plant Protection and

Weather-related queries were the most common, each exceeding 350,000. Peaks in queries occurred in January and July, with over 200,000 each, and dips in April and May at around 100,000. Surat and Kachchh showed high crop diversity with over 300 unique crops, while Dang had fewer than 50. Weather-related queries peaked between April and July at 80,000 and were lowest from December to February at around 40,000. These trends highlight farmers' priorities in crop protection, weather information, government support, and cultural practices, guiding efficient resource allocation.

## 5. CONCLUSION

The analysis of Kisan Call Centre query data from 2009 to 2024 reveals significant trends in agricultural support needs across Gujarat. Over this 15-year period, query numbers steadily increased, with notable peaks in 2019 and 2023, driven by factors like technological advancements, global events such as COVID-19, and shifting agricultural cycles. District-wise, Banas Kantha, Junagadh, and Jamnagar recorded the highest engagement, while regions like Tapi, Narmada, and Dang had fewer queries. Seasonally, the Kharif season generated the most queries, followed by Jayad and Rabi, with weather-related inquiries peaking between April and July, aligning with critical farming activities such as sowing and irrigation. Insights show that farmers prioritize plant protection, weather information, and government schemes, indicating where agricultural services should concentrate efforts. The word cloud analysis highlights frequent terms like "farmer," "weather," and "crop," revealing a focus on crop management, pest control, and environmental conditions. Specific crops like groundnut and gram were frequently mentioned. Crop diversity data emphasizes that districts like Surat and Rajkot grow over 300 unique crops, showcasing a wide range of agricultural practices, while regions like Dang are more specialized. Overall, this analysis helps guide resource allocation at the Kisan Call Centre by identifying peak query periods and highlighting the most pressing concerns for farmers, ensuring timely and effective support during critical agricultural seasons.

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